Results

Notes:
- Some of this is already in or was based on the blogpost/interface code. Hit show to see code. I switch between R and Python
- Some of this won't make it to the paper. You can probably skip preprocessing unless you want to check certain things, example: did we make sure to remove judgments based on X condition - If you want to clarify/comment anything do so at https://github.com/sm11197/sm11197.github.io/blob/main/analysis/debate-0923.Rmd) or message me elsewhere

Preprocessing

Importing, filtering, and adding columns

We have 3 sets of data from the interface:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
pd.options.mode.chained_assignment = None  # default='warn'

# Load summaries that can be downloaded from the interface
debates = pd.read_csv("/Users/bila/git/for-debate/debate/save/official/summaries/debates.csv", keep_defa
sessions = pd.read_csv("/Users/bila/git/for-debate/debate/save/official/summaries/sessions.csv", keep_de
turns = pd.read_csv("/Users/bila/git/for-debate/debate/save/official/summaries/turns.csv", keep_default_
print(f' {debates.shape} - Debates') ;print(f'{sessions.shape} - Sessions, which has multiple rows (of p
```

```
##  (632, 29) - Debates
## (1863, 46) - Sessions, which has multiple rows (of participants) for each debate
## (6220, 16) - and Turns, which has multiple rows (of participant turns) for each debate
```

```
# Only include debates within a given period
debates["Start time"] = pd.to_datetime(debates["Start time"], unit="ms")
debates["End time"] = pd.to_datetime(debates["End time"], unit="ms")
debates["Last modified time"] = pd.to_datetime(debates["Last modified time"], unit="ms")
debates = debates[
    (debates["Start time"] > pd.to_datetime("10/02/23", format="%d/%m/%y")) &
    (debates["End time"] < pd.to_datetime("01/09/23", format="%d/%m/%y"))
]
### for filtering to when we had AI debates: 16/07/23
# Filter sessions & turns to only the selected debates
sessions = sessions.merge(debates[["Room name"]], how="inner", on="Room name")
turns = turns.merge(debates[["Room name"]], how="inner", on="Room name")
print(f'We have {len(debates)} debates when filtering out the initial pilots last fall')
```

```
## We have 583 debates when filtering out the initial pilots last fall
```

```python
# Secondary analysis: Question Difficulty
# Create new columns with bin labels
debates['Untimed annotator context bins'] = pd.cut(debates['Untimed annotator context'].round(), bins=[(
debates['Speed annotator accuracy bins'] = pd.cut(debates['Speed annotator accuracy'], bins=[-0.999, 0.(
## respectively, those speed annotator accuracies probably mean 0 right, 1 right, 2 right

debates['Final_Accuracy'] = debates['Final probability correct'] > 0.5

print(f'Average accuracy per context required by question:\n{debates.groupby("Untimed annotator context
```

```
## Average accuracy per context required by question:
##                                   Proportion_True  Total_Count
## Untimed annotator context bins
## 1                                        0.781250           64
## 2                                        0.711382          246
## 3                                        0.702857          175
## 4                                        0.632653           98
##
## <string>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in
```

```python
print(f'Average accuracy per difficulty based on speed annotator accuracy:\n{debates.groupby("Speed ann
```

```
## Average accuracy per difficulty based on speed annotator accuracy:
##                                  Proportion_True  Total_Count
## Speed annotator accuracy bins
## 0                                       0.728682          129
## 0.2                                     0.697509          281
## 0.4                                     0.694118          170
## Hm, this seems less likely to be a good indicator of question difficulty
##
## <string>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in
```

```python
# Determine settings for each row
def setups(row):
    if 'GPT-4' in (row['Honest debater'], row['Dishonest debater']):
        if row['Is single debater']:
            return "AI Consultancy " + ("Honest" if row['Has honest debater'] else "Dishonest")
        else:
            return "AI Debate"
    else:
        if row['Is single debater']:
            return "Human Consultancy " + ("Honest" if row['Has honest debater'] else "Dishonest")
        else:
            return "Human Debate"

debates['Setting'] = debates.apply(setups, axis=1)
# Agregate settings - the 4 that we normally talk about:
debates['Final_Setting'] = debates['Setting'].str.replace(' Honest', '').str.replace(' Dishonest', '')
```

Merging, filtering for judgments

```
# Merge sessions with debates, so we have each judge's final probability correct and the debate's metad
source = sessions.merge(
        debates[["Room name", "Debater A","Debater B","Honest debater", "Dishonest debater",
                 "Is single debater", 'Has honest debater',
                 "Final_Setting", "Setting",
                 "Question", "Article ID",
                 "Speed annotator accuracy bins","Untimed annotator context bins",
                 "Speed annotator accuracy","Untimed annotator context", "Is offline",
                 'End time', 'Last modified time']],
        how="left",
        on="Room name",
    )
print(f'After merging debates with sessions, we have the following participant counts for those debates
```

```
## After merging debates with sessions, we have the following participant counts for those debates:
## Role
## Judge            549
## Debater B        487
## Debater A        458
## Offline Judge    223
## Name: count, dtype: int64
```

```
#[source['Is over'] == True] to check for completed online/offline debates

# Filter out incomplete judgments
judgments = source[source['Final probability correct'].notnull()]
print(f'After filtering to judges that have finalized their judgment, we have the following judgments p
```

```
## After filtering to judges that have finalized their judgment, we have the following judgments per rol
## Role
## Judge            508
## Offline Judge    214
## Name: count, dtype: int64
## for a total of 722 judgments.
```

```
judgments['Final_Accuracy'] = judgments['Final probability correct'] > 0.5

print(f'Of those judgments, we have this much for each setting (not consolidating honest - dishonest co
```

```
## Of those judgments, we have this much for each setting (not consolidating honest - dishonest consulta
## Setting
## Human Debate                     413
## AI Debate                         92
## Human Consultancy Dishonest       68
## AI Consultancy Honest             56
## Human Consultancy Honest          53
## AI Consultancy Dishonest          40
## Name: count, dtype: int64
```

```python
print(f'Of those judgments, we have this much for each setting (aggregated):\n{judgments.groupby("Final_
```

```
## Of those judgments, we have this much for each setting (aggregated):
##                      Proportion_True  Total_Count
## Final_Setting
## AI Consultancy              0.802083           96
## AI Debate                   0.782609           92
## Human Consultancy           0.719008          121
## Human Debate                0.876513          413
```

```python
# Remove judges who see the story more than once
judgments['base_room_name'] = judgments['Room name'].str.extract('(.*)\d+$', expand=False).fillna(judgme
judgments = judgments.sort_values(by=['base_room_name','End time']).groupby(['Participant', 'base_room_

print(f'1. We then filter to judgments where the judge has only seen a story once, and now we have this
```

```
## 1. We then filter to judgments where the judge has only seen a story once, and now we have this much
##                      Proportion_True  Total_Count
## Final_Setting
## AI Consultancy              0.802083           96
## AI Debate                   0.782609           92
## Human Consultancy           0.719008          121
## Human Debate                0.867374          377
```

```python
# Filter to online judges only
judgments_online = judgments[judgments["Role"] == "Judge"]
print(f'2. We\'ll make a copy of the online judgments only leaving us with the following judgments:\n{ju
```

```
## 2. We'll make a copy of the online judgments only leaving us with the following judgments:
##                      Proportion_True  Total_Count
## Final_Setting
## AI Consultancy              0.797872           94
## AI Debate                   0.791209           91
## Human Consultancy           0.709091          110
## Human Debate                0.861538          195
```

```python
judgments_online = judgments_online[judgments_online['Untimed annotator context bins'].isin(['2', '3',

print(f'3. We then filter to judgments which require more than a sentence or two, and now we have this m
```

```
## 3. We then filter to judgments which require more than a sentence or two, and now we have this much f
##                      Proportion_True  Total_Count
## Final_Setting
## AI Consultancy              0.806452           93
## AI Debate                   0.781609           87
## Human Consultancy           0.700935          107
## Human Debate                0.838710          155
```

```python
pd.set_option('display.max_columns', None)
total_counts_for_setting = judgments_online.groupby('Final_Setting').size()
```

```
result = judgments_online.groupby(["Final_Setting", "Untimed annotator context bins"]).agg(
    Proportion_True=pd.NamedAgg(column='Final_Accuracy', aggfunc=lambda x: x.mean()),
    Context_Count=pd.NamedAgg(column='Final_Accuracy', aggfunc='size'),
    Proportion_Context=pd.NamedAgg(column='Final_Setting', aggfunc=lambda x: len(x) / total_counts_for_s
)
```

```
## <string>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in
```

```
print(f'Are the difficult questions equally enough distributed amongst settings?:\n{result}')
```

```
## Are the difficult questions equally enough distributed amongst settings?:
##                                                    Proportion_True  \
## Final_Setting     Untimed annotator context bins
## AI Consultancy    1                                            NaN
##                   2                                       0.823529
##                   3                                       0.826087
##                   4                                       0.736842
## AI Debate         1                                            NaN
##                   2                                       0.777778
##                   3                                       0.772727
##                   4                                       0.800000
## Human Consultancy 1                                            NaN
##                   2                                       0.634146
##                   3                                       0.708333
##                   4                                       0.833333
## Human Debate      1                                            NaN
##                   2                                       0.890411
##                   3                                       0.816667
##                   4                                       0.727273
##
##                                                    Context_Count  \
## Final_Setting     Untimed annotator context bins
## AI Consultancy    1                                            0
##                   2                                           51
##                   3                                           23
##                   4                                           19
## AI Debate         1                                            0
##                   2                                           45
##                   3                                           22
##                   4                                           20
## Human Consultancy 1                                            0
##                   2                                           41
##                   3                                           48
##                   4                                           18
## Human Debate      1                                            0
##                   2                                           73
##                   3                                           60
##                   4                                           22
##
##                                                    Proportion_Context
## Final_Setting     Untimed annotator context bins
## AI Consultancy    1                                               NaN
##                   2                                          0.548387
```

```
##                   3                                         0.247312
##                   4                                         0.204301
## AI Debate         1                                              NaN
##                   2                                         0.517241
##                   3                                         0.252874
##                   4                                         0.229885
## Human Consultancy 1                                              NaN
##                   2                                         0.383178
##                   3                                         0.448598
##                   4                                         0.168224
## Human Debate      1                                              NaN
##                   2                                         0.470968
##                   3                                         0.387097
##                   4                                         0.141935
```

```
pd.reset_option('display.max_columns')
```

So question difficulty isn't perfectly balanced… but consultancies have a different relationship with question difficulty anyway? **need a second opinion**

Trying to balance the data

1. Balancing honest & dishonest consultancies
2. Question weights

Balancing honest & dishonest consultancies

```
def balance_consultancies(df, sample_setting, random_state):
    """
    Sample distinct questions, then use common questions, ensure equal counts.
    """
    consult_df = df[df['Setting'].str.contains(sample_setting, na=False)]
    honest_df = consult_df[consult_df['Setting'].str.contains('Honest')]
    dishonest_df = consult_df[consult_df['Setting'].str.contains('Dishonest')]
    sample_column_name = f'{sample_setting} Sample'
    df[sample_column_name] = False
    # Separate into distinct and common questions
    # First, let's extract the combinations of 'Article ID' and 'Question' for both honest and dishones
    honest_combinations = set(honest_df[['Article ID', 'Question']].itertuples(index=False, name=None))
    dishonest_combinations = set(dishonest_df[['Article ID', 'Question']].itertuples(index=False, name=
    # Identifying the common and distinct combinations
    common_combinations = honest_combinations.intersection(dishonest_combinations)
    distinct_honest_combinations = honest_combinations - common_combinations
    distinct_dishonest_combinations = dishonest_combinations - common_combinations
    # Filtering the original dataframes based on these combinations to get distinct and common datafram
    common_honest_df = honest_df[honest_df.set_index(['Article ID', 'Question']).index.isin(common_comb
    common_dishonest_df = dishonest_df[dishonest_df.set_index(['Article ID', 'Question']).index.isin(co
    distinct_honest_df = honest_df[honest_df.set_index(['Article ID', 'Question']).index.isin(distinct_
    distinct_dishonest_df = dishonest_df[dishonest_df.set_index(['Article ID', 'Question']).index.isin(
    def extract_correct_index(sample_df):
        if isinstance(sample_df.index, pd.MultiIndex):
```

```python
            return sample_df.index.get_level_values(2)
        else:
            return sample_df.index
    # Get distinct consultancies
    sample_size = min(len(distinct_honest_df.groupby(['Question', 'Article ID'])), len(distinct_dishones
    honest_sample = distinct_honest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sample(1, r
    dishonest_sample = distinct_dishonest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sampl
    df.loc[extract_correct_index(honest_sample), sample_column_name] = True
    df.loc[extract_correct_index(dishonest_sample), sample_column_name] = True
    # Drop sampled questions from distinct dataframes
    honest_remove_distinct = set(honest_sample[['Article ID', 'Question']].itertuples(index=False, name=
    dishonest_remove_distinct = set(dishonest_sample[['Article ID', 'Question']].itertuples(index=False
    distinct_honest_df = distinct_honest_df[~distinct_honest_df.set_index(['Article ID', 'Question']).in
    distinct_dishonest_df = distinct_dishonest_df[~distinct_dishonest_df.set_index(['Article ID', 'Ques
    honest_distinct_remaining = len(distinct_honest_df.groupby(['Question', 'Article ID']))
    dishonest_distinct_remaining = len(distinct_dishonest_df.groupby(['Question', 'Article ID']))
    # Sample from remaining distinct questions, using common questions for the other (bigger count) set
    if honest_distinct_remaining > dishonest_distinct_remaining:
        sample_size = min(honest_distinct_remaining, len(common_dishonest_df.groupby(['Question', 'Artic
        honest_sample = distinct_honest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sample
        dishonest_sample = common_dishonest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sam
        df.loc[extract_correct_index(dishonest_sample), sample_column_name] = True
        df.loc[extract_correct_index(honest_sample), sample_column_name] = True
        dishonest_remove_common = set(dishonest_sample[['Article ID', 'Question']].itertuples(index=Fals
        common_dishonest_df = common_dishonest_df[~common_dishonest_df.set_index(['Article ID', 'Questio
        common_honest_df = common_honest_df[~common_honest_df.set_index(['Article ID', 'Question']).inde
    else:
        sample_size = min(dishonest_distinct_remaining, len(common_honest_df.groupby(['Question', 'Artic
        honest_sample = common_honest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sample(1
        dishonest_sample = distinct_dishonest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.s
        df.loc[extract_correct_index(dishonest_sample), sample_column_name] = True
        df.loc[extract_correct_index(honest_sample), sample_column_name] = True
        honest_remove_common = set(honest_sample[['Article ID', 'Question']].itertuples(index=False, nam
        common_dishonest_df = common_dishonest_df[~common_dishonest_df.set_index(['Article ID', 'Questio
        common_honest_df = common_honest_df[~common_honest_df.set_index(['Article ID', 'Question']).inde
    # Remaining independent samples from common_honest_df
    if len(common_honest_df) or len(common_dishonest_df) > 0:
        sample_size = min(len(common_honest_df.groupby(['Question', 'Article ID'])), len(common_dishones
        honest_sample = common_honest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sample(1
        dishonest_sample = common_dishonest_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sam
        df.loc[extract_correct_index(honest_sample), sample_column_name] = True
        df.loc[extract_correct_index(dishonest_sample), sample_column_name] = True
    return df


# Run the sampling to balance the consultancies
judgments_online = balance_consultancies(judgments_online, 'Human Consultancy', random_state = 123)
judgments_online = balance_consultancies(judgments_online, 'AI Consultancy', random_state = 123)
# Create one sample column for easier indexing, create mask
#sample_columns = [col for col in judgments_online.columns if 'Sample' in col]
#judgments_online['Sample'] = judgments_online[sample_columns].any(axis=1)
#consultancy_balanced = (~judgments_online['Setting'].str.contains('Consultancy', case=False, na=False)
```

```
#print(f'Accuracy after balancing consultancies:\n{judgments_online[consultancy_balanced].groupby(["Fin


#from statsmodels.stats.proportion import proportions_ztest

def run_experiment(judgments_online):
    judgments_online['Sample'] = False
    judgments_online = balance_consultancies(judgments_online, 'Human Consultancy')
    judgments_online = balance_consultancies(judgments_online, 'AI Consultancy')
    sample_columns = [col for col in judgments_online.columns if 'Sample' in col]
    judgments_online['Sample'] = judgments_online[sample_columns].any(axis=1)
    consultancy_balanced = (~judgments_online['Setting'].str.contains('Consultancy', case=False, na=Fals
    result = judgments_online[consultancy_balanced].groupby(["Final_Setting"])["Final_Accuracy"].agg(Pro
    return result

# Number of iterations
#num_iterations = 1000

# Store results from each iteration
#results = []
#p_vals = []
# Run the experiment multiple times
#for _ in range(num_iterations):
#    result = run_experiment(judgments_online.copy())  # Use a copy to ensure original data remains unc
#    results.append(result)
#    # Run the proportions test
#    group_human_debate = result.loc['Human Debate']
#    group_human_consultancy = result.loc['Human Consultancy']
#    count = [group_human_debate.Proportion_True * group_human_debate.Total_Count, group_human_consulta
#    nobs = [group_human_debate.Total_Count, group_human_consultancy.Total_Count]
#    z_stat, p_val = proportions_ztest(count, nobs)
#    p_vals.append(p_val)

# Calculate the average of the results
#average_result = pd.concat(results).groupby(level=0).mean()

#print(f'\nAverage accuracy after {num_iterations} iterations:\n{average_result}')

#print(f'pval mean: {np.mean(p_vals)}')
```

Balance debates

```
def balance_debates(df, sample_setting, random_state):
    debates_df = df[df['Setting'].str.contains(sample_setting, na=False)]
    sample_column_name = f'{sample_setting} Sample'
    df[sample_column_name] = False
    def extract_correct_index(sample_df):
        if isinstance(sample_df.index, pd.MultiIndex):
            return sample_df.index.get_level_values(2)
        else:
            return sample_df.index
```

```
    # Get distinct consultancies
    sample_size = len(debates_df.groupby(['Question', 'Article ID']))
    sample_debates = debates_df.groupby(['Question', 'Article ID']).apply(lambda x: x.sample(1, random_s
    df.loc[extract_correct_index(sample_debates), sample_column_name] = True
    return df

# Run the sampling to balance the consultancies
judgments_online = balance_debates(judgments_online, 'Human Debate', random_state = 123)
judgments_online = balance_debates(judgments_online, 'AI Debate', random_state = 123)
# Create one sample column for easier indexing, create mask
sample_columns = [col for col in judgments_online.columns if 'Sample' in col]
consultancy_sample_columns = [col for col in judgments_online.columns if 'Consultancy Sample' in col]

judgments_online['Sample'] = judgments_online[sample_columns].any(axis=1)
judgments_online['Consultancy Sample'] = judgments_online[sample_columns].any(axis=1)

consultancy_balanced = (~judgments_online['Setting'].str.contains('Consultancy', case=False, na=False))

print(f'Accuracy after balancing consultancies:\n{judgments_online.groupby(["Final_Setting"])["Sample"]
```

```
## Accuracy after balancing consultancies:
## Final_Setting      Sample
## AI Consultancy     True       76
##                    False      17
## AI Debate          True       75
##                    False      12
## Human Consultancy  True       82
##                    False      25
## Human Debate       True      107
##                    False      48
## Name: count, dtype: int64
```

Question weights

```
def question_weights(data, columns, weight_column_name, consultancy_sample=None, debate_sample=None):
    # 0. Make a copy of the original data for weight calculations
    working_data = data.copy()
    # 0.1. Custom filtering based on the 'Setting' column
    consultancy_condition = working_data['Setting'].str.contains('Consultancy', case=False, na=False)
    debate_condition = ~consultancy_condition
    if consultancy_sample is not None:
        consultancy_condition &= (working_data['Sample'] == consultancy_sample)
    if debate_sample is not None: # uncomment if we want to sample debates
        debate_condition &= (working_data['Sample'] == debate_sample)
    combined_mask = consultancy_condition | debate_condition
    working_data = working_data[combined_mask]
    # 1. Calculate the frequency of each question in the dataset
    question_frequency = working_data.groupby(columns).size()
    # 2. Invert the frequency to get the weight for each question
    question_weights = 1 / question_frequency
    # 3. Normalize the weights
```

```
    #question_weights = question_weights / question_weights.sum() * len(question_weights)
    # 4. Assign the calculated weights to the original data and fill missing values with 0
    data.loc[combined_mask, weight_column_name] = data[combined_mask].set_index(columns).index.map(ques
    data[weight_column_name].fillna(0, inplace=True)
    return data

judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question'],
    weight_column_name='initial_question_weights'
)
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question', 'Final_Setting'],
    weight_column_name='initial_question_weights_grouped_setting'
)
```

```
def print_weight_summary_by_setting(df, weight_column, consultancy_sample=None):
    consultancy_condition = df['Setting'].str.contains('Consultancy', case=False, na=False)
    if consultancy_sample is not None:
        consultancy_condition &= (df['Sample'] == consultancy_sample)
    for setting in df['Setting'].unique():
        total_weight = df[df['Setting'] == setting][weight_column].sum()
        print(f"Total {weight_column} for {setting}: {total_weight:.2f}")
    print("\n")

print('Unsampled (initial) weights, by group setting')
```

```
## Unsampled (initial) weights, by group setting
```

```
print_weight_summary_by_setting(judgments_online, 'initial_question_weights_grouped_setting')
```

```
## Total initial_question_weights_grouped_setting for AI Consultancy Dishonest: 32.50
## Total initial_question_weights_grouped_setting for Human Debate: 107.00
## Total initial_question_weights_grouped_setting for AI Debate: 75.00
## Total initial_question_weights_grouped_setting for Human Consultancy Dishonest: 34.67
## Total initial_question_weights_grouped_setting for Human Consultancy Honest: 26.33
## Total initial_question_weights_grouped_setting for AI Consultancy Honest: 49.50
```

```
# Recalculate weights for balanced consultancies, all debates
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question'],
    weight_column_name='sampled_consultancies_all_debates_weights',
    consultancy_sample=True
)
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question', 'Final_Setting'],
    weight_column_name='sampled_consultancies_all_debates_weights_grouped_setting',
    consultancy_sample=True
)
```

```
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question', 'Setting'],
    weight_column_name='sampled_consultancies_all_debates_weights_setting',
    consultancy_sample=True
)
print('Consultancy balanced weights, by no/yes group setting')
```

```
## Consultancy balanced weights, by no/yes group setting
```

```
print_weight_summary_by_setting(judgments_online[consultancy_balanced], 'sampled_consultancies_all_deba
```

```
## Total sampled_consultancies_all_debates_weights for AI Consultancy Dishonest: 28.07
## Total sampled_consultancies_all_debates_weights for Human Debate: 82.48
## Total sampled_consultancies_all_debates_weights for AI Debate: 66.52
## Total sampled_consultancies_all_debates_weights for Human Consultancy Honest: 16.52
## Total sampled_consultancies_all_debates_weights for Human Consultancy Dishonest: 16.00
## Total sampled_consultancies_all_debates_weights for AI Consultancy Honest: 36.42
```

```
print_weight_summary_by_setting(judgments_online[consultancy_balanced], 'sampled_consultancies_all_deba
```

```
## Total sampled_consultancies_all_debates_weights_grouped_setting for AI Consultancy Dishonest: 38.00
## Total sampled_consultancies_all_debates_weights_grouped_setting for Human Debate: 107.00
## Total sampled_consultancies_all_debates_weights_grouped_setting for AI Debate: 75.00
## Total sampled_consultancies_all_debates_weights_grouped_setting for Human Consultancy Honest: 30.50
## Total sampled_consultancies_all_debates_weights_grouped_setting for Human Consultancy Dishonest: 30.5
## Total sampled_consultancies_all_debates_weights_grouped_setting for AI Consultancy Honest: 38.00
```

```
print_weight_summary_by_setting(judgments_online[consultancy_balanced], 'sampled_consultancies_all_deba
```

```
## Total sampled_consultancies_all_debates_weights_setting for AI Consultancy Dishonest: 38.00
## Total sampled_consultancies_all_debates_weights_setting for Human Debate: 107.00
## Total sampled_consultancies_all_debates_weights_setting for AI Debate: 75.00
## Total sampled_consultancies_all_debates_weights_setting for Human Consultancy Honest: 41.00
## Total sampled_consultancies_all_debates_weights_setting for Human Consultancy Dishonest: 41.00
## Total sampled_consultancies_all_debates_weights_setting for AI Consultancy Honest: 38.00
```

```
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question', 'Final_Setting'],
    weight_column_name='sampled_consultancies_debates_weights_grouped_setting',
    consultancy_sample=True,
    debate_sample=True
)
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question'],
    weight_column_name='sampled_consultancies_debates_weights',
    consultancy_sample=True,
    debate_sample=True
)
```

Note: we are not balancing *between settings*, and some of the counts of the debate settings are on the same questions

Load into R environment

```r
set.seed(123)
judgments <- py$judgments
judgments_online <- py$judgments_online
# Convert the Accuracy column to a factor for better plotting
judgments_online$Final_Accuracy_char <- as.logical.factor(as.character(judgments_online$Final_Accuracy))
judgments_online$Participant <- as.factor(judgments_online$Participant)
judgments_online$Setting <- as.factor(judgments_online$Setting)


subset_dishonest <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & judgments_onl
subset_honest <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & judgments_online
table(subset_dishonest$sampled_consultancies_all_debates_weights_grouped_setting, subset_dishonest$Final
```

```
##
##        FALSE TRUE
##   0.5     11   10
##   1        7   13
```

```r
table(subset_honest$sampled_consultancies_all_debates_weights_grouped_setting, subset_honest$Final_Accur
```

```
##
##        FALSE TRUE
##   0.5      5   16
##   1        1   19
```

```r
table(subset_dishonest$sampled_consultancies_all_debates_weights_grouped_setting)
```

```
##
## 0.5   1
##  21  20
```

```r
table(subset_honest$sampled_consultancies_all_debates_weights_grouped_setting)
```

```
##
## 0.5   1
##  21  20
```

```r
subset_human_consultancies <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & ju
table(subset_human_consultancies$sampled_consultancies_all_debates_weights_grouped_setting, subset_huma
```

```
##
##        FALSE TRUE
##   0.5     16   26
##   1        8   32
```

```r
table(judgments_online$Final_Setting, judgments_online$sampled_consultancies_all_debates_weights_groupe
```

```
##
##                       0 0.5  1
##   AI Consultancy    17   0 76
##   AI Debate          0  24 63
##   Human Consultancy 25  42 40
##   Human Debate       0  96 59
```

```r
table(judgments_online$Final_Setting, judgments_online$sampled_consultancies_debates_weights)
```

```
##
##                       0 0.2 0.25 0.333333333333333 0.5  1
##   AI Consultancy    17   1    9                 4   1 61
##   AI Debate         12   1    9                 3   1 61
##   Human Consultancy 25   2    9                32  32  7
##   Human Debate      48   1    9                15  20 62
```

Results

Accuracy

Difference in proportions

```r
acc_diff_test <- function(design, Setting){
  print(design)
  freq_table <- svytable(~Final_Setting+Final_Accuracy, design)
  chisq_result <- svychisq(~Final_Setting+Final_Accuracy, design, statistic = "Chisq")
  print(chisq_result)
  pairwise_result <- pairwise.prop.test(freq_table, p.adjust.method="none", alternative="two.sided")
  print(pairwise_result)
  freq_table <- cbind(freq_table, Accuracy = (freq_table[,2] / (freq_table[,1]+freq_table[,2]))*100)
  print(freq_table)
}

print("Really raw")
```

```
## [1] "Really raw"
```

```r
acc_diff_test(svydesign(ids = ~1, data = judgments))
```

```
## Warning in svydesign.default(ids = ~1, data = judgments): No weights or
## probabilities supplied, assuming equal probability
```

```
## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson's X^2: Rao & Scott adjustment
```

```
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 15.218, df = 3, p-value = 0.001657
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.88133        -         -
## Human Consultancy 0.20924        0.36922   -
## Human Debate      0.14538        0.05977   0.00026
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy       19   77 80.20833
## AI Debate            20   72 78.26087
## Human Consultancy    34   87 71.90083
## Human Debate         50  327 86.73740
```

```r
print("Raw")
```

```
## [1] "Raw"
```

```r
acc_diff_test(svydesign(ids = ~1, data = judgments_online))
```

```
## Warning in svydesign.default(ids = ~1, data = judgments_online): No weights or
## probabilities supplied, assuming equal probability
```

```
## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson's X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 7.4336, df = 3, p-value = 0.05973
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.820          -         -
## Human Consultancy 0.120          0.269     -
## Human Debate      0.634          0.352     0.012
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy       18   75 80.64516
## AI Debate            19   68 78.16092
## Human Consultancy    32   75 70.09346
## Human Debate         25  130 83.87097
```

```r
print("Balanced consultancies")
```

```
## [1] "Balanced consultancies"
```

```r
acc_diff_test(svydesign(ids = ~1, data = subset(judgments_online, `Consultancy Sample` == TRUE | !grepl
```

```
## Warning in svydesign.default(ids = ~1, data = subset(judgments_online,
## ‘Consultancy Sample‘ == : No weights or probabilities supplied, assuming equal
## probability

## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson’s X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 5.9826, df = 3, p-value = 0.1132
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                    AI Consultancy AI Debate Human Consultancy
## AI Debate          0.729          -         -
## Human Consultancy 0.159          0.352     -
## Human Debate       0.803          0.352     0.027
##
## P value adjustment method: none
##                    FALSE TRUE Accuracy
## AI Consultancy        14   62 81.57895
## AI Debate             19   68 78.16092
## Human Consultancy     24   58 70.73171
## Human Debate          25  130 83.87097
```

```r
print("Balanced consultancies, question weights (grouped settings)")
```

```
## [1] "Balanced consultancies, question weights (grouped settings)"
```

```r
acc_diff_test(svydesign(ids = ~1, data = subset(judgments_online, `Consultancy Sample` == TRUE | !grepl
```

```
## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson’s X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 3.7897, df = 3, p-value = 0.3186
##
##
```

```
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.89           -         -
## Human Consultancy 0.37           0.58      -
## Human Debate      0.74           0.47      0.13
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy     14.0 62.0 81.57895
## AI Debate          15.5 59.5 79.33333
## Human Consultancy  16.0 45.0 73.77049
## Human Debate       16.5 90.5 84.57944
```

```
acc_diff_test(svydesign(ids = ~1, data = subset(judgments_online, `Consultancy Sample` == TRUE | !grepl
```

```
## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson's X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 7.6386, df = 3, p-value = 0.09546
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         1.000          -         -
## Human Consultancy 0.409          0.446     -
## Human Debate      0.335          0.286     0.059
##
## P value adjustment method: none
##                       FALSE     TRUE Accuracy
## AI Consultancy    13.200000 51.28333 79.52959
## AI Debate         14.016667 52.50000 78.92759
## Human Consultancy  9.866667 22.65000 69.65659
## Human Debate      10.850000 71.63333 86.84583
```

```
print("Balanced consultancies sampled debates, question weights (grouped settings)")
```

```
## [1] "Balanced consultancies sampled debates, question weights (grouped settings)"
```

```
acc_diff_test(svydesign(ids = ~1, data = subset(judgments_online, `Sample` == TRUE), weights = ~sampled_
```

```
## Independent Sampling design (with replacement)
## print(design)
##
```

```
##  Pearson's X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 3.4707, df = 3, p-value = 0.3286
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.97           -         -
## Human Consultancy 0.37           0.51      -
## Human Debate      0.67           0.49      0.11
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy       14   62 81.57895
## AI Debate            15   60 80.00000
## Human Consultancy    16   45 73.77049
## Human Debate         16   91 85.04673
```

```
acc_diff_test(svydesign(ids = ~1, data = judgments_online, weights = ~sampled_consultancies_debates_wei
```

```
## Independent Sampling design (with replacement)
## print(design)
##
##  Pearson's X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 4.5119, df = 3, p-value = 0.3283
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.97           -         -
## Human Consultancy 0.37           0.51      -
## Human Debate      0.67           0.49      0.11
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy       14   62 81.57895
## AI Debate            15   60 80.00000
## Human Consultancy    16   45 73.77049
## Human Debate         16   91 85.04673
```

```
design = svydesign(ids = ~1, data = subset(judgments_online, `Human Consultancy Sample` == TRUE | !grepl
acc_diff_test(design)
```

```
## Independent Sampling design (with replacement)
```

```
## svydesign(ids = ~1, data = subset(judgments_online, ‘Human Consultancy Sample‘ ==
##     TRUE | !grepl("Consultancy", Final_Setting) & !grepl("AI",
##     Final_Setting)), weights = ~sampled_consultancies_all_debates_weights_grouped_setting)
##
##  Pearson’s X^2: Rao & Scott adjustment
##
## data:  svychisq(~Final_Setting + Final_Accuracy, design, statistic = "Chisq")
## X-squared = 4.104, df = 1, p-value = 0.05155
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##              Human Consultancy
## Human Debate 0.13
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## Human Consultancy  16.0 45.0 73.77049
## Human Debate       16.5 90.5 84.57944
```

```r
final_table <- svytable(~Final_Setting+Final_Accuracy,
                        design = svydesign(ids = ~1,
                                           data = subset(judgments_online, `Consultancy Sample` == TRUE
                                           weights = ~sampled_consultancies_all_debates_weights_grouped
final_table
```

```
##                      Final_Accuracy
## Final_Setting         FALSE TRUE
##   AI Consultancy       14.0 62.0
##   AI Debate            15.5 59.5
##   Human Consultancy    16.0 45.0
##   Human Debate         16.5 90.5
```

```r
# Add accuracy
final_table <- cbind(final_table, Accuracy = (final_table[,2] / (final_table[,1]+final_table[,2]))*100)
# Calculate the difference in accuracy for each row compared to "Human Debate"
difference_with_debate <- final_table[,"Accuracy"] - final_table["Human Debate", "Accuracy"]
# Bind the difference column to the final_table
final_table <- cbind(final_table, difference_with_debate)

# Loop through each setting
ci_lowers <- c()
ci_uppers <- c()
p_values <- c()
# Loop through each setting
for (setting in rownames(final_table)) {
  # Use prop.test to compare the setting's accuracy with "Human Debate"
  results <- prop.test(c(final_table["Human Debate", "TRUE"], final_table[setting, "TRUE"]), c((final_ta

  # Extract the confidence interval and store it as a string in the format "lower - upper"
  ci_lower <- results$conf.int[1] * 100  # Multiply by 100 to convert to percentage
```

```r
  ci_upper <- results$conf.int[2] * 100  # Multiply by 100 to convert to percentage
  ci_lowers <- c(ci_lowers, ci_lower)
  ci_uppers <- c(ci_uppers, ci_upper)
  p_values <- c(p_values, results$p.value)
}
final_table <- cbind(final_table, ci_lowers, ci_uppers, p_values)
final_table
```

```
##                     FALSE TRUE Accuracy difference_with_debate ci_lowers
## AI Consultancy       14.0 62.0 81.57895              -3.000492 -9.205452
## AI Debate            15.5 59.5 79.33333              -5.246106 -7.324725
## Human Consultancy    16.0 45.0 73.77049             -10.808947 -3.465654
## Human Debate         16.5 90.5 84.57944               0.000000 -9.677288
##                     ci_uppers  p_values
## AI Consultancy      15.206436 0.7372949
## AI Debate           17.816936 0.4731832
## Human Consultancy   25.083549 0.1329563
## Human Debate         9.677288 1.0000000
```

```r
# Display the updated table using knitr::kable
knitr::kable(final_table, booktab = TRUE,  digits = c(rep(1,6),3),
             col.names = c("# Incorrect (weighted)", "# Correct (weighted)", "Accuracy", "Difference",
```

	# Incorrect (weighted)	# Correct (weighted)	Accuracy	Difference	95% CI Lower Limit	95% CI Upper Limit	p-value
AI Consultancy	14.0	62.0	81.6	-3.0	-9.2	15.2	0.737
AI Debate	15.5	59.5	79.3	-5.2	-7.3	17.8	0.473
Human Consultancy	16.0	45.0	73.8	-10.8	-3.5	25.1	0.133
Human Debate	16.5	90.5	84.6	0.0	-9.7	9.7	1.000

```r
human_only <- subset(judgments_online, `Human Consultancy Sample` == TRUE | !grepl("Consultancy", Final_
human_only$Setting <- droplevels(human_only$Setting)
table(human_only$Setting)
```

```
## 
## Human Consultancy Dishonest    Human Consultancy Honest 
##                          41                          41 
##                Human Debate 
##                         155
```

```r
final_table <- svytable(~Setting+Final_Accuracy,
                        design = svydesign(ids = ~1,
                                           data = human_only,
                                           weights = ~sampled_consultancies_all_debates_weights_setting)
final_table
```

```
##                               Final_Accuracy
## Setting                        FALSE TRUE
##   Human Consultancy Dishonest  18.0 23.0
##   Human Consultancy Honest      6.0 35.0
##   Human Debate                 16.5 90.5
```

```
# Add accuracy
final_table <- cbind(final_table, Accuracy = (final_table[,2] / (final_table[,1]+final_table[,2]))*100)
# Calculate the difference in accuracy for each row compared to "Human Debate"
difference_with_debate <- final_table[,"Accuracy"] - final_table["Human Debate", "Accuracy"]
# Bind the difference column to the final_table
final_table <- cbind(final_table, difference_with_debate)

# Loop through each setting
ci_lowers <- c()
ci_uppers <- c()
p_values <- c()
# Loop through each setting
for (setting in rownames(final_table)) {
  # Use prop.test to compare the setting's accuracy with "Human Debate"
  results <- prop.test(c(final_table["Human Debate", "TRUE"], final_table[setting, "TRUE"]), c((final_ta

  # Extract the confidence interval and store it as a string in the format "lower - upper"
  ci_lower <- results$conf.int[1] * 100  # Multiply by 100 to convert to percentage
  ci_upper <- results$conf.int[2] * 100  # Multiply by 100 to convert to percentage
  ci_lowers <- c(ci_lowers, ci_lower)
  ci_uppers <- c(ci_uppers, ci_upper)
  p_values <- c(p_values, results$p.value)
}
final_table <- cbind(final_table, ci_lowers, ci_uppers, p_values)
final_table
```

```
##                              FALSE TRUE Accuracy difference_with_debate
## Human Consultancy Dishonest  18.0 23.0 56.09756            -28.4818783
## Human Consultancy Honest      6.0 35.0 85.36585              0.7864144
## Human Debate                 16.5 90.5 84.57944              0.0000000
##                              ci_lowers ci_uppers     p_values
## Human Consultancy Dishonest  10.134444 46.829313 0.0005598759
## Human Consultancy Honest    -14.374115 12.801286 1.0000000000
## Human Debate                 -9.677288  9.677288 1.0000000000
```

```
# Display the updated table using knitr::kable
knitr::kable(final_table, booktab = TRUE,  digits = c(rep(1,6),3),
             col.names = c("# Incorrect (weighted)", "# Correct (weighted)", "Accuracy", "Difference",
```

	# Incorrect (weighted)	# Correct (weighted)	Accuracy	Difference	95% CI Lower Limit	95% CI Upper Limit	p-value
Human Consultancy Dishonest	18.0	23.0	56.1	-28.5	10.1	46.8	0.001

	# Incorrect (weighted)	# Correct (weighted)	Accuracy	Difference	95% CI Lower Limit	95% CI Upper Limit	p-value
Human Consultancy Honest	6.0	35.0	85.4	0.8	-14.4	12.8	1.000
Human Debate	16.5	90.5	84.6	0.0	-9.7	9.7	1.000

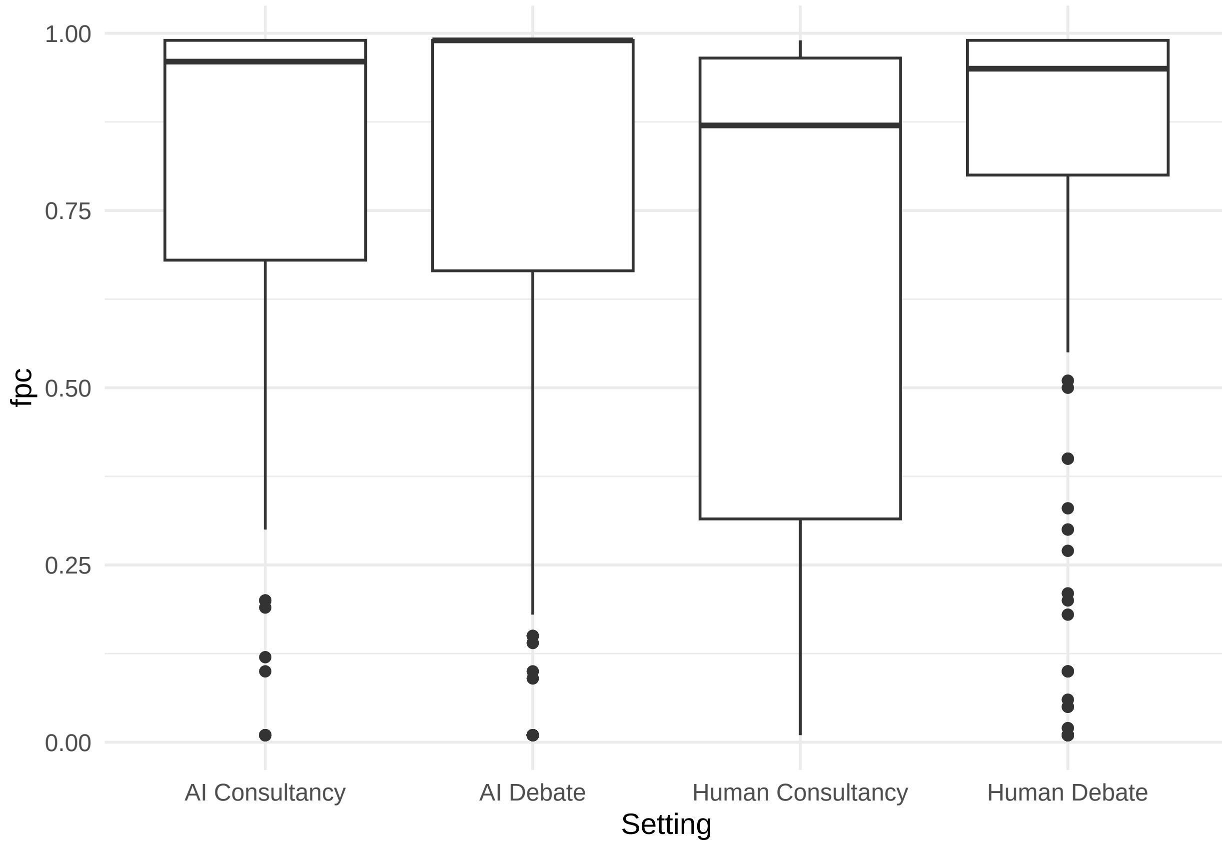
```
prop_table <- svytable(~Final_Setting+Final_Accuracy, design = svydesign(ids = ~1, data = subset(judgmen
#prop_table <- svytable(~Final_Setting+Final_Accuracy, design = svydesign(ids = ~1, data = subset(judgm
prop_table
```

```
##                    Final_Accuracy
## Final_Setting           FALSE      TRUE
##   Human Consultancy  9.866667 22.650000
##   Human Debate      10.850000 71.633333
```

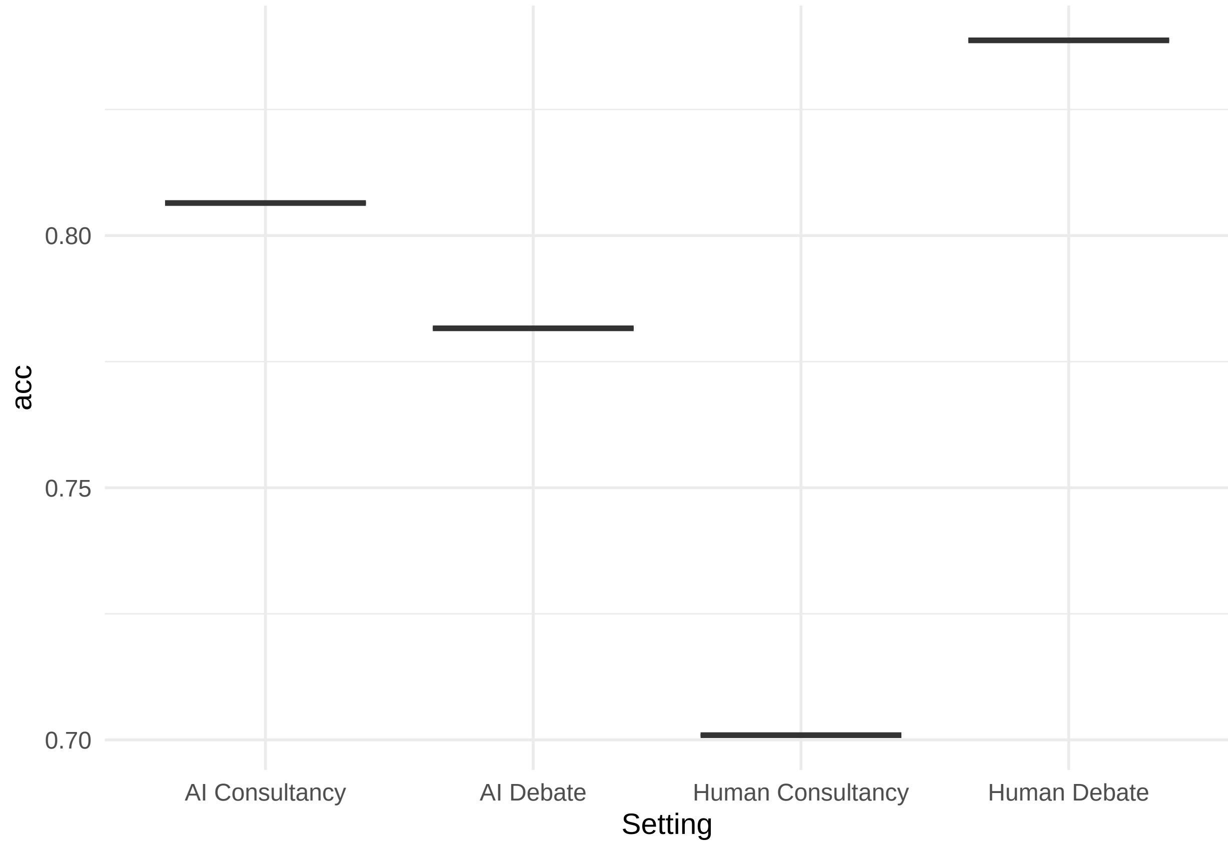
```
print(prop.test(c(prop_table["Human Consultancy","TRUE"],prop_table["Human Debate","TRUE"]),c(prop_tabl
```

```
##
##  2-sample test for equality of proportions with continuity correction
##
## data:  c(prop_table["Human Consultancy", "TRUE"], prop_table["Human Debate", "TRUE"]) out of c(prop_
## X-squared = 3.5746, df = 1, p-value = 0.05867
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.36737199  0.02358717
## sample estimates:
##    prop 1    prop 2
## 0.6965659 0.8684583
```

```
judgments_online$fpc <- judgments_online$`Final probability correct`
judgments_online %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = fpc)) +
  labs(y = "fpc", x = "Setting")+
  theme_minimal()
```




```
judgments_online %>%
  group_by(Final_Setting) %>% summarise(fpcmed = median(fpc),
                                        fpcmean = mean(Final_Accuracy)) %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = fpcmean)) +
  labs(y = "acc", x = "Setting")+
  theme_minimal()
```




```r
consultancy_design <- svydesign(ids = ~1, data = subset(judgments_online, `Consultancy Sample` == TRUE


human_consultancy_design <- svydesign(ids = ~1, data = subset(judgments_online, `Human Consultancy Sampl


svyranktest(fpc~Final_Setting, human_consultancy_design)
```

```
##
##  Design-based KruskalWallis test
##
## data:  fpc ~ Final_Setting
## t = 2.4508, df = 235, p-value = 0.01499
## alternative hypothesis: true difference in mean rank score is not equal to 0
## sample estimates:
## difference in mean rank score
##                     0.0969166
```

```r
judgments_online %>% group_by(Final_Setting) %>% summarise(fpcmed = median(fpc),
                                                          fpcmean = mean(fpc))
```

```
## # A tibble: 4 x 3
##   Final_Setting     fpcmed fpcmean
```

```
##   <chr>              <dbl>   <dbl>
## 1 AI Consultancy      0.96   0.764
## 2 AI Debate           0.99   0.754
## 3 Human Consultancy   0.87   0.672
## 4 Human Debate        0.95   0.792
```

```r
svyranktest(fpc~Final_Setting, consultancy_design, test = "median")
```

```
##
##  Design-based median test
##
## data:  fpc ~ Final_Setting
## df = 3, Chisq = 13.969, p-value = 0.003272
```

```r
svyranktest(fpc~Final_Setting, consultancy_design, test = "wilcoxon")
```

```
##
##  Design-based KruskalWallis test
##
## data:  fpc ~ Final_Setting
## df = 3, Chisq = 12.446, p-value = 0.006514
```

```r
svyranktest(fpc~Final_Setting, consultancy_design, test = "vanderWaerden")
```

```
##
##  Design-based vanderWaerden test
##
## data:  fpc ~ Final_Setting
## df = 3, Chisq = 9.8037, p-value = 0.02133
```

```r
weighted_mannwhitney(fpc ~ Final_Setting + sampled_consultancies_all_debates_weights_grouped_setting, j
```

```
## Warning in summary.glm(glm.object): observations with zero weight not used for
## calculating dispersion
```

```
##
## # Weighted Kruskal-Wallis test
##
##   comparison of fpc by Final_Setting
##   Chisq=3.00  df=12  p-value=0.006
```

```r
data(efc)
str(efc)
```

```
## 'data.frame':    908 obs. of  26 variables:
##  $ c12hour : num  16 148 70 168 168 16 161 110 28 40 ...
##   ..- attr(*, "label")= chr "average number of hours of care per week"
##  $ e15relat: num  2 2 1 1 2 2 1 4 2 2 ...
##   ..- attr(*, "label")= chr "relationship to elder"
##   ..- attr(*, "labels")= Named num [1:8] 1 2 3 4 5 6 7 8
```

```
##   .. ..- attr(*, "names")= chr [1:8] "spouse/partner" "child" "sibling" "daughter or son -in-law" ..
##  $ e16sex  : num  2 2 2 2 2 2 1 2 2 2 ...
##   ..- attr(*, "label")= chr "elder's gender"
##   ..- attr(*, "labels")= Named num [1:2] 1 2
##   .. ..- attr(*, "names")= chr [1:2] "male" "female"
##  $ e17age  : num  83 88 82 67 84 85 74 87 79 83 ...
##   ..- attr(*, "label")= chr "elder' age"
##  $ e42dep  : num  3 3 3 4 4 4 4 4 4 4 ...
##   ..- attr(*, "label")= chr "elder's dependency"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "independent" "slightly dependent" "moderately dependent" "sever
##  $ c82cop1 : num  3 3 2 4 3 2 4 3 3 3 ...
##   ..- attr(*, "label")= chr "do you feel you cope well as caregiver?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "never" "sometimes" "often" "always"
##  $ c83cop2 : num  2 3 2 1 2 2 2 2 2 2 ...
##   ..- attr(*, "label")= chr "do you find caregiving too demanding?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c84cop3 : num  2 3 1 3 1 3 4 2 3 1 ...
##   ..- attr(*, "label")= chr "does caregiving cause difficulties in your relationship with your frien
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c85cop4 : num  2 3 4 1 2 3 1 1 2 2 ...
##   ..- attr(*, "label")= chr "does caregiving have negative effect on your physical health?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c86cop5 : num  1 4 1 1 2 3 1 1 2 1 ...
##   ..- attr(*, "label")= chr "does caregiving cause difficulties in your relationship with your famil
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c87cop6 : num  1 1 1 1 2 2 2 1 1 1 ...
##   ..- attr(*, "label")= chr "does caregiving cause financial difficulties?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c88cop7 : num  2 3 1 1 1 2 4 2 3 1 ...
##   ..- attr(*, "label")= chr "do you feel trapped in your role as caregiver?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "Never" "Sometimes" "Often" "Always"
##  $ c89cop8 : num  3 2 4 2 4 1 1 3 1 1 ...
##   ..- attr(*, "label")= chr "do you feel supported by friends/neighbours?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "never" "sometimes" "often" "always"
##  $ c90cop9 : num  3 2 3 4 4 1 4 3 3 3 ...
##   ..- attr(*, "label")= chr "do you feel caregiving worthwhile?"
##   ..- attr(*, "labels")= Named num [1:4] 1 2 3 4
##   .. ..- attr(*, "names")= chr [1:4] "never" "sometimes" "often" "always"
##  $ c160age : num  56 54 80 69 47 56 61 67 59 49 ...
##   ..- attr(*, "label")= chr "carer' age"
##  $ c161sex : num  2 2 1 1 2 1 2 2 2 2 ...
##   ..- attr(*, "label")= chr "carer's gender"
##   ..- attr(*, "labels")= Named num [1:2] 1 2
##   .. ..- attr(*, "names")= chr [1:2] "Male" "Female"
##  $ c172code: num  2 2 1 2 2 2 2 2 NA 2 ...
```

```
##   ..- attr(*, "label")= chr "carer's level of education"
##   ..- attr(*, "labels")= Named num [1:3] 1 2 3
##   .. ..- attr(*, "names")= chr [1:3] "low level of education" "intermediate level of education" "hig
##  $ c175empl: num  1 1 0 0 0 1 0 0 0 0 ...
##   ..- attr(*, "label")= chr "are you currently employed?"
##   ..- attr(*, "labels")= Named num [1:2] 0 1
##   .. ..- attr(*, "names")= chr [1:2] "no" "yes"
##  $ barthtot: num  75 75 35 0 25 60 5 35 15 0 ...
##   ..- attr(*, "label")= chr "Total score BARTHEL INDEX"
##  $ neg_c_7 : num  12 20 11 10 12 19 15 11 15 10 ...
##   ..- attr(*, "label")= chr "Negative impact with 7 items"
##  $ pos_v_4 : num  12 11 13 15 15 9 13 14 13 13 ...
##   ..- attr(*, "label")= chr "Positive value with 4 items"
##  $ quol_5  : num  14 10 7 12 19 8 20 20 8 15 ...
##   ..- attr(*, "label")= chr "Quality of life 5 items"
##  $ resttotn: num  0 4 0 2 2 1 0 0 0 1 ...
##   ..- attr(*, "label")= chr "Job restrictions"
##  $ tot_sc_e: num  4 0 1 0 1 3 0 1 2 1 ...
##   ..- attr(*, "label")= chr "Services for elderly"
##  $ n4pstu  : num  0 0 2 3 2 2 3 1 3 3 ...
##   ..- attr(*, "label")= chr "Care level"
##   ..- attr(*, "labels")= Named chr [1:5] "0" "1" "2" "3" ...
##   .. ..- attr(*, "names")= chr [1:5] "No Care Level" "Care Level 1" "Care Level 2" "Care Level 3" ..
##  $ nur_pst : num  NA NA 2 3 2 2 3 1 3 3 ...
##   ..- attr(*, "label")= chr "Care level"
##   ..- attr(*, "labels")= Named chr [1:3] "1" "2" "3"
##   .. ..- attr(*, "names")= chr [1:3] "Care Level 1" "Care Level 2" "Care Level 3/3+"
```

```r
efc$weight <- abs(rnorm(nrow(efc), 1, .3))
weighted_mannwhitney(c12hour ~ c161sex + weight, efc)
```

```
##
## # Weighted Mann-Whitney-U test
##
##   comparison of c12hour by c161sex
##   Chisq=2.47  df=899  p-value=0.014
```

```r
weighted_mannwhitney(fpc ~ Final_Setting + sampled_consultancies_all_debates_weights_grouped_setting, j
```

```
## Warning in summary.glm(glm.object): observations with zero weight not used for
## calculating dispersion
```

```
##
## # Weighted Kruskal-Wallis test
##
##   comparison of fpc by Final_Setting
##   Chisq=3.00  df=12  p-value=0.006
```

```r
wilcox.test(efc$c12hour,efc$c161sex)
```

```
##
```

```
##  Wilcoxon rank sum test with continuity correction
##
## data:  efc$c12hour and efc$c161sex
## W = 812702, p-value < 0.00000000000000022
## alternative hypothesis: true location shift is not equal to 0
```

```
judgments_online$fpcw <- judgments_online$fpc *judgments_online$sampled_consultancies_all_debates_weigh
wilcox.test(fpcw~Final_Setting, subset(judgments_online, `Human Consultancy Sample` == TRUE | !grepl("C
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  fpcw by Final_Setting
## W = 5837, p-value = 0.3003
## alternative hypothesis: true location shift is not equal to 0
## 95 percent confidence interval:
##  -0.09001393  0.01492054
## sample estimates:
## difference in location
##            -0.01505394
```

Logistic regression

```
#judgments_online$Final_Setting <- relevel(judgments_online$Final_Setting, ref = "Human Debate")
model1 <- glm(Final_Accuracy ~ relevel(factor(Final_Setting), 'Human Debate'), family = 'binomial', data

summary(model1)
```

```
##
## Call:
## glm(formula = Final_Accuracy ~ relevel(factor(Final_Setting),
##     "Human Debate"), family = "binomial", data = judgments_online)
##
## Coefficients:
##                                                                   Estimate
## (Intercept)                                                         1.6487
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy       -0.2215
## relevel(factor(Final_Setting), "Human Debate")AI Debate            -0.3736
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy  -0.7969
##                                                                   Std. Error
## (Intercept)                                                           0.2184
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy         0.3414
## relevel(factor(Final_Setting), "Human Debate")AI Debate              0.3392
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy      0.3038
##                                                                   z value
## (Intercept)                                                         7.549
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy       -0.649
## relevel(factor(Final_Setting), "Human Debate")AI Debate            -1.102
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy  -2.623
##                                                                             Pr(>|z|)
## (Intercept)                                                       0.0000000000000438
```

```
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy              0.51644
## relevel(factor(Final_Setting), "Human Debate")AI Debate                   0.27067
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy           0.00871
##
## (Intercept)                                                          ***
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy
## relevel(factor(Final_Setting), "Human Debate")AI Debate
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 457.45  on 441  degrees of freedom
## Residual deviance: 450.23  on 438  degrees of freedom
## AIC: 458.23
##
## Number of Fisher Scoring iterations: 4
```

```
table(model1$fitted.values > 0.5)
```

```
##
## TRUE
##  442
```

```
table(judgments_online$Final_Accuracy)
```

```
##
## FALSE  TRUE
##    94   348
```

```
model2 <- glm(Final_Accuracy ~ relevel(factor(Participant),'Aliyaah Toussaint') + relevel(factor(Final_S

summary(model2)
```

```
##
## Call:
## glm(formula = Final_Accuracy ~ relevel(factor(Participant), "Aliyaah Toussaint") +
##     relevel(factor(Final_Setting), "Human Debate"), family = "binomial",
##     data = judgments_online)
##
## Coefficients:
##                                                                     Estimate
## (Intercept)                                                          2.19432
## relevel(factor(Participant), "Aliyaah Toussaint")Adelle Fernando    -0.79600
## relevel(factor(Participant), "Aliyaah Toussaint")Anuj Jain          -0.89691
## relevel(factor(Participant), "Aliyaah Toussaint")David Rein         -0.43887
## relevel(factor(Participant), "Aliyaah Toussaint")Emmanuel Makinde  -17.76039
## relevel(factor(Participant), "Aliyaah Toussaint")Ethan Rosen        -0.24841
## relevel(factor(Participant), "Aliyaah Toussaint")Jackson Petty      -0.55820
## relevel(factor(Participant), "Aliyaah Toussaint")Jessica Li         -0.16347
## relevel(factor(Participant), "Aliyaah Toussaint")Julian Michael     -0.08063
```

```
## relevel(factor(Participant), "Aliyaah Toussaint")Julien Dirani        13.37175
## relevel(factor(Participant), "Aliyaah Toussaint")Max Layden           13.37175
## relevel(factor(Participant), "Aliyaah Toussaint")Noor Mirza-Rashid    -1.27803
## relevel(factor(Participant), "Aliyaah Toussaint")Reeya Kansra         -0.96379
## relevel(factor(Participant), "Aliyaah Toussaint")Salsabila Mahdi      -0.17942
## relevel(factor(Participant), "Aliyaah Toussaint")Sam Jin              -0.01031
## relevel(factor(Participant), "Aliyaah Toussaint")Sean Wang             0.17177
## relevel(factor(Participant), "Aliyaah Toussaint")Shlomo Kofman        -1.13135
## relevel(factor(Participant), "Aliyaah Toussaint")Shreeram Modi        -1.16733
## relevel(factor(Participant), "Aliyaah Toussaint")Vishakh Padmakumar   -0.40256
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy          -0.27193
## relevel(factor(Final_Setting), "Human Debate")AI Debate               -0.42241
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy       -0.74485
##                                                                     Std. Error
## (Intercept)                                                            0.49853
## relevel(factor(Participant), "Aliyaah Toussaint")Adelle Fernando       0.63661
## relevel(factor(Participant), "Aliyaah Toussaint")Anuj Jain             0.53893
## relevel(factor(Participant), "Aliyaah Toussaint")David Rein            0.77471
## relevel(factor(Participant), "Aliyaah Toussaint")Emmanuel Makinde   1455.39762
## relevel(factor(Participant), "Aliyaah Toussaint")Ethan Rosen           1.17957
## relevel(factor(Participant), "Aliyaah Toussaint")Jackson Petty         0.66085
## relevel(factor(Participant), "Aliyaah Toussaint")Jessica Li            0.64365
## relevel(factor(Participant), "Aliyaah Toussaint")Julian Michael        0.75783
## relevel(factor(Participant), "Aliyaah Toussaint")Julien Dirani      1029.12159
## relevel(factor(Participant), "Aliyaah Toussaint")Max Layden         1029.12159
## relevel(factor(Participant), "Aliyaah Toussaint")Noor Mirza-Rashid     0.97393
## relevel(factor(Participant), "Aliyaah Toussaint")Reeya Kansra          0.58143
## relevel(factor(Participant), "Aliyaah Toussaint")Salsabila Mahdi       0.90289
## relevel(factor(Participant), "Aliyaah Toussaint")Sam Jin               0.56587
## relevel(factor(Participant), "Aliyaah Toussaint")Sean Wang             0.67879
## relevel(factor(Participant), "Aliyaah Toussaint")Shlomo Kofman         0.50759
## relevel(factor(Participant), "Aliyaah Toussaint")Shreeram Modi         0.63420
## relevel(factor(Participant), "Aliyaah Toussaint")Vishakh Padmakumar    1.18962
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy           0.39222
## relevel(factor(Final_Setting), "Human Debate")AI Debate                0.39204
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy        0.36432
##                                                                     z value
## (Intercept)                                                           4.402
## relevel(factor(Participant), "Aliyaah Toussaint")Adelle Fernando     -1.250
## relevel(factor(Participant), "Aliyaah Toussaint")Anuj Jain           -1.664
## relevel(factor(Participant), "Aliyaah Toussaint")David Rein          -0.566
## relevel(factor(Participant), "Aliyaah Toussaint")Emmanuel Makinde    -0.012
## relevel(factor(Participant), "Aliyaah Toussaint")Ethan Rosen         -0.211
## relevel(factor(Participant), "Aliyaah Toussaint")Jackson Petty       -0.845
## relevel(factor(Participant), "Aliyaah Toussaint")Jessica Li          -0.254
## relevel(factor(Participant), "Aliyaah Toussaint")Julian Michael      -0.106
## relevel(factor(Participant), "Aliyaah Toussaint")Julien Dirani        0.013
## relevel(factor(Participant), "Aliyaah Toussaint")Max Layden           0.013
## relevel(factor(Participant), "Aliyaah Toussaint")Noor Mirza-Rashid   -1.312
## relevel(factor(Participant), "Aliyaah Toussaint")Reeya Kansra        -1.658
## relevel(factor(Participant), "Aliyaah Toussaint")Salsabila Mahdi     -0.199
## relevel(factor(Participant), "Aliyaah Toussaint")Sam Jin             -0.018
## relevel(factor(Participant), "Aliyaah Toussaint")Sean Wang            0.253
## relevel(factor(Participant), "Aliyaah Toussaint")Shlomo Kofman       -2.229
```

```
## relevel(factor(Participant), "Aliyaah Toussaint")Shreeram Modi       -1.841
## relevel(factor(Participant), "Aliyaah Toussaint")Vishakh Padmakumar  -0.338
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy         -0.693
## relevel(factor(Final_Setting), "Human Debate")AI Debate              -1.077
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy      -2.045
##                                                                     Pr(>|z|)
## (Intercept)                                                        0.0000107
## relevel(factor(Participant), "Aliyaah Toussaint")Adelle Fernando      0.2112
## relevel(factor(Participant), "Aliyaah Toussaint")Anuj Jain            0.0961
## relevel(factor(Participant), "Aliyaah Toussaint")David Rein           0.5711
## relevel(factor(Participant), "Aliyaah Toussaint")Emmanuel Makinde     0.9903
## relevel(factor(Participant), "Aliyaah Toussaint")Ethan Rosen          0.8332
## relevel(factor(Participant), "Aliyaah Toussaint")Jackson Petty        0.3983
## relevel(factor(Participant), "Aliyaah Toussaint")Jessica Li           0.7995
## relevel(factor(Participant), "Aliyaah Toussaint")Julian Michael       0.9153
## relevel(factor(Participant), "Aliyaah Toussaint")Julien Dirani        0.9896
## relevel(factor(Participant), "Aliyaah Toussaint")Max Layden           0.9896
## relevel(factor(Participant), "Aliyaah Toussaint")Noor Mirza-Rashid    0.1894
## relevel(factor(Participant), "Aliyaah Toussaint")Reeya Kansra         0.0974
## relevel(factor(Participant), "Aliyaah Toussaint")Salsabila Mahdi      0.8425
## relevel(factor(Participant), "Aliyaah Toussaint")Sam Jin              0.9855
## relevel(factor(Participant), "Aliyaah Toussaint")Sean Wang            0.8002
## relevel(factor(Participant), "Aliyaah Toussaint")Shlomo Kofman        0.0258
## relevel(factor(Participant), "Aliyaah Toussaint")Shreeram Modi        0.0657
## relevel(factor(Participant), "Aliyaah Toussaint")Vishakh Padmakumar   0.7351
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy          0.4881
## relevel(factor(Final_Setting), "Human Debate")AI Debate               0.2813
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy       0.0409
##
## (Intercept)                                                        ***
## relevel(factor(Participant), "Aliyaah Toussaint")Adelle Fernando
## relevel(factor(Participant), "Aliyaah Toussaint")Anuj Jain         .
## relevel(factor(Participant), "Aliyaah Toussaint")David Rein
## relevel(factor(Participant), "Aliyaah Toussaint")Emmanuel Makinde
## relevel(factor(Participant), "Aliyaah Toussaint")Ethan Rosen
## relevel(factor(Participant), "Aliyaah Toussaint")Jackson Petty
## relevel(factor(Participant), "Aliyaah Toussaint")Jessica Li
## relevel(factor(Participant), "Aliyaah Toussaint")Julian Michael
## relevel(factor(Participant), "Aliyaah Toussaint")Julien Dirani
## relevel(factor(Participant), "Aliyaah Toussaint")Max Layden
## relevel(factor(Participant), "Aliyaah Toussaint")Noor Mirza-Rashid
## relevel(factor(Participant), "Aliyaah Toussaint")Reeya Kansra      .
## relevel(factor(Participant), "Aliyaah Toussaint")Salsabila Mahdi
## relevel(factor(Participant), "Aliyaah Toussaint")Sam Jin
## relevel(factor(Participant), "Aliyaah Toussaint")Sean Wang
## relevel(factor(Participant), "Aliyaah Toussaint")Shlomo Kofman     *
## relevel(factor(Participant), "Aliyaah Toussaint")Shreeram Modi     .
## relevel(factor(Participant), "Aliyaah Toussaint")Vishakh Padmakumar
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy
## relevel(factor(Final_Setting), "Human Debate")AI Debate
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy    *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 457.45  on 441  degrees of freedom
## Residual deviance: 429.05  on 420  degrees of freedom
## AIC: 473.05
##
## Number of Fisher Scoring iterations: 14
```

LMER

```r
random.intercept.model = lmer(`Final probability correct` ~ (1|Final_Setting),
                              data = judgments, REML = TRUE)
judgments$random.intercept.preds = predict(random.intercept.model)
summary(random.intercept.model)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: ‘Final probability correct‘ ~ (1 | Final_Setting)
##    Data: judgments
##
## REML criterion at convergence: 364
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5652 -0.2013  0.5015  0.5654  0.9255
##
## Random effects:
##  Groups        Name        Variance Std.Dev.
##  Final_Setting (Intercept) 0.00272  0.05215
##  Residual                  0.09799  0.31304
## Number of obs: 686, groups:  Final_Setting, 4
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)  0.75723    0.02948 3.33321   25.68  0.00006 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
ranef(random.intercept.model)
```

```
## $Final_Setting
##                      (Intercept)
## AI Consultancy     0.002319435
## AI Debate         -0.001131440
## Human Consultancy -0.056960042
## Human Debate       0.055772047
##
## with conditional variances for "Final_Setting"
```

```r
ranova(random.intercept.model)
```

```
## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## `Final probability correct` ~ (1 | Final_Setting)
##                       npar  logLik    AIC    LRT Df Pr(>Chisq)
## <none>                   3 -182.00 370.00
## (1 | Final_Setting)     2 -187.23 378.46 10.456  1   0.001222 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
random.intercept.model = lmer(`Final probability correct` ~ (1|Participant) + (1|Final_Setting),
                              data = judgments, REML = TRUE)
judgments$random.intercept.preds = predict(random.intercept.model)
summary(random.intercept.model)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: `Final probability correct` ~ (1 | Participant) + (1 | Final_Setting)
##    Data: judgments
##
## REML criterion at convergence: 357.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.7461 -0.1555  0.4368  0.5996  1.1083
##
## Random effects:
##  Groups        Name        Variance Std.Dev.
##  Participant   (Intercept) 0.002215 0.04707
##  Final_Setting (Intercept) 0.002718 0.05213
##  Residual                  0.095721 0.30939
## Number of obs: 686, groups:  Participant, 19; Final_Setting, 4
##
## Fixed effects:
##             Estimate Std. Error      df t value   Pr(>|t|)
## (Intercept)  0.75549    0.03211 4.44845   23.52 0.00000772 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
ranef(random.intercept.model)
```

```
## $Participant
##                       (Intercept)
## Adelle Fernando     -0.0231887667
## Aliyaah Toussaint    0.0445495902
## Anuj Jain           -0.0460548530
## David Rein           0.0107246587
## Emmanuel Makinde    -0.0115704647
## Ethan Rosen         -0.0171199427
```

```
## Jackson Petty      -0.0051104119
## Jessica Li         -0.0047621455
## Julian Michael      0.0348708056
## Julien Dirani      -0.0008138972
## Max Layden         -0.0038287458
## Noor Mirza-Rashid  -0.0117445230
## Reeya Kansra       -0.0261229696
## Salsabila Mahdi     0.0321800144
## Sam Jin             0.0480694982
## Sean Wang           0.0477306783
## Shlomo Kofman      -0.0519667486
## Shreeram Modi       0.0020512016
## Vishakh Padmakumar -0.0178929784
##
## $Final_Setting
##                     (Intercept)
## AI Consultancy     0.0012586597
## AI Debate         -0.0009034629
## Human Consultancy -0.0564188188
## Human Debate       0.0560636219
##
## with conditional variances for "Participant" "Final_Setting"
```

```
ranova(random.intercept.model)
```

```
## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## `Final probability correct` ~ (1 | Participant) + (1 | Final_Setting)
##                     npar  logLik   AIC    LRT Df Pr(>Chisq)
## <none>                 4 -178.95 365.9
## (1 | Participant)      3 -182.00 370.0 6.0957  1   0.013551 *
## (1 | Final_Setting)    3 -183.65 373.3 9.4004  1   0.002169 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

BRMS

```
#brm1 <- brm(data = judgments_online,
#             formula = as.numeric(Final_Accuracy) | trials(2) ~ 1 + (1 | Final_Setting),
#             family = binomial("identity"),
#             iter = 2000, warmup = 1000, chains = 4, cores = 4,
#             control = list(adapt_delta = .975, max_treedepth = 20),
#             seed = 190831)
#plot(brm1)
```

Efficiency

Quotes %, caveats

```
characters = turns.merge(
        debates[["Room name", "Question", "Story length",
                 "Untimed annotator context","Untimed annotator context bins",
                 "Setting", "Final_Setting", "Final_Accuracy",
                 "Is offline"]],
        how="left",
        on="Room name",
    )



# Filtering for specific roles
characters = characters[characters['Role (honest/dishonest)'].isin(['Honest debater', 'Dishonest debate

# Extracting the spans
def extract_spans(span_str):
    """Extract numerical spans from the given string."""
    if pd.isna(span_str):
        return []
    spans = re.findall(r'<<(\d+)-(\d+)>>', span_str)
    return [(int(start), int(end)) for start, end in spans]

# Merging overlapping spans
def merge_overlapping_spans(span_str):
    if not isinstance(span_str, str):
        return span_str
    spans = extract_spans(span_str)
    if not spans:
        return span_str
    spans.sort(key=lambda x: x[0])
    merged = [spans[0]]
    for current in spans:
        previous = merged[-1]
        if current[0] <= previous[1]:
            upper_bound = max(previous[1], current[1])
            merged[-1] = (previous[0], upper_bound)
        else:
            merged.append(current)
    return ' '.join(f'<<{start}-{end}>>' for start, end in merged)

# Aggregating function to concatenate quote spans
def custom_join(series):
    return ' '.join(filter(lambda x: isinstance(x, str), series))

# Identify questions with more than one setting and filter out the characters dataframe
questions_with_multi_settings = characters.groupby("Question").filter(lambda x: len(x["Setting"].unique
filtered_characters = characters[characters["Question"].isin(questions_with_multi_settings)]

# Aggregating data
```

```
aggregates = {
    'Quote length': 'sum',
    'Story length': 'mean',
    'Num previous judging rounds': 'max',
    'Participant quote span': custom_join
}
# Grouping by 'Room name' and aggregating
characters_agg_by_room = filtered_characters.groupby('Room name').agg(aggregates).reset_index()

# Merging the aggregated results with the original data to reintroduce the desired columns
characters_agg = characters_agg_by_room.merge(
    filtered_characters[['Room name', 'Setting', 'Final_Setting', 'Question', 'Untimed annotator contex
    on='Room name'
)

# Merge overlapping spans after the aggregation
characters_agg["merged_quote_spans"] = characters_agg["Participant quote span"].apply(merge_overlapping

# Functions to compute and compare spans across settings
def extract_numbers_from_span(span_str):
    spans = extract_spans(span_str)
    numbers = set()
    for start, end in spans:
        numbers.update(range(int(start), int(end)+1))
    return numbers

def quote_length(span_str):
  spans = extract_spans(span_str)
  numbers = set()
  for start, end in spans:
    numbers.update(range(int(start), int(end)))
  return numbers

characters_agg["quote_length"] = characters_agg["Participant quote span"].apply(lambda row: len(quote_le
#characters_agg["merged_quote_length"] = characters_agg["Participant quote span"].apply(lambda row: len
#print(characters_agg["merged_quote_length"][1])
#print((characters_agg["merged_quote_length"]==characters_agg["quote_length"]).value_counts())

#print((characters_agg['quote_length'].fillna(0)/characters_agg['Story length'].fillna(0)).describe())


def convert_to_span_format(numbers):
    sorted_numbers = sorted(list(numbers))
    spans = []
    if sorted_numbers:
        start = sorted_numbers[0]
        end = sorted_numbers[0]
        for num in sorted_numbers[1:]:
            if num == end + 1:
                end = num
            else:
                spans.append((start, end))
                start = end = num
```

```python
        spans.append((start, end))
    return ' '.join(f'<<{start}-{end}>>' for start, end in spans)

def compute_span_differences(dataframe):
    differences = {}
    for question, group in dataframe.groupby("Question"):
        settings = group["Setting"].unique()
        if len(settings) > 1:
            for i in range(len(settings)):
                for j in range(i+1, len(settings)):
                    setting_1 = settings[i]
                    setting_2 = settings[j]
                    room_1 = group[group["Setting"] == setting_1]["Room name"].values[0]
                    room_2 = group[group["Setting"] == setting_2]["Room name"].values[0]
                    acc_1 = group[group["Setting"] == setting_1]["Final_Accuracy"].values[0]
                    acc_2 = group[group["Setting"] == setting_2]["Final_Accuracy"].values[0]
                    span_str_1 = group[group["Setting"] == setting_1]["merged_quote_spans"].values[0]
                    span_str_2 = group[group["Setting"] == setting_2]["merged_quote_spans"].values[0]
                    numbers_1 = extract_numbers_from_span(span_str_1)
                    numbers_2 = extract_numbers_from_span(span_str_2)
                    diff_1 = numbers_1 - numbers_2
                    diff_2 = numbers_2 - numbers_1
                    key = (question, setting_1, room_1, acc_1, setting_2, room_2, acc_2)
                    value = (convert_to_span_format(diff_1), convert_to_span_format(diff_2))
                    differences[key] = value
    return differences

span_differences_all = compute_span_differences(characters_agg)

#print(span_differences_all.keys())
#for span in span_differences_all[('Why were Jorgenson and Ganti not put to death?', 'Human Consultancy
#  print(len(quote_length(span)))
```

```python
split_span_differences_with_room = []
# Iterate over the span differences
for (question, setting_1, room_1, acc_1, setting_2, room_2, acc_2), (diff_1, diff_2) in span_differences
    split_span_differences_with_room.append((question, setting_1, room_1, acc_1, setting_2, room_2, acc_
    split_span_differences_with_room.append((question, setting_2, room_2, acc_2, setting_1, room_1, acc_

# Convert the list to a DataFrame
split_span_df = pd.DataFrame(split_span_differences_with_room, columns=['Question', 'Setting 1', 'Room 

split_span_df["Span Difference Count"] = split_span_df["Span Difference"].apply(lambda x: len(quote_leng
split_span_df["Settings"] = split_span_df["Setting 1"] + " - " + split_span_df["Setting 2"]


# Group by the new 'Settings' column and compute aggregated counts and average of 'Span Difference Coun
grouped_data = split_span_df.groupby("Settings").agg(
    Count=('Span Difference Count', 'size'),
    Average_Span_Difference=('Span Difference Count', 'mean')
).reset_index()

grouped_data
```

```
##                                               Settings  Count  Average_Span_Difference
## 0    AI Consultancy Dishonest - AI Consultancy Honest     12               137.416667
## 1                AI Consultancy Dishonest - AI Debate     12               141.500000
## 2   AI Consultancy Dishonest - Human Consultancy D...     12               169.833333
## 3   AI Consultancy Dishonest - Human Consultancy H...     13                96.384615
## 4             AI Consultancy Dishonest - Human Debate     13               129.153846
## 5    AI Consultancy Honest - AI Consultancy Dishonest     12               202.916667
## 6                   AI Consultancy Honest - AI Debate     12               189.750000
## 7   AI Consultancy Honest - Human Consultancy Dish...     12               211.333333
## 8    AI Consultancy Honest - Human Consultancy Honest     12               177.416667
## 9                AI Consultancy Honest - Human Debate     12               197.833333
## 10               AI Debate - AI Consultancy Dishonest     12                85.083333
## 11                  AI Debate - AI Consultancy Honest     12                65.500000
## 12            AI Debate - Human Consultancy Dishonest     12                94.500000
## 13               AI Debate - Human Consultancy Honest     12                78.000000
## 14                           AI Debate - Human Debate     16                88.062500
## 15  Human Consultancy Dishonest - AI Consultancy D...     12               340.166667
## 16  Human Consultancy Dishonest - AI Consultancy H...     12               315.000000
## 17            Human Consultancy Dishonest - AI Debate     12               404.750000
## 18  Human Consultancy Dishonest - Human Consultanc...     38               334.815789
## 19         Human Consultancy Dishonest - Human Debate     46               300.847826
## 20  Human Consultancy Honest - AI Consultancy Dish...     13               280.692308
## 21   Human Consultancy Honest - AI Consultancy Honest     12               293.333333
## 22               Human Consultancy Honest - AI Debate     12               299.083333
## 23  Human Consultancy Honest - Human Consultancy D...     38               272.763158
## 24            Human Consultancy Honest - Human Debate     42               255.380952
## 25            Human Debate - AI Consultancy Dishonest     13               179.153846
## 26               Human Debate - AI Consultancy Honest     12               201.250000
## 27                           Human Debate - AI Debate     16               188.625000
## 28         Human Debate - Human Consultancy Dishonest     46               163.956522
## 29            Human Debate - Human Consultancy Honest     42               147.880952
```

```
filtered_df = split_span_df[
    (split_span_df["Setting 1"] == "Human Debate") &
    ((split_span_df["Setting 2"] == "Human Consultancy Honest") | (split_span_df["Setting 2"] == "Human
]

print(filtered_df.groupby(['Setting 2','Acc_1','Acc_2'])['Span Difference Count'].describe())
```

```
##                                        count        mean         std    min     25%    50%     75%
## Setting 2                   Acc_1 Acc_2
## Human Consultancy Dishonest False False   5.0  187.200000   90.698401   92.0  131.00  145.0  275.00
##                                   True    8.0  149.625000  100.637876   39.0   42.75  156.5  236.25
##                             True  False  16.0  148.687500   81.308236   47.0   89.75  128.0  182.00
##                                   True   17.0  178.235294  115.183294   57.0   92.00  161.0  233.00
## Human Consultancy Honest    False False   4.0  144.750000  134.321443   14.0   36.50  149.0  257.25
##                                   True   12.0  122.416667   95.625651   30.0   55.50   83.0  164.75
##                             True  False   4.0  197.000000   63.050245  120.0  170.25  197.5  224.25
##                                   True   22.0  153.409091   94.780277   30.0   75.00  130.0  195.00
```

```
# Calculate the IQR and bounds for each group in 'Setting 2'
grouped = filtered_df.groupby('Setting 2')['Span Difference Count']
```

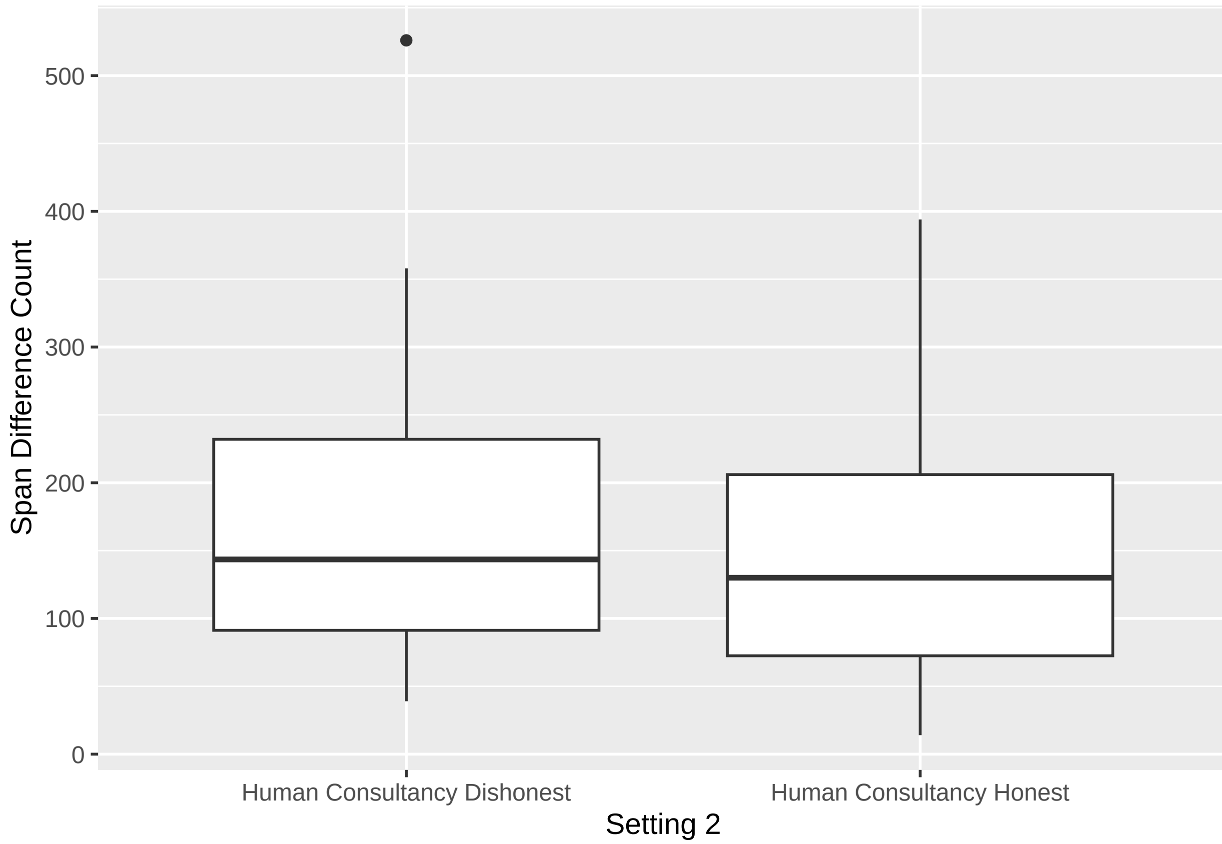
```
Q1 = grouped.quantile(0.25)
Q3 = grouped.quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out the outliers based on the computed bounds
filtered_no_outliers = filtered_df[
    (filtered_df['Setting 2'].map(lower_bound) <= filtered_df['Span Difference Count']) &
    (filtered_df['Setting 2'].map(upper_bound) >= filtered_df['Span Difference Count'])
]

filtered_no_outliers
```

```
##                                               Question  ...                                   Setti
## 0    By the end of the passage. what can we underst...  ...     Human Debate - Human Consultancy Hone
## 2    By the end of the passage. what can we underst...  ...  Human Debate - Human Consultancy Dishone
## 30   Did the questions Tremaine needed answers to g...  ...     Human Debate - Human Consultancy Hone
## 32   Did the questions Tremaine needed answers to g...  ...  Human Debate - Human Consultancy Dishone
## 60   From the information the story provides, do yo...  ...     Human Debate - Human Consultancy Hone
## ..                                                 ...  ...
## 510  Why was the main character daydreaming about b...  ...  Human Debate - Human Consultancy Dishone
## 514            Why was the murderer trying to kill Bo?  ...     Human Debate - Human Consultancy Hone
## 516            Why was the murderer trying to kill Bo?  ...  Human Debate - Human Consultancy Dishone
## 544     Why were Jorgenson and Ganti not put to death?  ...  Human Debate - Human Consultancy Dishone
## 546     Why were Jorgenson and Ganti not put to death?  ...     Human Debate - Human Consultancy Hone
##
## [87 rows x 10 columns]
```

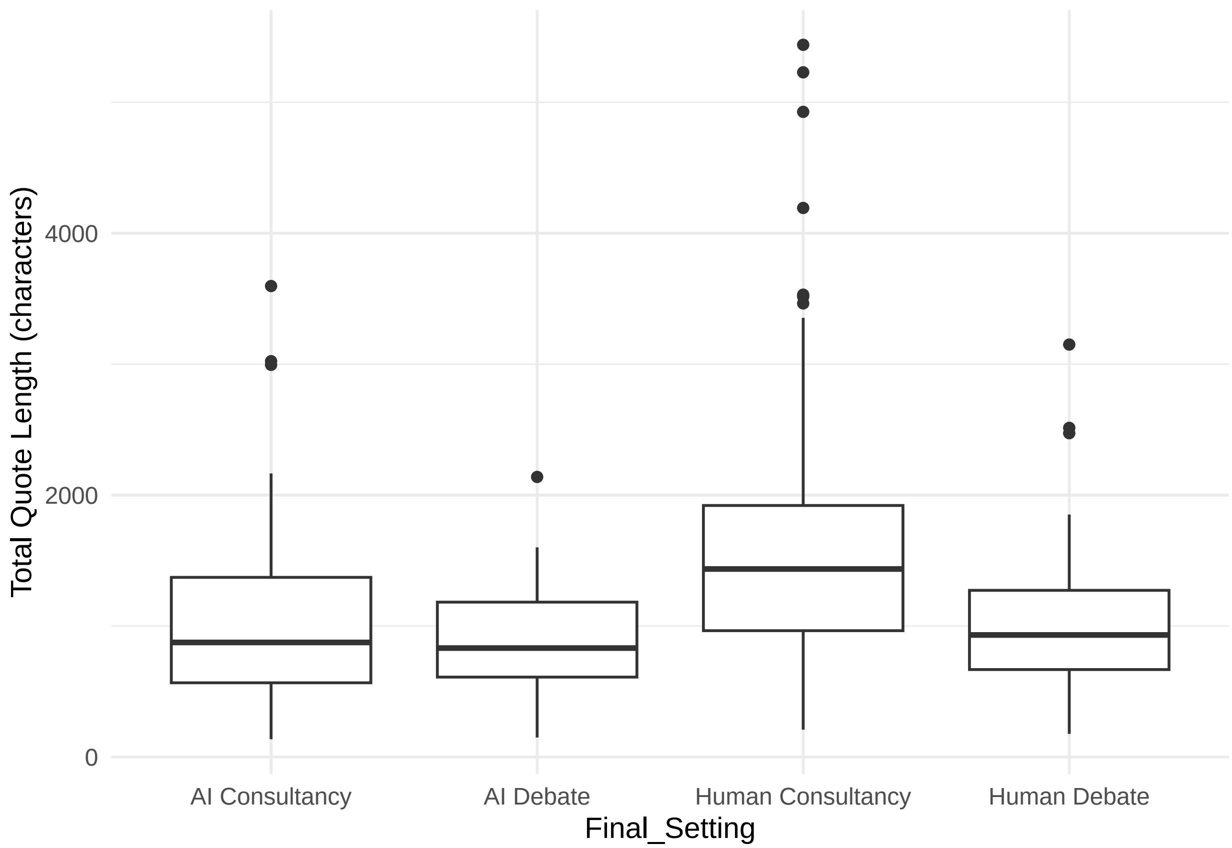
```
print(filtered_no_outliers.groupby(['Setting 2','Acc_1','Acc_2'])['Span Difference Count'].describe())
```

```
##                                          count        mean         std    min     25%    50%     75%
## Setting 2                    Acc_1 Acc_2
## Human Consultancy Dishonest False False    5.0  187.200000   90.698401   92.0  131.00  145.0  275.00
##                                    True     8.0  149.625000  100.637876   39.0   42.75  156.5  236.25
##                              True  False   16.0  148.687500   81.308236   47.0   89.75  128.0  182.00
##                                    True    16.0  156.500000   74.733304   57.0   91.25  143.0  220.25
## Human Consultancy Honest     False False    4.0  144.750000  134.321443   14.0   36.50  149.0  257.25
##                                    True    12.0  122.416667   95.625651   30.0   55.50   83.0  164.75
##                              True  False    4.0  197.000000   63.050245  120.0  170.25  197.5  224.25
##                                    True    22.0  153.409091   94.780277   30.0   75.00  130.0  195.00
```

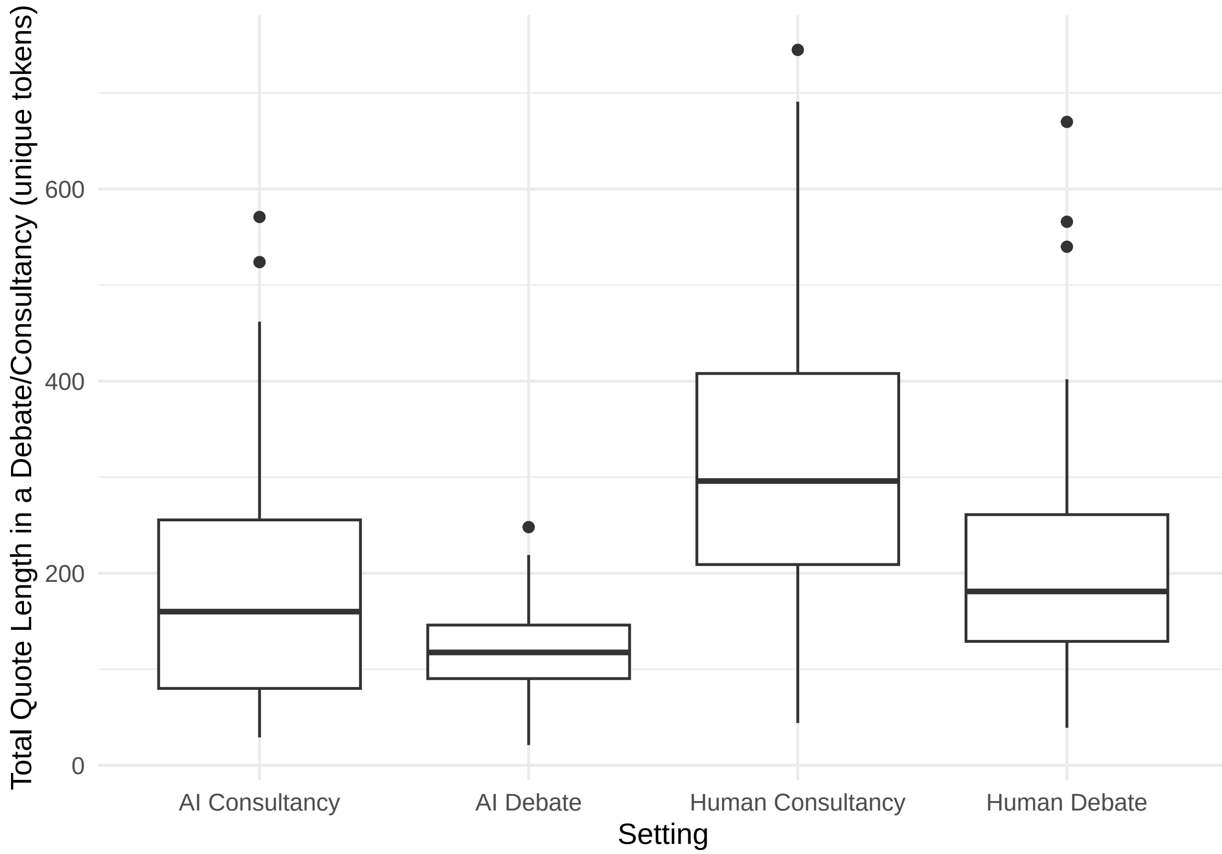
```
characters<- py$characters_agg
span_difference_debate_consultancies<-py$filtered_df
ggplot(span_difference_debate_consultancies) +
  geom_boxplot(aes(x = `Setting 2`, y = `Span Difference Count`))
```



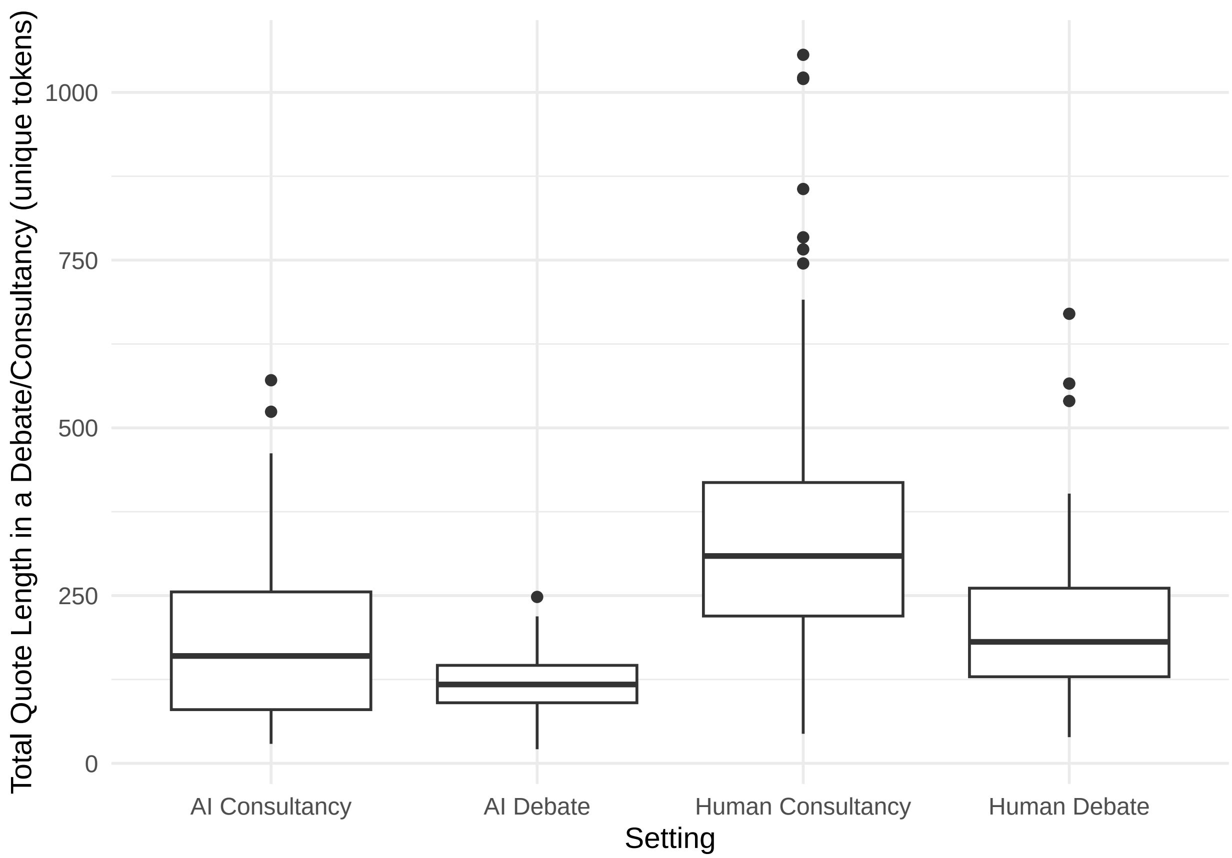

```
filtered_outliers <- characters %>%
  group_by(Final_Setting) %>%
  mutate(Q1 = quantile(quote_length, 0.25),
         Q3 = quantile(quote_length, 0.75),
         IQR = Q3 - Q1,
         lower_bound = Q1 - 1.5 * IQR,
         upper_bound = Q3 + 1.5 * IQR)

ggplot(characters) +
  geom_boxplot(aes(x = Final_Setting, y = `Quote length`)) +
  labs(y = "Total Quote Length (characters)")+
  theme_minimal()
```




```
filtered <- characters %>%
  group_by(Final_Setting) %>%
  mutate(Q1 = quantile(quote_length, 0.25),
         Q3 = quantile(quote_length, 0.75),
         IQR = Q3 - Q1,
         lower_bound = Q1 - 1.5 * IQR,
         upper_bound = Q3 + 1.5 * IQR) %>%
  filter(quote_length > 0 & quote_length < 750) %>%
  select(-Q1, -Q3, -IQR, -lower_bound, -upper_bound)
filtered %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = quote_length)) +
  labs(y = "Total Quote Length in a Debate/Consultancy (unique tokens)", x = "Setting")+
  theme_minimal()
```




```
characters %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = quote_length)) +
  labs(y = "Total Quote Length in a Debate/Consultancy (unique tokens)", x = "Setting")+
  theme_minimal()
```




```
pairwise.t.test(filtered$quote_length, filtered$Final_Setting)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  filtered$quote_length and filtered$Final_Setting
##
##                   AI Consultancy AI Debate      Human Consultancy
## AI Debate         0.04290        -              -
## Human Consultancy 0.00017        0.000000000018 -
## Human Debate      0.80222        0.00443        0.000000019213
##
## P value adjustment method: holm
```

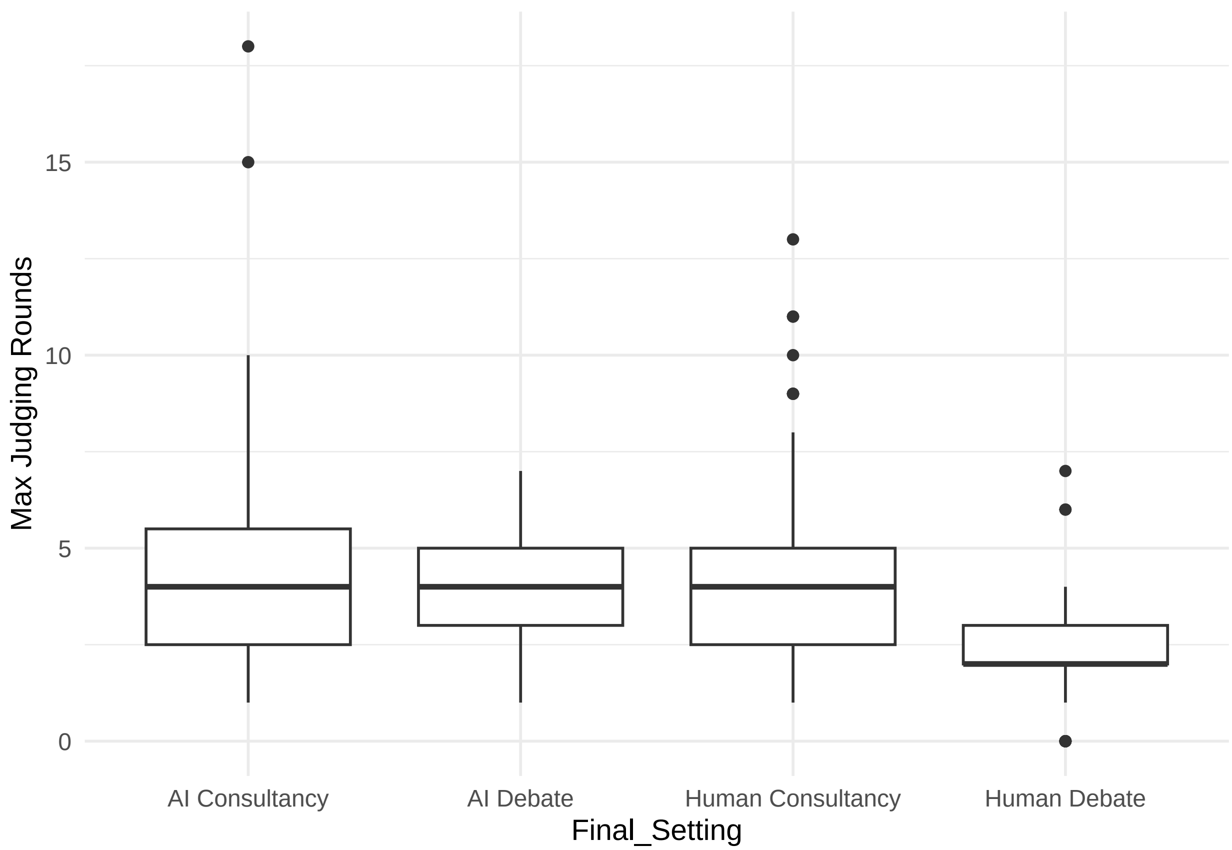
```
filtered %>% group_by(Final_Setting) %>% summarise(avground = median(quote_length))
```

```
## # A tibble: 4 x 2
##   Final_Setting     avground
##   <chr>                <dbl>
## 1 AI Consultancy        160
## 2 AI Debate             118.
## 3 Human Consultancy     296
## 4 Human Debate          181
```

```r
characters %>% group_by(Final_Setting) %>% summarise(avground = median(quote_length))
```

```
## # A tibble: 4 x 2
##   Final_Setting     avground
##   <chr>                <dbl>
## 1 AI Consultancy         160
## 2 AI Debate              118.
## 3 Human Consultancy      309
## 4 Human Debate           181
```

```r
characters <- characters %>%
  group_by(`Room name`,) %>%
  mutate(`Max judge rounds by room` = max(`Num previous judging rounds`, na.rm = TRUE)) %>%
  ungroup()
ggplot(characters) +
  geom_boxplot(aes(x = Final_Setting, y = `Max judge rounds by room`)) +
  labs(y = 'Max Judging Rounds') +
  theme_minimal()
```

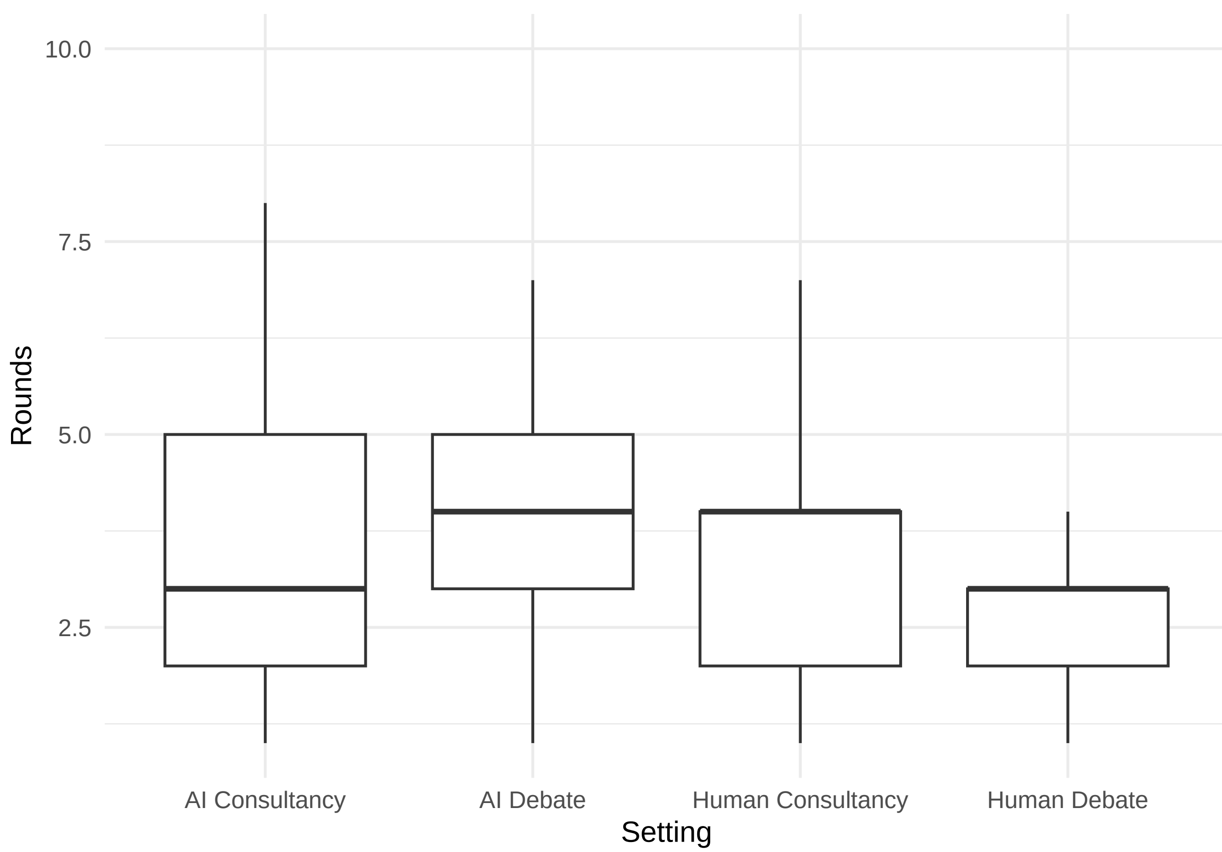



```r
pairwise.t.test(characters$`Max judge rounds by room`, characters$Final_Setting)
```

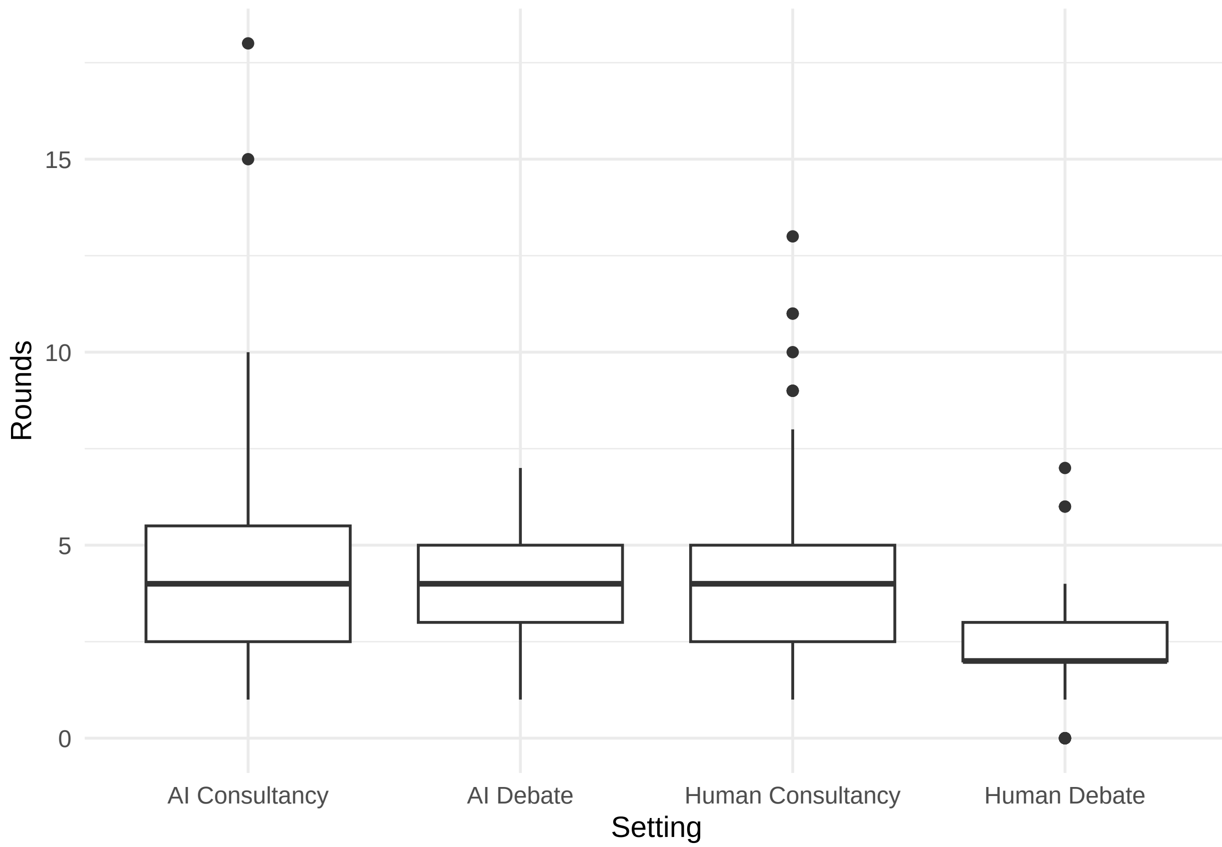
```
##
##  Pairwise comparisons using t tests with pooled SD
##
```

```
## data:  characters$‘Max judge rounds by room‘ and characters$Final_Setting
##
##                     AI Consultancy AI Debate Human Consultancy
## AI Debate           0.137          -         -
## Human Consultancy 0.055          0.914     -
## Human Debate        0.0000003      0.002     0.0000020
##
## P value adjustment method: holm
```

```r
filtered <- characters %>%
  group_by(Final_Setting) %>%
  mutate(Q1 = quantile(`Max judge rounds by room`, 0.25),
         Q3 = quantile(`Max judge rounds by room`, 0.75),
         IQR = Q3 - Q1,
         lower_bound = Q1 - 1.5 * IQR,
         upper_bound = Q3 + 1.5 * IQR) %>%
  filter(`Max judge rounds by room` >= lower_bound & `Max judge rounds by room` <= upper_bound) %>%
  select(-Q1, -Q3, -IQR, -lower_bound, -upper_bound)
filtered %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = `Max judge rounds by room`), outlier.shape = NA) +
  labs(y = "Rounds", x = "Setting")+
  theme_minimal()
```



```r
characters %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = `Max judge rounds by room`)) +
  labs(y = "Rounds", x = "Setting")+
  theme_minimal()
```




```r
pairwise.t.test(filtered$quote_length, filtered$Final_Setting)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  filtered$quote_length and filtered$Final_Setting
##
##                   AI Consultancy   AI Debate        Human Consultancy
## AI Debate         0.192            -                -
## Human Consultancy 0.00000150627713 0.00000000000097 -
## Human Debate      0.560            0.018            0.00000000003675
##
## P value adjustment method: holm
```

```r
filtered %>% group_by(Final_Setting) %>% summarise(avground = mean(`Max judge rounds by room`))
```

```
## # A tibble: 4 x 2
##   Final_Setting     avground
```

```
##   <chr>                <dbl>
## 1 AI Consultancy        4.24
## 2 AI Debate             4.07
## 3 Human Consultancy     3.61
## 4 Human Debate          2.52
```

Length of debates, stratified

```
per_turn = turns.merge(
        debates[["Room name", "Honest debater", "Dishonest debater", "Question", "Article ID",
                 "Speed annotator accuracy","Untimed annotator context","Untimed annotator context bins
        how="left",
        on="Room name",
    )

print(per_turn.groupby('Final_Setting')['Num previous judging rounds'].mean())
```

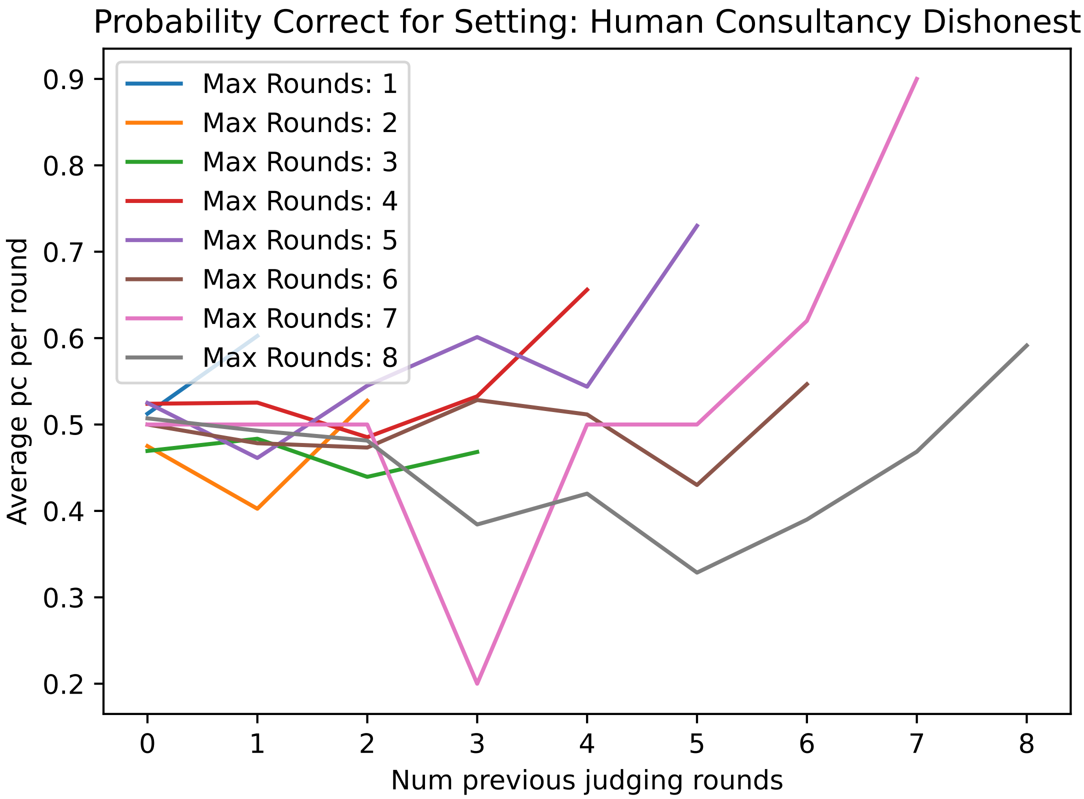
```
## Final_Setting
## AI Consultancy       4.173252
## AI Debate            2.986231
## Human Consultancy    2.759310
## Human Debate         1.475072
## Name: Num previous judging rounds, dtype: float64
```

```
# Calculate the IQR and bounds for each group in 'Setting 2'
grouped = per_turn.groupby('Setting')['Num previous judging rounds']

Q1 = grouped.quantile(0.25)
Q3 = grouped.quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out the outliers based on the computed bounds
filtered_no_outliers = per_turn[
    (per_turn['Setting'].map(lower_bound) <= per_turn['Num previous judging rounds']) &
    (per_turn['Setting'].map(upper_bound) >= per_turn['Num previous judging rounds'])
]

filtered_no_outliers
```

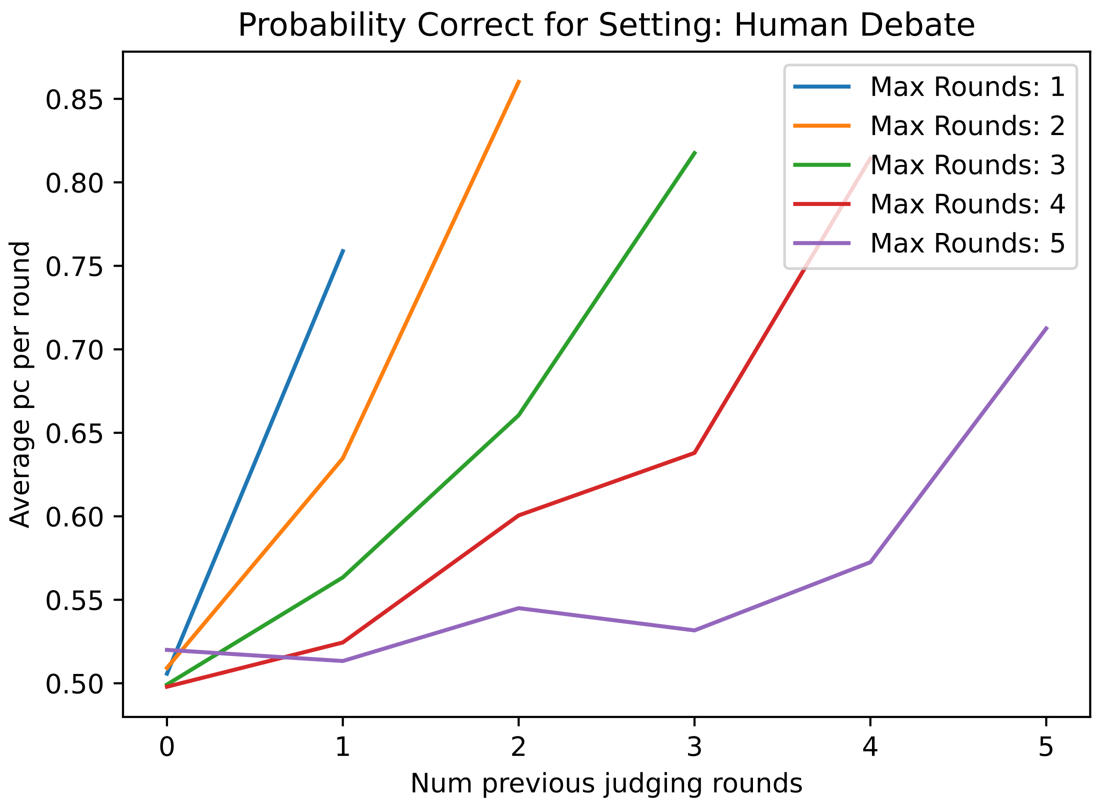
```
##                             Room name  Room start time  ...                     Setting Final_Accura
## 0                         ambition-8    1686950589862  ...  Human Consultancy Dishonest           Tr
## 1                         ambition-8    1686950589862  ...  Human Consultancy Dishonest           Tr
## 2                         ambition-8    1686950589862  ...  Human Consultancy Dishonest           Tr
## 3                         ambition-8    1686950589862  ...  Human Consultancy Dishonest           Tr
## 4                         ambition-8    1686950589862  ...  Human Consultancy Dishonest           Tr
## ...                              ...              ...  ...                         ...            .
## 6013                   break-a-leg-3    1682110823449  ...                Human Debate           Tr
## 6014                   break-a-leg-3    1682110823449  ...                Human Debate           Tr
```

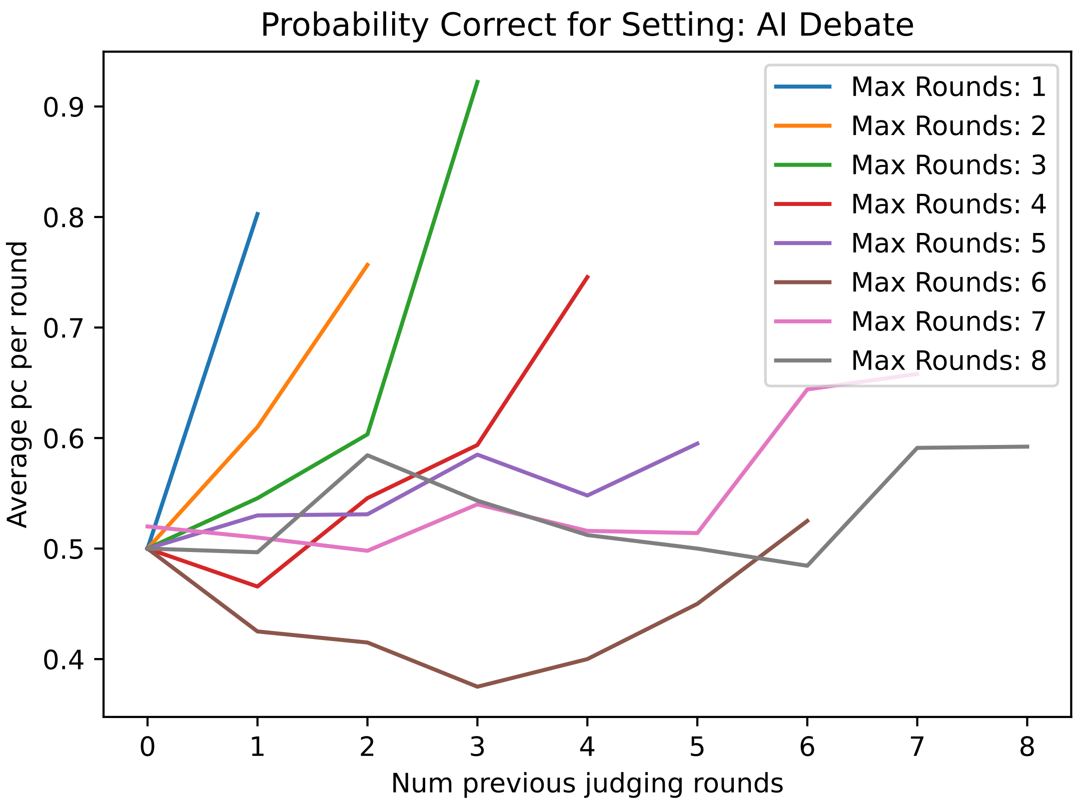
```
## 6015  the-absurdity-of-family-love-2    1689876267578  ...     Human Consultancy Honest           Tru
## 6016  the-absurdity-of-family-love-2    1689876267578  ...     Human Consultancy Honest           Tru
## 6017  the-absurdity-of-family-love-2    1689876267578  ...     Human Consultancy Honest           Tru
##
## [5875 rows x 27 columns]
```

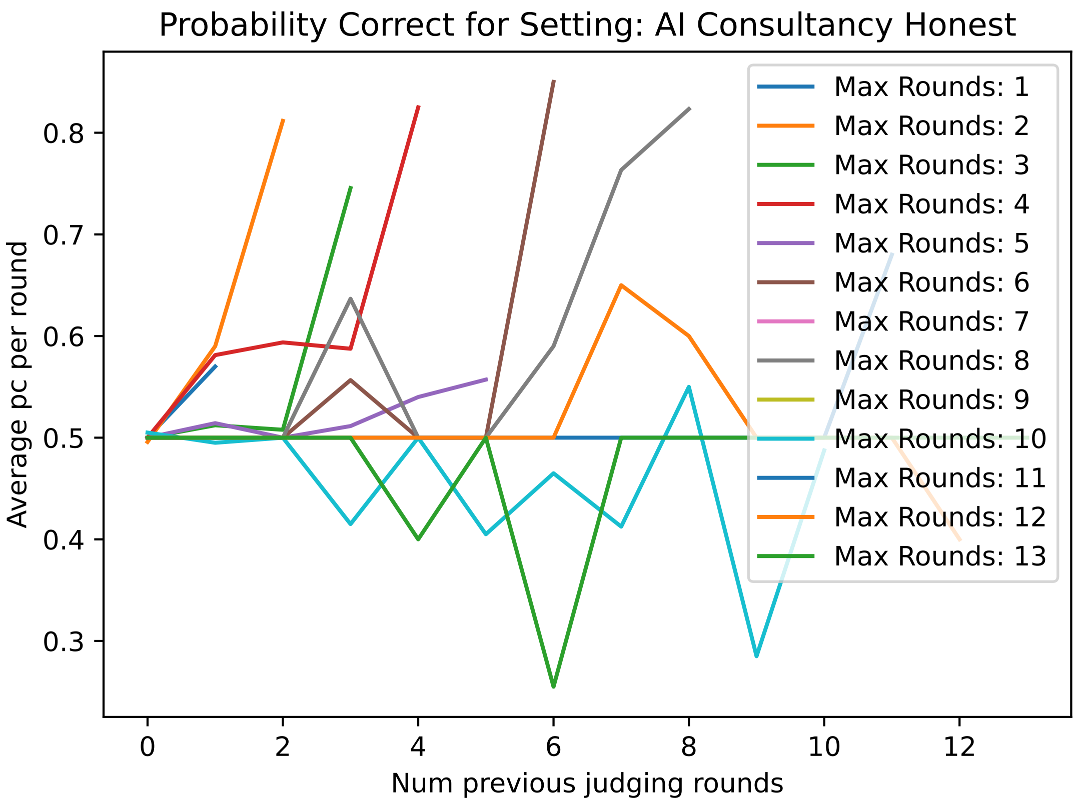
```
for setting in filtered_no_outliers['Setting'].unique():
  per_turn_setting = filtered_no_outliers[filtered_no_outliers['Setting']==setting]
  print(setting)
  # Calculate the maximum 'Num previous judging rounds' for each combination of 'Room name' and 'Partic
  per_turn_setting['Max judge rounds by room'] = per_turn_setting.groupby(['Room name', 'Participant'])
  ## Just based on the number of rounds

  for i in range(1, per_turn_setting['Max judge rounds by room'].max() + 1):
      max_rounds = per_turn_setting[(per_turn_setting['Max judge rounds by room'] == i) & (per_turn_sett
      print(len(max_rounds))
      # Group by 'Num previous judging rounds' and calculate the mean of 'Probability correct'
      average_pc_per_round = max_rounds.groupby('Num previous judging rounds')['Probability correct'].me

      # Create a new DataFrame with 'Num previous judging rounds' and 'Average pc per round'
      probability_correct_round = pd.DataFrame({'Num previous judging rounds': average_pc_per_round.inde
                                                'Average pc per round': average_pc_per_round.values})

      # Plotting the data with label for the line
      plt.plot(probability_correct_round['Num previous judging rounds'], probability_correct_round['Aver

  plt.title(f"Probability Correct for Setting: {setting}")
  plt.xlabel('Num previous judging rounds')
  plt.ylabel('Average pc per round')
  plt.legend()
  plt.show()
```



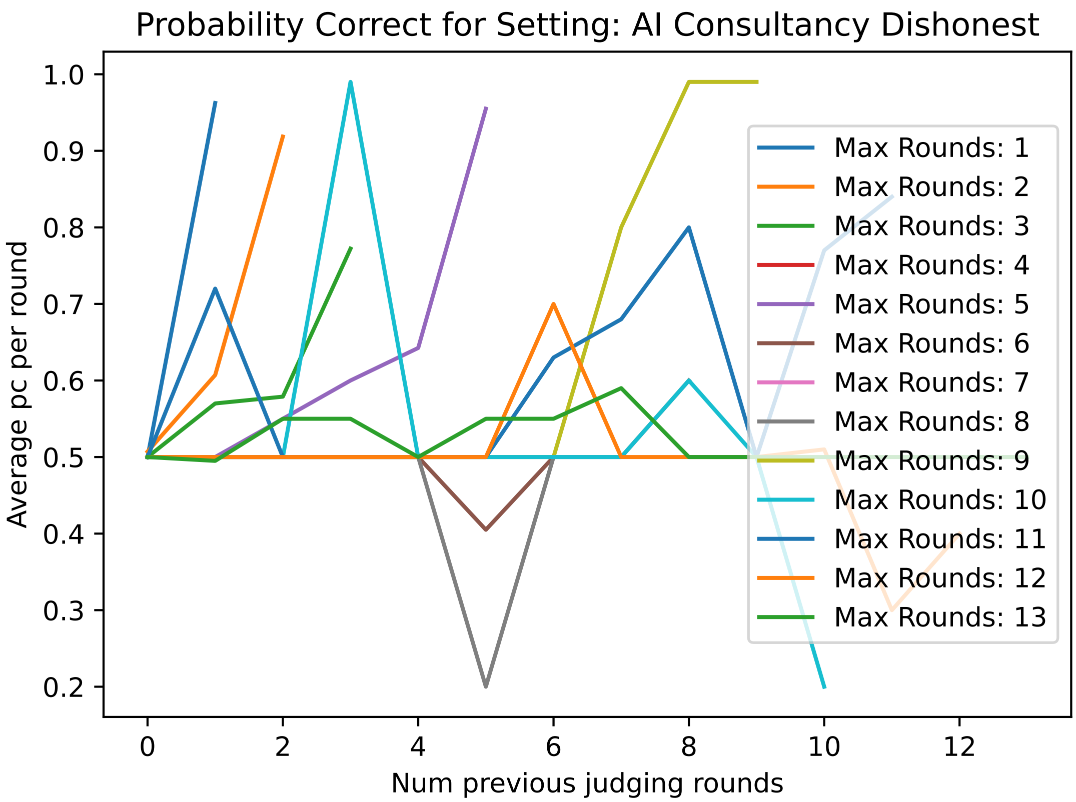
Probability Correct for Setting: Human Consultancy Dishonest
Max Rounds: 1
Max Rounds: 2
Max Rounds: 3
Max Rounds: 4
Max Rounds: 5
Max Rounds: 6
Max Rounds: 7
Max Rounds: 8
Average pc per round
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
1
2
3
4
5
6
7
8
Num previous judging rounds

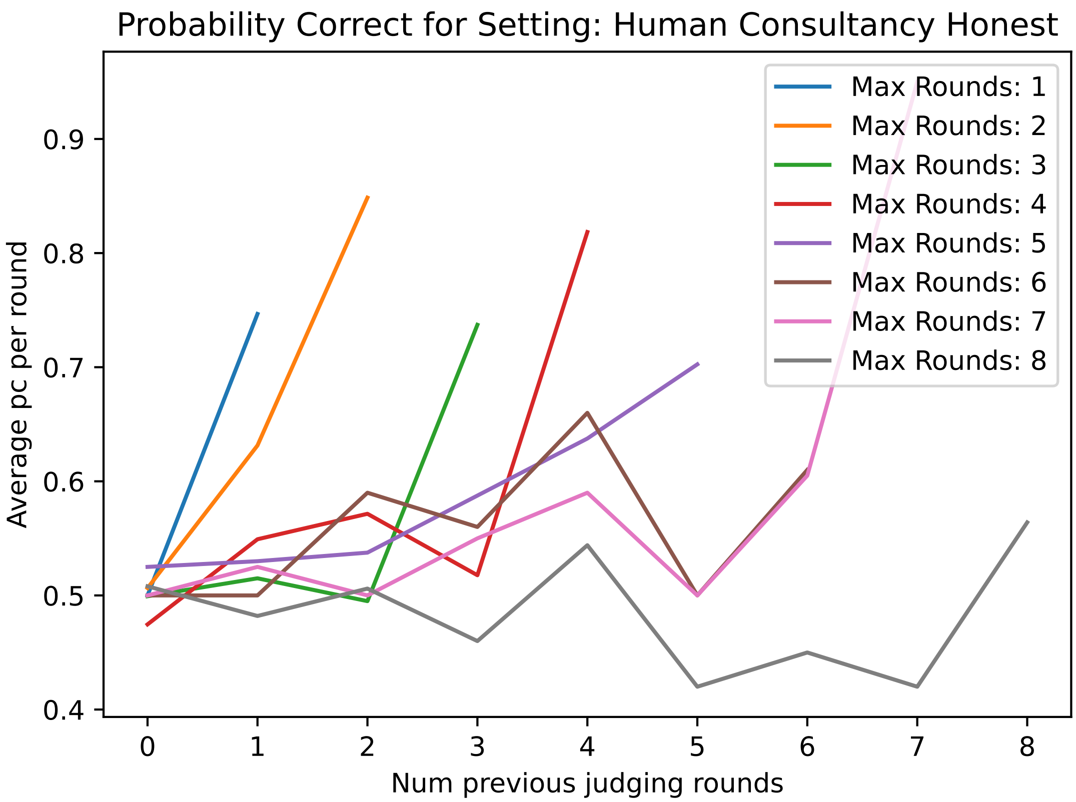

Probability Correct for Setting: Human Debate
Average pc per round
Num previous judging rounds
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0
1
2
3
4
5
Max Rounds: 1
Max Rounds: 2
Max Rounds: 3
Max Rounds: 4
Max Rounds: 5


Probability Correct for Setting: AI Debate
Max Rounds: 1
Max Rounds: 2
Max Rounds: 3
Max Rounds: 4
Max Rounds: 5
Max Rounds: 6
Max Rounds: 7
Max Rounds: 8
Average pc per round
0.4
0.5
0.6
0.7
0.8
0.9
0
1
2
3
4
5
6
7
8
Num previous judging rounds



Probability Correct for Setting: AI Consultancy Honest
Average pc per round
Num previous judging rounds
0.3
0.4
0.5
0.6
0.7
0.8
0
2
4
6
8
10
12
Max Rounds: 1
Max Rounds: 2
Max Rounds: 3
Max Rounds: 4
Max Rounds: 5
Max Rounds: 6
Max Rounds: 7
Max Rounds: 8
Max Rounds: 9
Max Rounds: 10
Max Rounds: 11
Max Rounds: 12
Max Rounds: 13

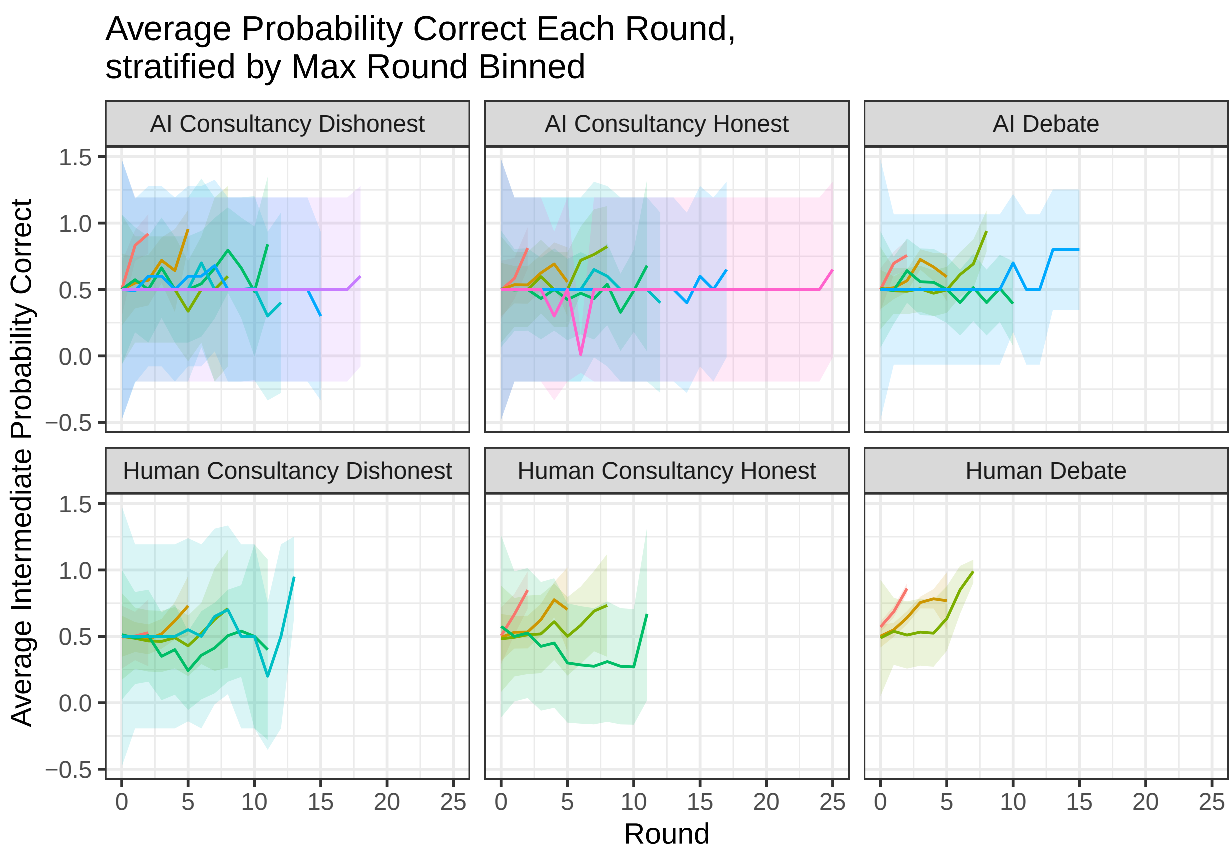

Probability Correct for Setting: AI Consultancy Dishonest
Average pc per round
Num previous judging rounds
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
2
4
6
8
10
12
Max Rounds: 1
Max Rounds: 2
Max Rounds: 3
Max Rounds: 4
Max Rounds: 5
Max Rounds: 6
Max Rounds: 7
Max Rounds: 8
Max Rounds: 9
Max Rounds: 10
Max Rounds: 11
Max Rounds: 12
Max Rounds: 13




```r
strat <- py$per_turn
strat <- strat %>%
  group_by(`Room name`, Participant) %>%
  mutate(`Max judge rounds by room` = max(`Num previous judging rounds`, na.rm = TRUE)) %>%
  ungroup()
strat <- strat %>%
  mutate(`Max judge rounds bin` = cut(`Max judge rounds by room`,
                                      breaks = seq(0, max(`Max judge rounds by room`, na.rm = TRUE) + 3
                                      labels = FALSE,
                                      include.lowest = TRUE,
                                      right = FALSE))

# Plot using ggplot2
strat %>%
  group_by(Setting, `Num previous judging rounds`, `Max judge rounds bin`) %>%
  summarize(
    `Average Probability Correct` = mean(`Probability correct`, na.rm = TRUE),
    n = n(),
    se = sqrt(`Average Probability Correct` * (1 - `Average Probability Correct`) / n)
  ) %>%
  mutate(
    lower_ci = `Average Probability Correct` - 1.96 * se,
    upper_ci = `Average Probability Correct` + 1.96 * se
  ) %>%
  ggplot(aes(x = `Num previous judging rounds`, y = `Average Probability Correct`, col = as.factor(`Max
  geom_ribbon(aes(ymin = lower_ci, ymax = upper_ci, fill = as.factor(`Max judge rounds bin`), group = as
```

```
  labs(title = "Average Probability Correct Each Round, \nstratified by Max Round Binned",
       x = "Round",
       y = "Average Intermediate Probability Correct") +
  geom_line() +
  facet_wrap(~Setting) +
  theme_bw() +
  theme(legend.position = "none")
```

```
## 'summarise()' has grouped output by 'Setting', 'Num previous judging rounds'. You can override using
## argument.
```

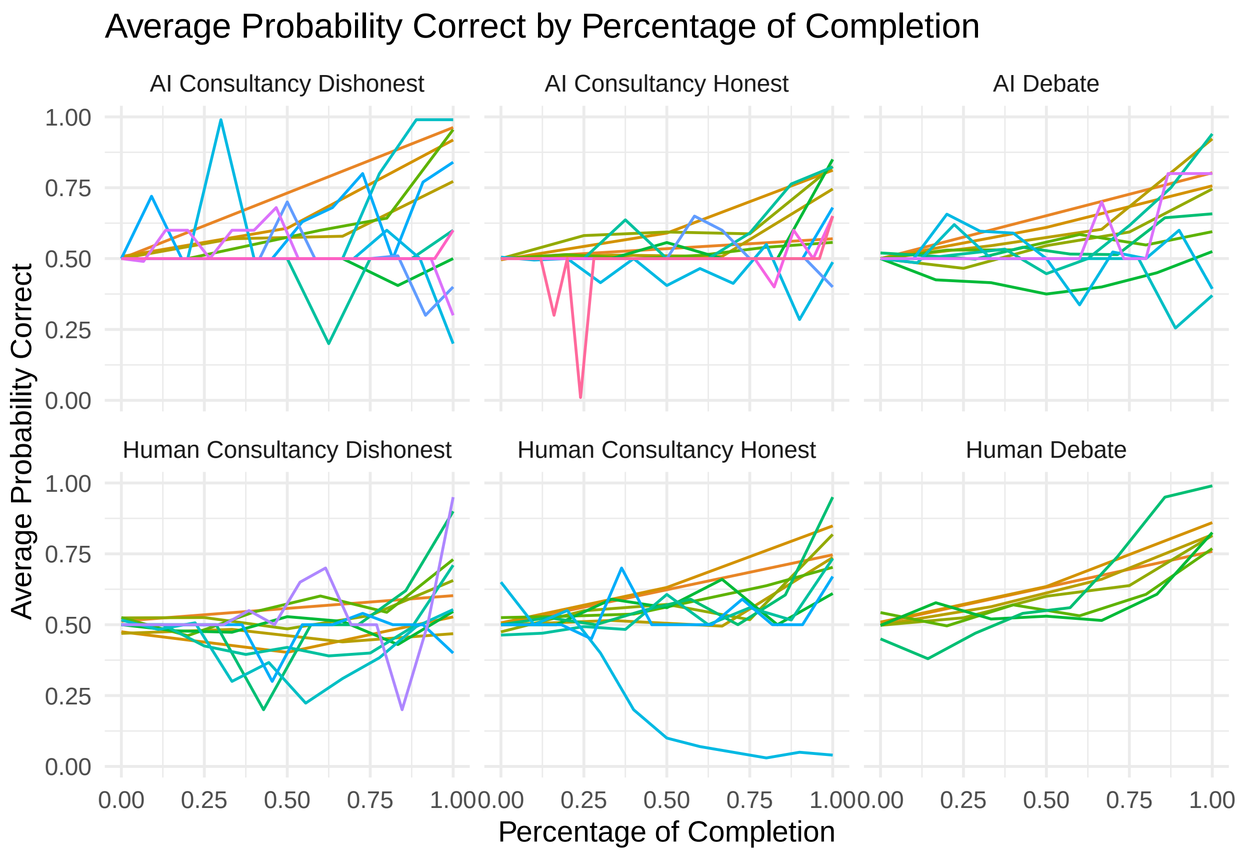



```
strat %>%
  group_by(Setting, `Num previous judging rounds`, `Max judge rounds by room`) %>%
  summarize(`Average Probability Correct` = mean(`Probability correct`, na.rm = TRUE)) %>%
  mutate(Completion = `Num previous judging rounds` / `Max judge rounds by room`) %>%
  ggplot(aes(x = Completion, y = `Average Probability Correct`, col = as.factor(`Max judge rounds by ro
  geom_line() +
  labs(title = "Average Probability Correct by Percentage of Completion",
       x = "Percentage of Completion",
       y = "Average Probability Correct") +
  facet_wrap(~Setting) +
  theme_minimal() +
  theme(legend.position = "none")
```

```
## 'summarise()' has grouped output by 'Setting', 'Num previous judging rounds'. You can override using
```

```
## argument.
```

```
## Warning: Removed 10 rows containing missing values (‘geom_line()‘).
```



Time (offline judging..?)

```
# Convert to datetime
judgments["Offline judging start time"] = pd.to_datetime(judgments["Offline judging start time"], unit=
judgments["Offline judging end time"] = pd.to_datetime(judgments["Offline judging end time"], unit="ms"

# Calculate offline judging time in minutes
judgments["Offline judging time"] = (judgments["Offline judging end time"] - judgments["Offline judging


print(f"Number of offline judgments on consultancies:\n{judgments[judgments['Setting'].str.contains('Co
```

```
## Number of offline judgments on consultancies:
## count      13.000000
## mean      447.514203
## std      1236.792144
## min         1.169167
## 25%         1.836600
## 50%         5.664767
```

```
## 75%         13.967783
## max       4369.697933
## Name: Offline judging time, dtype: float64
## Only 13...
```

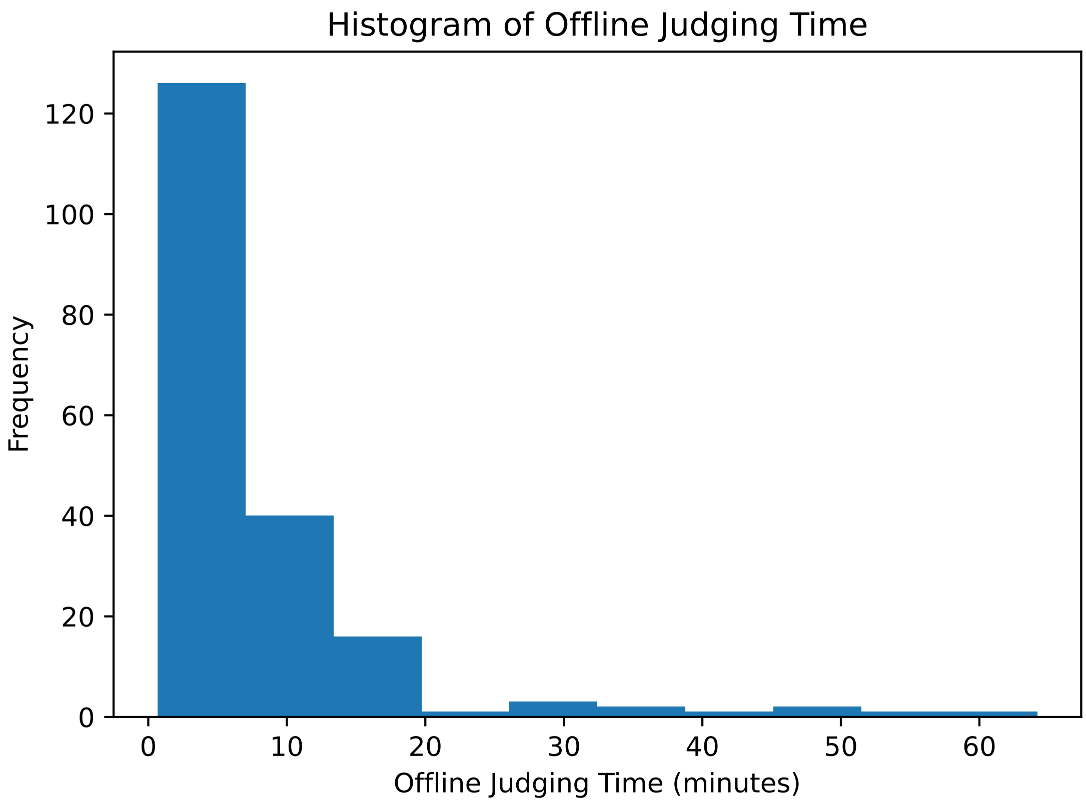
```python
# Filter out rows with NaT values
valid_judging_time = judgments["Offline judging time"].dropna()

# Calculate summary statistics
summary_stats = valid_judging_time.describe()
print(summary_stats)
```

```
## count      203.000000
## mean       255.826710
## std       1372.208730
## min          0.667467
## 25%          2.867950
## 50%          5.176250
## 75%         10.295583
## max      14202.493917
## Name: Offline judging time, dtype: float64
```

```python
# Filter judgments with offline judging time above 65 minutes
filtered_judgments = judgments[(judgments["Offline judging time"] < 65) & (judgments["Untimed annotator

# Print filtered judgments
# print("Filtered judgments with offline judging time above 65 minutes:")
print(filtered_judgments['Offline judging time'].describe())
```

```
## count    193.000000
## mean       8.013787
## std        9.410150
## min        0.667467
## 25%        2.850450
## 50%        5.107450
## 75%        8.716300
## max       64.173267
## Name: Offline judging time, dtype: float64
```

```python
# Create the histogram
plt.hist(filtered_judgments['Offline judging time'], bins=10)

# Set labels and title
plt.xlabel("Offline Judging Time (minutes)")
plt.ylabel("Frequency")
plt.title("Histogram of Offline Judging Time")

# Display the histogram
plt.show()
```




```
aggregates = {
    'Final probability correct': 'mean',
    'Untimed annotator context': 'mean'
}
filtered_judgments = filtered_judgments.groupby('Offline judging time').agg(aggregates).reset_index()
```

Analysis

Question Difficulty

confounder rounds, quotes

```
judgments["Number of judge continues bins"] = pd.cut(
    judgments["Number of judge continues"],
    bins=[0, 3, 6, 9, float('inf')],  # bin edges
    labels=['1-3', '4-6', '7-9', '10+'],  # labels for the resulting bins
    right=True  # includes the right edge of the bin
)
aggregated_df = judgments.groupby(["Setting", "Number of judge continues bins"])["Final_Accuracy"].agg(
    Proportion_True=lambda x: x.mean(),
    Total_Count="size"
).reset_index()
```

```
## <string>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True i
```

```
pd.set_option('display.max_columns', None)
print(aggregated_df)
```

```
##                          Setting Number of judge continues bins  \
## 0      AI Consultancy Dishonest                             1-3
## 1      AI Consultancy Dishonest                             4-6
## 2      AI Consultancy Dishonest                             7-9
## 3      AI Consultancy Dishonest                             10+
## 4         AI Consultancy Honest                             1-3
## 5         AI Consultancy Honest                             4-6
## 6         AI Consultancy Honest                             7-9
## 7         AI Consultancy Honest                             10+
## 8                     AI Debate                             1-3
## 9                     AI Debate                             4-6
## 10                    AI Debate                             7-9
## 11                    AI Debate                             10+
## 12  Human Consultancy Dishonest                             1-3
## 13  Human Consultancy Dishonest                             4-6
## 14  Human Consultancy Dishonest                             7-9
## 15  Human Consultancy Dishonest                             10+
## 16     Human Consultancy Honest                             1-3
## 17     Human Consultancy Honest                             4-6
## 18     Human Consultancy Honest                             7-9
## 19     Human Consultancy Honest                             10+
## 20                 Human Debate                             1-3
## 21                 Human Debate                             4-6
## 22                 Human Debate                             7-9
## 23                 Human Debate                             10+
##
##     Proportion_True  Total_Count
## 0          0.962963           27
## 1          0.833333            6
## 2          1.000000            2
## 3          0.400000            5
## 4          0.740741           27
## 5          0.777778           18
## 6          1.000000            3
## 7          0.625000            8
## 8          0.843137           51
## 9          0.740741           27
## 10         0.700000           10
## 11         0.500000            4
## 12         0.483871           31
## 13         0.655172           29
## 14         0.833333            6
## 15         0.500000            2
## 16         0.928571           28
## 17         0.833333           18
## 18         1.000000            5
## 19         0.500000            2
## 20         0.871069          318
## 21         0.859649           57
```

```
## 22          1.000000             1
## 23               NaN             0
```

```
pd.reset_option('display.max_columns')

total_counts_for_setting = judgments.groupby('Final_Setting').size()
result = judgments.groupby(["Final_Setting", "Untimed annotator context bins", "Number of judge continu
    Proportion_True=pd.NamedAgg(column='Final_Accuracy', aggfunc=lambda x: x.mean()),
    Context_Count=pd.NamedAgg(column='Final_Accuracy', aggfunc='size'),
    Proportion_Context=pd.NamedAgg(column='Final_Setting', aggfunc=lambda x: len(x) / total_counts_for_s
).reset_index()
```

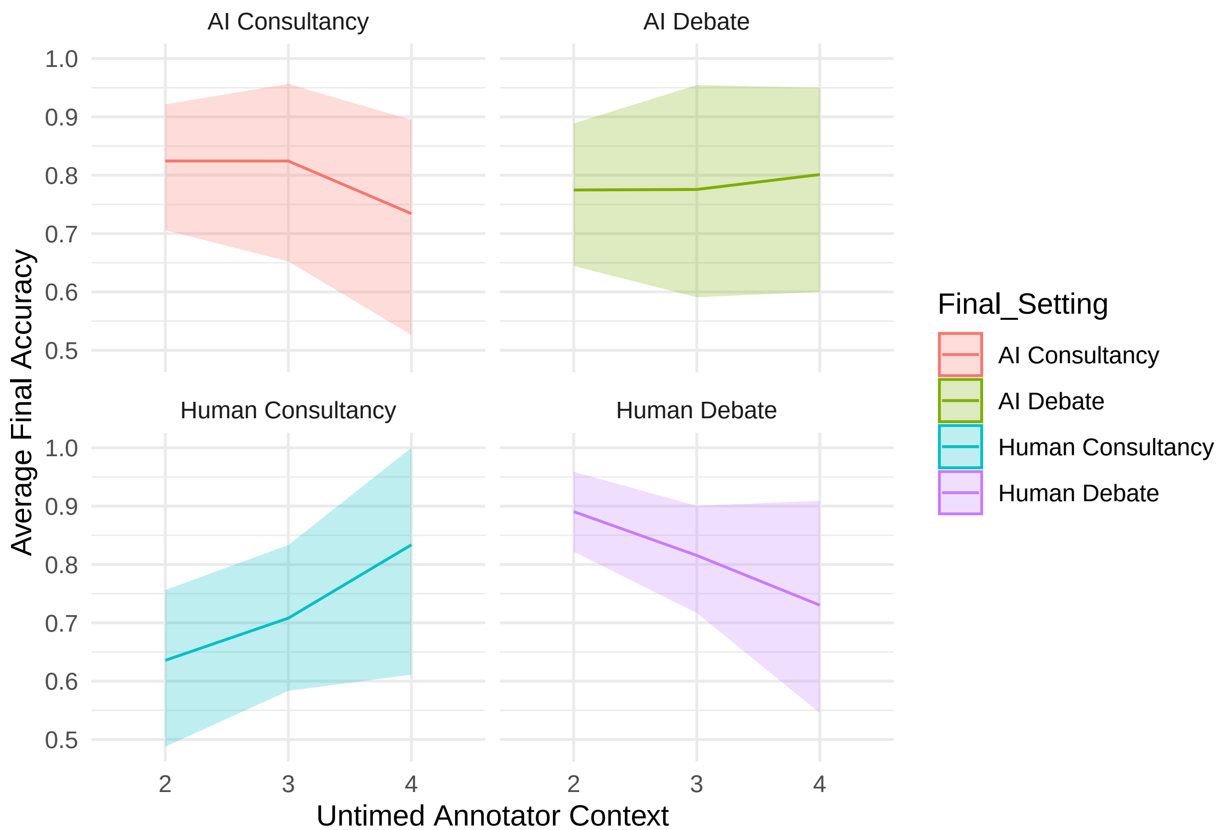
```
## <string>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True i
```

```
print(f'Is it number of rounds (meaning more evidence) that confounds the consultancy accuracy?:\n{resul
```

```
## Is it number of rounds (meaning more evidence) that confounds the consultancy accuracy?:
##      Final_Setting Untimed annotator context bins  ... Context_Count  Proportion_Context
## 0   AI Consultancy                              1  ...             0                 NaN
## 1   AI Consultancy                              1  ...             1            0.010417
## 2   AI Consultancy                              1  ...             0                 NaN
## 3   AI Consultancy                              1  ...             0                 NaN
## 4   AI Consultancy                              2  ...            28            0.291667
## ..             ...                            ...  ...           ...                 ...
## 59    Human Debate                              3  ...             0                 NaN
## 60    Human Debate                              4  ...            29            0.076923
## 61    Human Debate                              4  ...             7            0.018568
## 62    Human Debate                              4  ...             0                 NaN
## 63    Human Debate                              4  ...             0                 NaN
##
## [64 rows x 6 columns]
```

```
judgments$`Untimed annotator context bins` <- as.factor(judgments$`Untimed annotator context bins`)

bootstrap_mean <- function(data, indices) {
  return(mean(data[indices], na.rm = TRUE))
}

judgments_online %>%
  group_by(`Untimed annotator context bins`, Final_Setting) %>%
  do({
    boot_result <- boot(data = .$Final_Accuracy, statistic = bootstrap_mean, R = 1000)
    data.frame(
      mean_accuracy = mean(boot_result$t, na.rm = TRUE),
      lower_ci = quantile(boot_result$t, 0.025),
      upper_ci = quantile(boot_result$t, 0.975)
    )
  }) %>%
  ggplot(aes(x = `Untimed annotator context bins`, y = mean_accuracy, color = Final_Setting, group = Fi
  geom_line() +
  geom_ribbon(aes(ymin = lower_ci, ymax = upper_ci, fill = Final_Setting, color = NULL), alpha = 0.25) +
  labs(y = "Average Final Accuracy", x = "Untimed Annotator Context") +
```

```
  theme_minimal() +
  facet_wrap(~ Final_Setting)
```

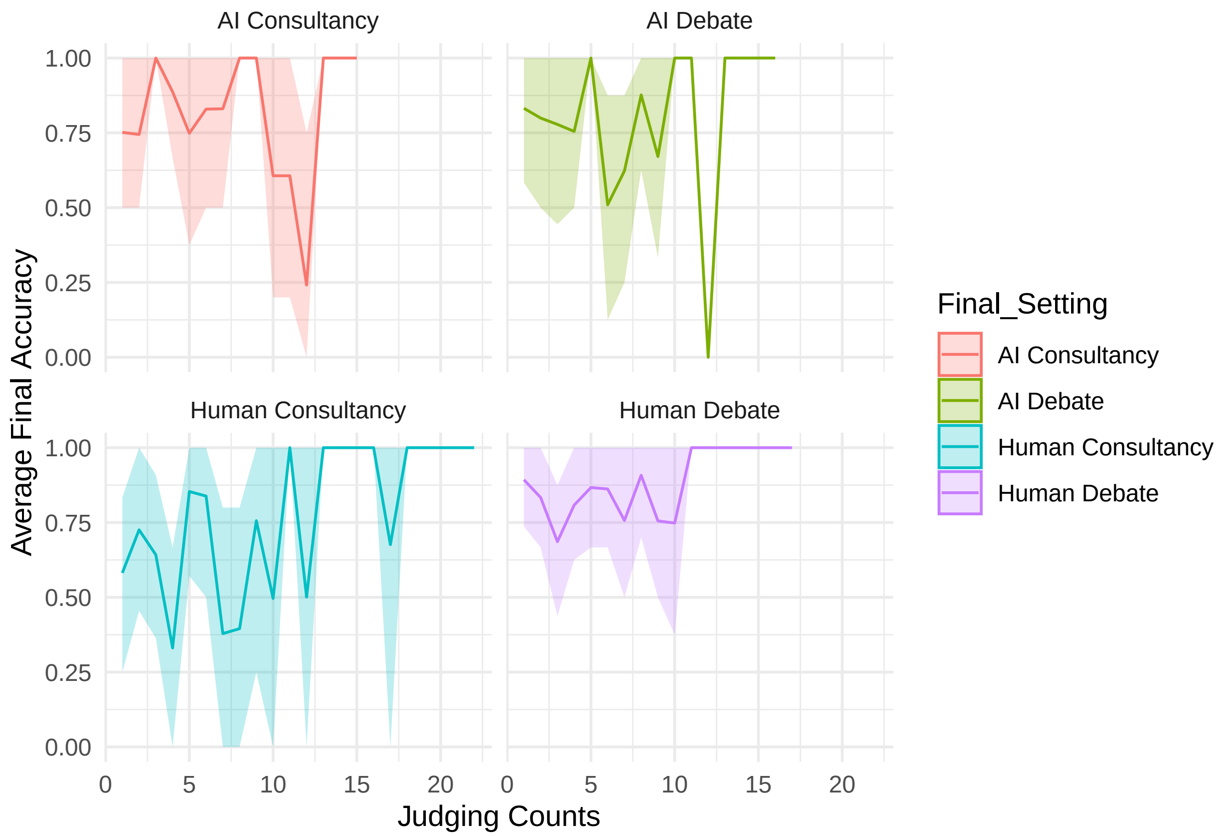


Judge Skill

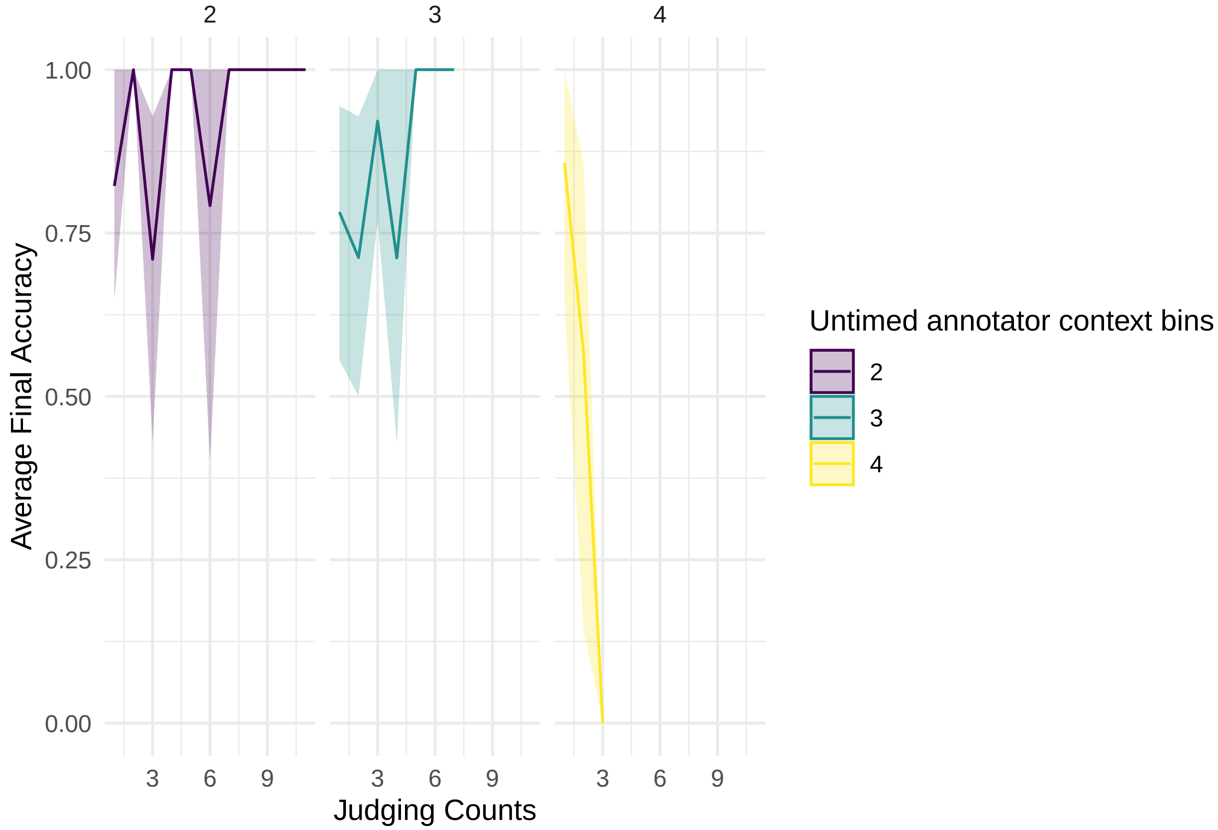
Judge "Experience"

```
judgments_online %>%
  group_by(Final_Setting, Participant) %>%
  arrange(`End time`) %>%
  mutate(count=row_number()) %>%
  group_by(Final_Setting, count) %>%
  do({
    boot_result <- boot(data = .$Final_Accuracy, statistic = bootstrap_mean, R = 1000)
    data.frame(
      mean_accuracy = mean(boot_result$t, na.rm = TRUE),
      lower_ci = quantile(boot_result$t, 0.025, na.rm = TRUE),
      upper_ci = quantile(boot_result$t, 0.975, na.rm = TRUE)
    )
  }) %>%
  ggplot(aes(x = count, y = mean_accuracy, color = Final_Setting, group = Final_Setting)) +
  geom_line() +
  geom_ribbon(aes(ymin = lower_ci, ymax = upper_ci, fill = Final_Setting, color = NULL), alpha = 0.25) +
```

```
  labs(y = "Average Final Accuracy", x = "Judging Counts") +
  theme_minimal() +
  facet_wrap(~ Final_Setting)
```




```
subset(judgments_online, judgments_online['Setting'] == 'Human Debate') %>%
  group_by(`Untimed annotator context bins`, Participant) %>%
  arrange(`End time`) %>%
  mutate(count=row_number()) %>%
  group_by(`Untimed annotator context bins`, count) %>%
  do({
    boot_result <- boot(data = .$Final_Accuracy, statistic = bootstrap_mean, R = 1000)
    data.frame(
      mean_accuracy = mean(boot_result$t, na.rm = TRUE),
      lower_ci = quantile(boot_result$t, 0.025, na.rm = TRUE),
      upper_ci = quantile(boot_result$t, 0.975, na.rm = TRUE)
    )
  }) %>%
  ggplot(aes(x = count, y = mean_accuracy, color = `Untimed annotator context bins`, group = `Untimed an
  geom_line() +
  geom_ribbon(aes(ymin = lower_ci, ymax = upper_ci, fill = `Untimed annotator context bins`, color = NUl
  labs(y = "Average Final Accuracy", x = "Judging Counts") +
  theme_minimal() +
  facet_wrap(~ `Untimed annotator context bins`)
```



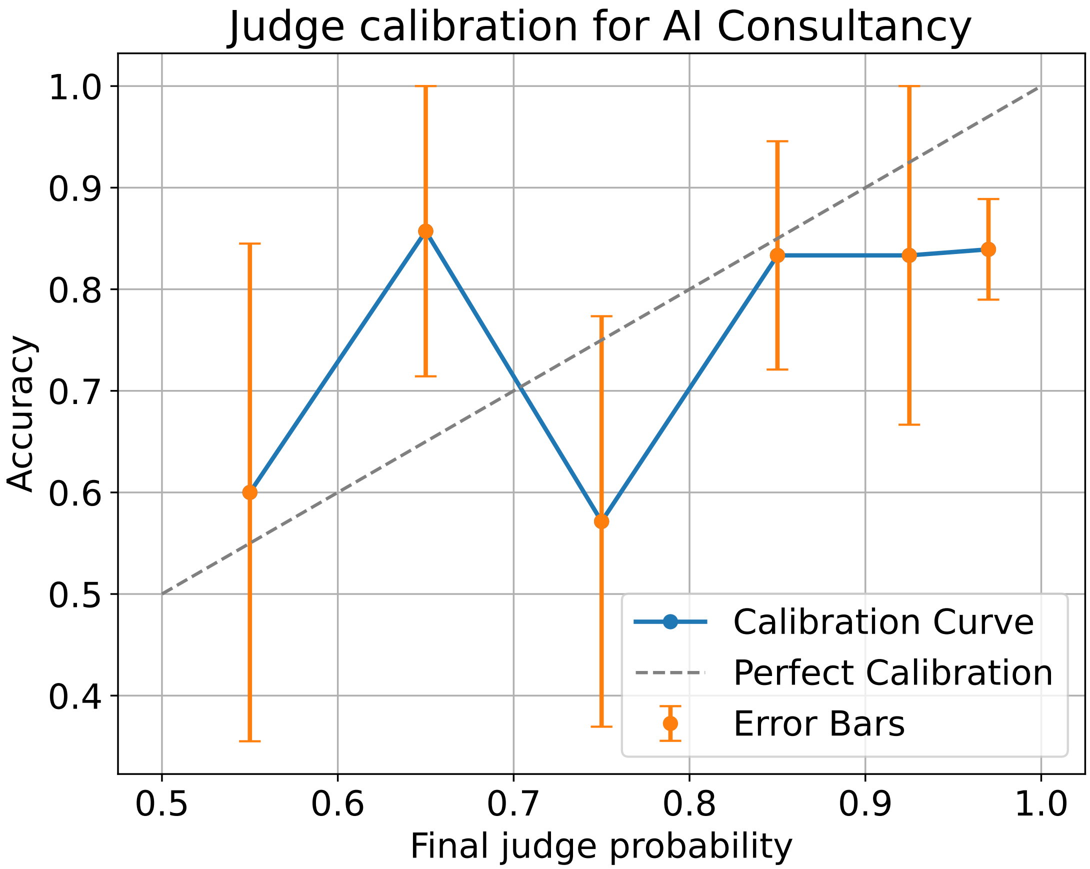
Calibration

S: (1) debaters didnt learn calibration -> calibration over time? S: (2) dishonest debater tricks

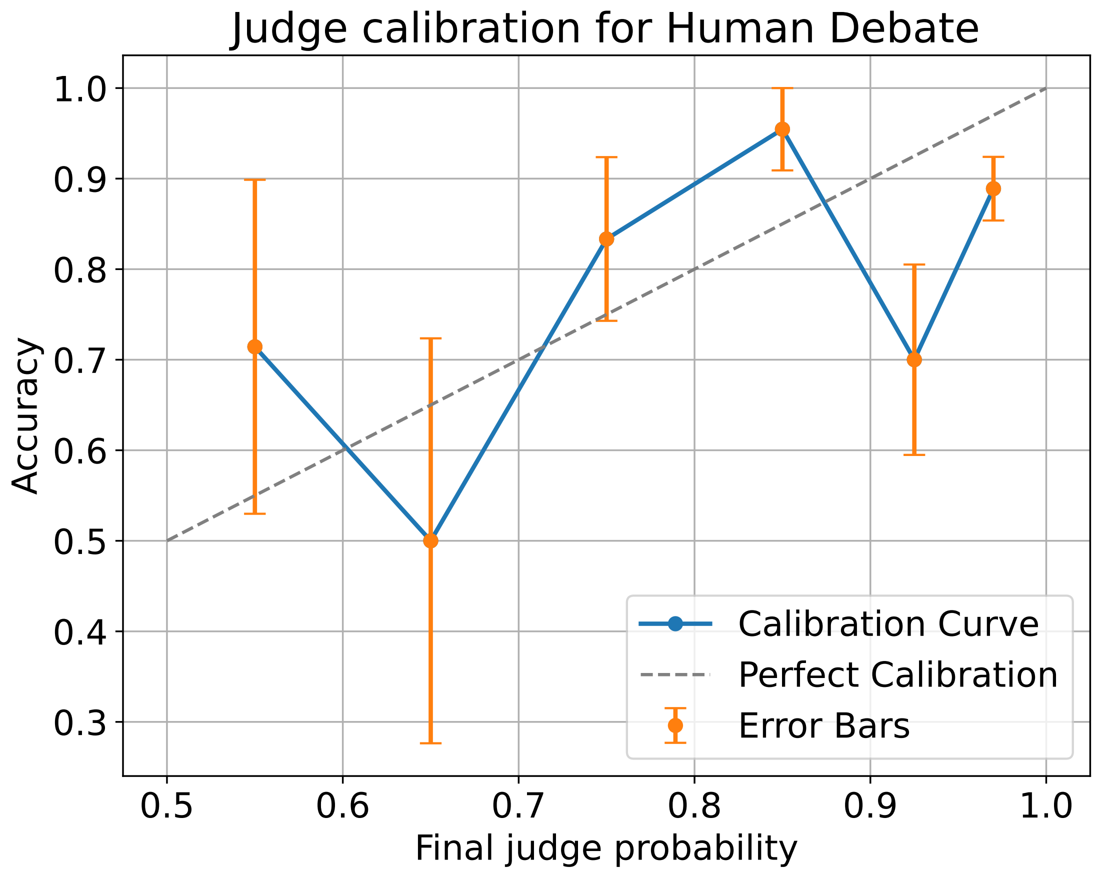
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.calibration import calibration_curve

def calibration_plot(df, setting_name, ax=None):
    df['outcome'] = pd.Series(df['Final probability correct'] > 0.5, dtype=int)
    df['confidence'] = df['Final probability correct'].apply(lambda x: x if x > 0.5 else 1 - x)
    df['bins'] = pd.cut(df['confidence'], [0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 0.99])
    # Group by bins and calculate the mean outcome
    df_grouped = df.groupby('bins')['outcome'].mean().reset_index()
    # Compute standard error in each bin
    std_error = df.groupby('bins')['outcome'].apply(lambda x: x.std() / np.sqrt(len(x)) if len(x) > 1 el
    df_grouped['std_error'] = df['bins'].cat.categories.map(std_error)
    if ax is None:
        plt.rcParams.update({'font.size': 16})
        fig, ax = plt.subplots(figsize=(8, 6))
    # Plot the calibration curve with error bars
    ax.plot(df_grouped['bins'].apply(lambda x: x.mid), df_grouped['outcome'], marker='o', linewidth=2, l
    ax.errorbar(df_grouped['bins'].apply(lambda x: x.mid), df_grouped['outcome'], yerr=df_grouped['std_e
    ax.set_xlabel('Final judge probability')
```

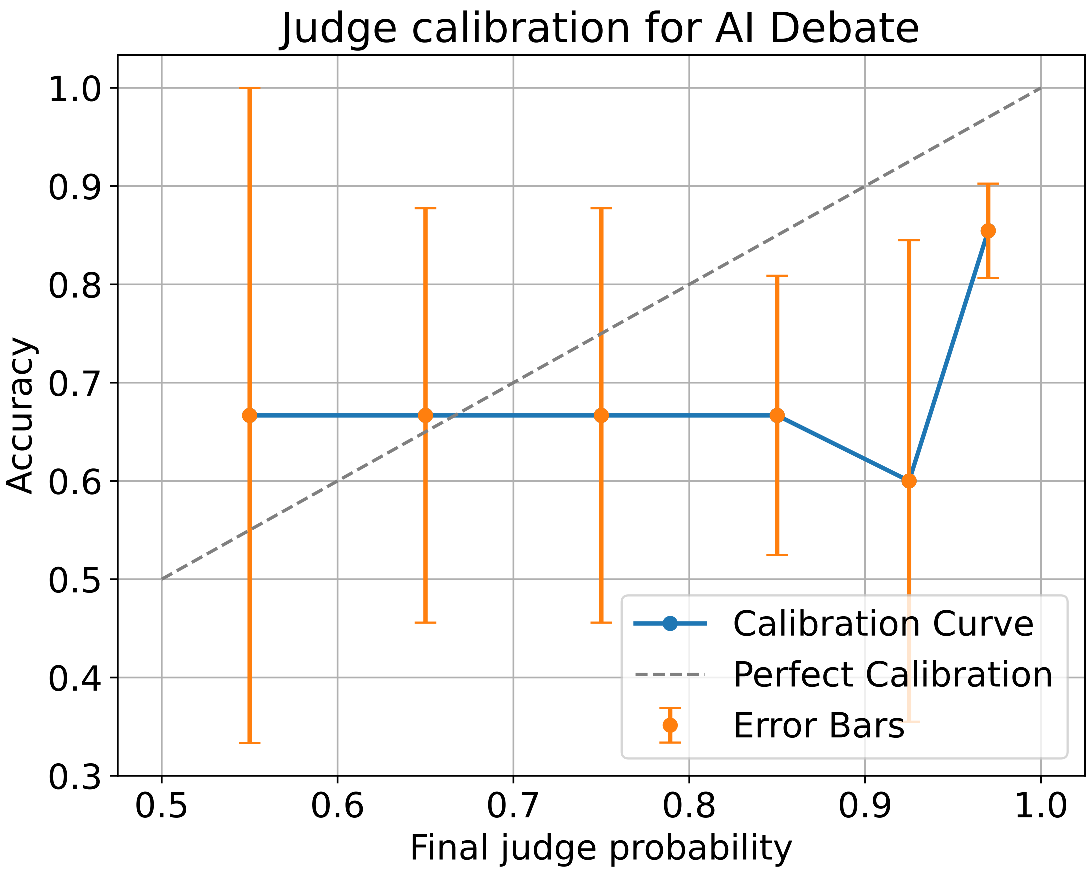
```python
    ax.set_ylabel('Accuracy')
    ax.set_title(f'Judge calibration for {setting_name}')
    ax.plot([0.5, 1], [0.5, 1], linestyle='--', color='gray', label='Perfect Calibration')
    ax.grid(True)
    ax.legend()
    # Calculate ECE
    actual_labels = df['outcome'].values
    predicted_probs = df['Final probability correct'].values
    prob_true, prob_pred = calibration_curve(actual_labels, predicted_probs, n_bins=10)
    ece = np.mean(np.abs(prob_pred - prob_true) * (prob_true.size / len(actual_labels)))
    # Print ECE
    print(f"Expected Calibration Error (ECE) for {setting_name}: {ece:.4f}")
    plt.show()
    plt.rcParams.update({'font.size': plt.rcParamsDefault['font.size']})

# Loop through each unique setting and create a calibration plot
for setting in judgments_online['Final_Setting'].unique():
    setting_df = judgments_online[judgments['Final_Setting'] == setting].copy()
    calibration_plot(setting_df, setting)
```

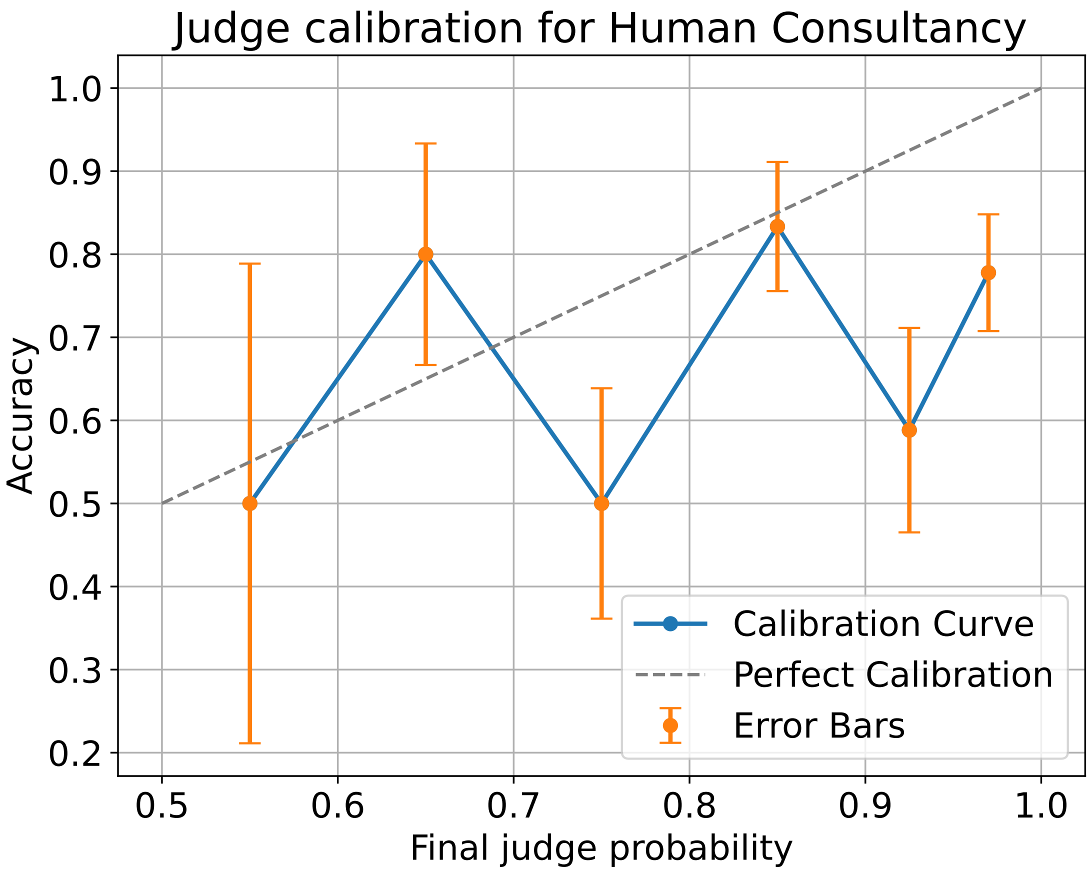
```
## Expected Calibration Error (ECE) for AI Consultancy: 0.0213
## Expected Calibration Error (ECE) for Human Debate: 0.0152
## Expected Calibration Error (ECE) for AI Debate: 0.0268
## Expected Calibration Error (ECE) for Human Consultancy: 0.0220
##
## <string>:4: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
## <string>:7: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:9: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:4: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
## <string>:7: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:9: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:4: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
## <string>:7: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:9: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:4: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
## <string>:7: FutureWarning: The default of observed=False is deprecated and will be changed to True i
## <string>:9: FutureWarning: The default of observed=False is deprecated and will be changed to True i
```



Judge calibration for AI Consultancy
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Accuracy
0.5
0.6
0.7
0.8
0.9
1.0
Final judge probability
Calibration Curve
Perfect Calibration
Error Bars


Judge calibration for Human Debate
Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.5
0.6
0.7
0.8
0.9
1.0
Final judge probability
Calibration Curve
Perfect Calibration
Error Bars


Judge calibration for AI Debate
Accuracy
Final judge probability
Calibration Curve
Perfect Calibration
Error Bars
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.5
0.6
0.7
0.8
0.9
1.0



Judge Involvement

Judge Mistakes

Debater Skill

```
random.intercept.model = lmer(`Final probability correct` ~  (1|Final_Setting),
                              data = judgments, REML = TRUE)

judgments$random.intercept.preds = predict(random.intercept.model)

colnames(judgments)
```

```
##   [1] "Participant"
##   [2] "base_room_name"
##   [3] "Room name"
##   [4] "Room start time"
##   [5] "Role"
##   [6] "Is turn"
##   [7] "Is over"
##   [8] "Number of judge continues"
```

```
##  [9] "Final probability correct"
## [10] "Offline judging start time"
## [11] "Offline judging end time"
## [12] "other"
## [13] "factual informativeness (comparative).1"
## [14] "factual informativeness (comparative).2"
## [15] "facts versus semantics (single)"
## [16] "factual accuracy (single)"
## [17] "clarity.1"
## [18] "clarity.2"
## [19] "factual accuracy.1"
## [20] "factual accuracy.2"
## [21] "judge reasoning"
## [22] "reason for outcome"
## [23] "protocol"
## [24] "evidence use.1"
## [25] "evidence use.2"
## [26] "evidence in story.1"
## [27] "evidence in story.2"
## [28] "other factors"
## [29] "judge adaptation (single)"
## [30] "evidence in debate.1"
## [31] "evidence in debate.2"
## [32] "interface"
## [33] "evidence in debate (single)"
## [34] "facts versus semantics.1"
## [35] "facts versus semantics.2"
## [36] "clash.1"
## [37] "clash.2"
## [38] "identity guesses.Judge"
## [39] "identity guesses.Debater A"
## [40] "identity guesses.Debater B"
## [41] "judge adaptation.1"
## [42] "judge adaptation.2"
## [43] "subjective correctness"
## [44] "evidence use (single)"
## [45] "factual informativeness (total)"
## [46] "judge strategies"
## [47] "clarity (single)"
## [48] "Debater A"
## [49] "Debater B"
## [50] "Honest debater"
## [51] "Dishonest debater"
## [52] "Is single debater"
## [53] "Has honest debater"
## [54] "Final_Setting"
## [55] "Setting"
## [56] "Question"
## [57] "Article ID"
## [58] "Speed annotator accuracy bins"
## [59] "Untimed annotator context bins"
## [60] "Speed annotator accuracy"
## [61] "Untimed annotator context"
## [62] "Is offline"
```

```
## [63] "End time"
## [64] "Last modified time"
## [65] "Final_Accuracy"
## [66] "random.intercept.preds"
```

```
dishonest <- judgments[!is.na(judgments$`Dishonest debater`), ]
model3 <- glm(Final_Accuracy ~ relevel(factor(`Dishonest debater`), 'Shlomo Kofman') + relevel(factor(Fi
summary(model3)
```

```
##
## Call:
## glm(formula = Final_Accuracy ~ relevel(factor(`Dishonest debater`),
##     "Shlomo Kofman") + relevel(factor(Final_Setting), "Human Debate"),
##     family = "binomial", data = judgments[!is.na(judgments$`Dishonest debater`),
##         ])
##
## Coefficients: (1 not defined because of singularities)
##                                                                  Estimate
## (Intercept)                                                       0.52739
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Adelle Fernando      0.95584
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Aliyaah Toussaint    2.41514
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Anuj Jain            1.47707
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")David Rein           1.41852
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Emmanuel Makinde    17.03868
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Ethan Rosen          1.45361
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")GPT-4                0.75355
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Jackson Petty        2.08187
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Jessica Li           0.53268
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Julian Michael       2.41705
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Julien Dirani        1.55205
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Max Layden          17.03868
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Noor Mirza-Rashid   -0.05738
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Reeya Kansra         1.44916
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Salsabila Mahdi      1.47874
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Sam Jin              1.30012
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Sean Wang            1.43988
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Shreeram Modi        1.45605
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Vishakh Padmakumar  17.03868
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy              0.66498
## relevel(factor(Final_Setting), "Human Debate")AI Debate                        NA
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy          -1.33091
##                                                                  Std. Error
## (Intercept)                                                       0.66115
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Adelle Fernando      0.73718
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Aliyaah Toussaint    1.23691
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Anuj Jain            0.84884
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")David Rein           0.90447
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Emmanuel Makinde  2797.44202
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Ethan Rosen          0.84947
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")GPT-4                0.70782
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Jackson Petty        0.98698
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Jessica Li           0.74081
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Julian Michael       1.22055
## relevel(factor(`Dishonest debater`), "Shlomo Kofman")Julien Dirani        1.24985
```

```
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Max Layden        3956.18038
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Noor Mirza-Rashid     0.87300
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Reeya Kansra          0.90748
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Salsabila Mahdi       0.79085
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sam Jin               0.93690
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sean Wang             0.75579
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Shreeram Modi         0.75586
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Vishakh Padmakumar  863.30958
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy               0.54080
## relevel(factor(Final_Setting), "Human Debate")AI Debate                         NA
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy            0.32388
##                                                                        z value
## (Intercept)                                                              0.798
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Adelle Fernando     1.297
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Aliyaah Toussaint   1.953
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Anuj Jain           1.740
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")David Rein          1.568
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Emmanuel Makinde    0.006
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Ethan Rosen         1.711
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")GPT-4               1.065
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jackson Petty       2.109
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jessica Li          0.719
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julian Michael      1.980
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julien Dirani       1.242
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Max Layden          0.004
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Noor Mirza-Rashid  -0.066
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Reeya Kansra        1.597
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Salsabila Mahdi     1.870
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sam Jin             1.388
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sean Wang           1.905
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Shreeram Modi       1.926
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Vishakh Padmakumar  0.020
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy             1.230
## relevel(factor(Final_Setting), "Human Debate")AI Debate                     NA
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy         -4.109
##                                                                        Pr(>|z|)
## (Intercept)                                                              0.4251
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Adelle Fernando     0.1948
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Aliyaah Toussaint   0.0509
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Anuj Jain           0.0818
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")David Rein          0.1168
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Emmanuel Makinde    0.9951
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Ethan Rosen         0.0870
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")GPT-4               0.2871
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jackson Petty       0.0349
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jessica Li          0.4721
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julian Michael      0.0477
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julien Dirani       0.2143
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Max Layden          0.9966
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Noor Mirza-Rashid   0.9476
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Reeya Kansra        0.1103
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Salsabila Mahdi     0.0615
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sam Jin             0.1652
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sean Wang           0.0568
```

```
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Shreeram Modi         0.0541
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Vishakh Padmakumar    0.9843
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy              0.2188
## relevel(factor(Final_Setting), "Human Debate")AI Debate                       NA
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy        0.0000397
##
## (Intercept)
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Adelle Fernando
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Aliyaah Toussaint  .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Anuj Jain          .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")David Rein
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Emmanuel Makinde
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Ethan Rosen        .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")GPT-4
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jackson Petty      *
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Jessica Li
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julian Michael     *
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Julien Dirani
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Max Layden
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Noor Mirza-Rashid
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Reeya Kansra
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Salsabila Mahdi    .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sam Jin
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Sean Wang          .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Shreeram Modi      .
## relevel(factor(‘Dishonest debater‘), "Shlomo Kofman")Vishakh Padmakumar
## relevel(factor(Final_Setting), "Human Debate")AI Consultancy
## relevel(factor(Final_Setting), "Human Debate")AI Debate
## relevel(factor(Final_Setting), "Human Debate")Human Consultancy        ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 541.37  on 576  degrees of freedom
## Residual deviance: 487.85  on 555  degrees of freedom
## AIC: 531.85
##
## Number of Fisher Scoring iterations: 16
```

```r
result <- judgments_online %>%
  group_by(`Dishonest debater`) %>%
  summarize(
    Win_Rate = sum(Final_Accuracy == "FALSE") / n()
  ) %>%
  ungroup() %>%
  arrange(desc(Win_Rate))

result
```

```
## # A tibble: 20 x 2
##    ‘Dishonest debater‘ Win_Rate
##    <chr>                  <dbl>
##  1 Shlomo Kofman          0.545
```

```
##   2 Salsabila Mahdi       0.357
##   3 Jessica Li            0.353
##   4 Noor Mirza-Rashid     0.333
##   5 Adelle Fernando       0.296
##   6 Sean Wang             0.28
##   7 Reeya Kansra          0.273
##   8 Sam Jin               0.25
##   9 Shreeram Modi         0.24
##  10 GPT-4                 0.192
##  11 <NA>                  0.184
##  12 Anuj Jain             0.143
##  13 Julian Michael        0.125
##  14 Aliyaah Toussaint     0.111
##  15 Ethan Rosen           0.0909
##  16 Jackson Petty         0.0769
##  17 David Rein            0
##  18 Julien Dirani         0
##  19 Max Layden            0
##  20 Vishakh Padmakumar    0
```

```
result1 <- judgments_online %>%
  group_by(`Honest debater`) %>%
  summarize(
    Win_Rate = sum(Final_Accuracy == "TRUE") / n()
  ) %>%
  ungroup() %>%
  arrange(desc(Win_Rate))

result1
```

```
## # A tibble: 20 x 2
##    `Honest debater`   Win_Rate
##    <chr>                 <dbl>
##  1 Julian Michael        1
##  2 Julien Dirani         1
##  3 Noor Mirza-Rashid     1
##  4 Sean Wang             0.96
##  5 Jessica Li            0.923
##  6 Salsabila Mahdi       0.917
##  7 Adelle Fernando       0.905
##  8 Reeya Kansra          0.9
##  9 Vishakh Padmakumar    0.857
## 10 Shlomo Kofman         0.833
## 11 Anuj Jain             0.8
## 12 David Rein            0.8
## 13 Shreeram Modi         0.8
## 14 Ethan Rosen           0.786
## 15 GPT-4                 0.775
## 16 <NA>                  0.680
## 17 Jackson Petty         0.667
## 18 Sam Jin               0.667
## 19 Aliyaah Toussaint     0.625
## 20 Emmanuel Makinde      0
```

```r
# Filter for high win rate debaters
high_win_rate_debaters <- result1 %>%
  filter(Win_Rate > 0.90)  # Set the threshold for high win rate

# Filter original data for debates with 'Debate' in Final_Setting
filtered_data <- judgments_online %>%
  filter(grepl("Debate", Final_Setting))

# Find cases where high win rate debaters lost
cases_high_win_rate_lost <- filtered_data %>%
  filter(`Honest debater` %in% high_win_rate_debaters$`Honest debater` & Final_Accuracy != "TRUE")

cases_high_win_rate_lost
```

```
##     Participant          base_room_name                Room name
## 146   Anuj Jain          survival-type-          survival-type-5
## 214 Ethan Rosen the-great-nebraska-sea- the-great-nebraska-sea-0
## 289  Jessica Li                     rx-                     rx-1
##     Room start time  Role Is turn Is over Number of judge continues
## 146   1681159356736 Judge   FALSE    TRUE                         5
## 214   1683321454611 Judge   FALSE    TRUE                         2
## 289   1683298141840 Judge   FALSE    TRUE                         2
##     Final probability correct Offline judging start time
## 146                      0.33                        NaN
## 214                      0.01                        NaN
## 289                      0.01                        NaN
##     Offline judging end time other factual informativeness (comparative).1
## 146                      NaN  <NA>                                        4
## 214                      NaN  <NA>                                        1
## 289                      NaN  <NA>                                        4
##     factual informativeness (comparative).2 facts versus semantics (single)
## 146                                       4                             NaN
## 214                                       1                             NaN
## 289                                       2                             NaN
##     factual accuracy (single) clarity.1 clarity.2 factual accuracy.1
## 146                       NaN         3         3                NaN
## 214                       NaN         2         2                NaN
## 289                       NaN         4         1                NaN
##     factual accuracy.2 judge reasoning
## 146                NaN               3
## 214                NaN               1
## 289                NaN               4
##                                                                                                     reason for out
## 146                                                                                                               i
## 214 I thought "like" was over-technical compared to what these questions typically ask for. I was wr
## 289                            B's last arg was literally 2 sentences, and A's ev was very convinci
##     protocol evidence use.1 evidence use.2 evidence in story.1
## 146     <NA>            NaN            NaN                 NaN
## 214     <NA>            NaN            NaN                 NaN
## 289     <NA>            NaN            NaN                 NaN
##     evidence in story.2 other factors judge adaptation (single)
## 146                 NaN          <NA>                       NaN
## 214                 NaN          <NA>                       NaN
```

```
## 289                 NaN          <NA>                       NaN
##     evidence in debate.1 evidence in debate.2 interface
## 146                    2                    4      <NA>
## 214                    3                    2      <NA>
## 289                    4                    2      <NA>
##     evidence in debate (single) facts versus semantics.1
## 146                         NaN                        3
## 214                         NaN                        1
## 289                         NaN                        1
##     facts versus semantics.2 clash.1 clash.2 identity guesses.Judge
## 146                        3       3       3                   <NA>
## 214                        3       4       4                   <NA>
## 289                        3       4       2                   <NA>
##     identity guesses.Debater A identity guesses.Debater B judge adaptation.1
## 146                       <NA>                       <NA>                  3
## 214                       <NA>                       <NA>                  4
## 289                       <NA>                       <NA>                  4
##     judge adaptation.2 subjective correctness evidence use (single)
## 146                  3                    NaN                   NaN
## 214                  3                    NaN                   NaN
## 289                  2                    NaN                   NaN
##     factual informativeness (total) judge strategies clarity (single)
## 146                               3             <NA>              NaN
## 214                               1             <NA>              NaN
## 289                               3             <NA>              NaN
##           Debater A       Debater B  Honest debater Dishonest debater
## 146 Adelle Fernando     Ethan Rosen Adelle Fernando       Ethan Rosen
## 214 Salsabila Mahdi       Sean Wang       Sean Wang   Salsabila Mahdi
## 289    Reeya Kansra Adelle Fernando Adelle Fernando      Reeya Kansra
##     Is single debater Has honest debater Final_Setting      Setting
## 146             FALSE               TRUE  Human Debate Human Debate
## 214             FALSE               TRUE  Human Debate Human Debate
## 289             FALSE               TRUE  Human Debate Human Debate
##                                                                 Question
## 146 How did the planet of Niobe compare to others that Earth was exploring?
## 214                                            How is this article written?
## 289   What were the specialties of the Red and Green Doctors, respectively?
##     Article ID Speed annotator accuracy bins Untimed annotator context bins
## 146      51395                           0.2                              3
## 214      50893                           0.2                              3
## 289      60412                           0.2                              3
##     Speed annotator accuracy Untimed annotator context Is offline
## 146                0.1666667                  2.750000      FALSE
## 214                0.2000000                  3.333333      FALSE
## 289                0.2000000                  2.800000      FALSE
##                End time  Last modified time Final_Accuracy
## 146 2023-04-17 17:12:59 2023-04-28 12:29:25          FALSE
## 214 2023-05-08 17:14:28 2023-06-22 15:20:58          FALSE
## 289 2023-06-22 15:18:02 2023-06-22 15:18:02          FALSE
##     Human Consultancy Sample AI Consultancy Sample Human Debate Sample
## 146                    FALSE                 FALSE               FALSE
## 214                    FALSE                 FALSE                TRUE
## 289                    FALSE                 FALSE                TRUE
##     AI Debate Sample Sample Consultancy Sample initial_question_weights
```

```
## 146            FALSE  FALSE              FALSE                0.5000000
## 214            FALSE   TRUE               TRUE                0.2000000
## 289            FALSE   TRUE               TRUE                0.3333333
##     initial_question_weights_grouped_setting
## 146                                      0.5
## 214                                      0.5
## 289                                      0.5
##     sampled_consultancies_all_debates_weights
## 146                                 0.5000000
## 214                                 0.2500000
## 289                                 0.3333333
##     sampled_consultancies_all_debates_weights_grouped_setting
## 146                                                       0.5
## 214                                                       0.5
## 289                                                       0.5
##     sampled_consultancies_all_debates_weights_setting
## 146                                               0.5
## 214                                               0.5
## 289                                               0.5
##     sampled_consultancies_debates_weights_grouped_setting
## 146                                                     0
## 214                                                     1
## 289                                                     1
##     sampled_consultancies_debates_weights Final_Accuracy_char  fpc  fpcw
## 146                             0.0000000                  NA 0.33 0.165
## 214                             0.3333333                  NA 0.01 0.005
## 289                             0.5000000                  NA 0.01 0.005
```

```
# Filter for high win rate debaters
high_win_rate_debaters <- result %>%
  filter(Win_Rate > 0.20)  # Set the threshold for high win rate

# Filter original data for debates with 'Debate' in Final_Setting
filtered_data <- judgments_online %>%
  filter(grepl("Debate", Final_Setting))

# Find cases where high win rate debaters lost
cases_high_win_rate_lost <- filtered_data %>%
  filter(`Dishonest debater` %in% high_win_rate_debaters$`Dishonest debater` & Final_Accuracy != "FALSE

cases_high_win_rate_lost
```

```
##           Participant                      base_room_name
## 21     Adelle Fernando                           monopoly-
## 43     Adelle Fernando                     tollivers-orbit-
## 78   Aliyaah Toussaint                                 rx-
## 81   Aliyaah Toussaint                 stranger-from-space-
## 91   Aliyaah Toussaint         the-long-remembered-thunder-
## 94   Aliyaah Toussaint      the-princess-and-the-physicist-
## 99   Aliyaah Toussaint                 the-starsent-knaves-
## 113          Anuj Jain                        cosmic-yoyo-
## 136          Anuj Jain               out-of-the-iron-womb-
## 140          Anuj Jain                     planet-of-dread-
## 149          Anuj Jain               the-air-of-castor-oil-
```

```
## 177          David Rein                          monopoly-
## 179          David Rein           peggy-finds-the-theatre-
## 185          David Rein                stalemate-in-space-
## 186          David Rein               stranger-from-space-
## 191          David Rein            the-great-nebraska-sea-
## 202         Ethan Rosen                       cosmic-yoyo-
## 211         Ethan Rosen               stranger-from-space-
## 215         Ethan Rosen               the-man-who-was-six-
## 216         Ethan Rosen                 the-monster-maker-
## 219       Jackson Petty atom-mystery-young-atom-detective-
## 236       Jackson Petty                          muck-man-
## 240       Jackson Petty                                rx-
## 241       Jackson Petty                  silence-isdeadly-
## 254       Jackson Petty   the-princess-and-the-physicist-
## 270          Jessica Li                  doctor-universe-
## 276          Jessica Li              how-to-make-friends-1
## 290          Jessica Li                  silence-isdeadly-
## 306          Jessica Li   the-princess-and-the-physicist-
## 324      Julian Michael                         monopoly-
## 331      Julian Michael               stranger-from-space-
## 332      Julian Michael                     survival-type-
## 338      Julian Michael                 the-monster-maker-
## 342      Julian Michael       the-spicy-sound-of-success-
## 348       Julien Dirani              manners-and-customs-
## 356  Noor Mirza-Rashid                  doctor-universe-
## 366  Noor Mirza-Rashid                            volpla-
## 378        Reeya Kansra              how-to-make-friends-
## 387        Reeya Kansra                          muck-man-
## 401        Reeya Kansra                 the-monster-maker-
## 411     Salsabila Mahdi                       break-a-leg-
## 414     Salsabila Mahdi                       cosmic-yoyo-
## 421     Salsabila Mahdi              manners-and-customs-
## 424     Salsabila Mahdi                          muck-man-
## 425     Salsabila Mahdi                   planet-of-dread-
## 429     Salsabila Mahdi                  silence-isdeadly-
## 431     Salsabila Mahdi               stranger-from-space-
## 433     Salsabila Mahdi                the-happy-castaway-
## 436     Salsabila Mahdi              the-reluctant-heroes-
## 439     Salsabila Mahdi              the-starsent-knaves-
## 448             Sam Jin               coming-of-the-gods-
## 510             Sam Jin            venus-is-a-mans-world-
## 533           Sean Wang              lost-in-translation-
## 538           Sean Wang           peggy-finds-the-theatre-
## 544           Sean Wang                     survival-type-
## 550           Sean Wang                      the-cool-war-
## 561           Sean Wang                            volpla-
## 598       Shlomo Kofman             out-of-the-iron-womb-
## 602       Shlomo Kofman                pied-piper-of-mars-
## 606       Shlomo Kofman                                rx-
## 626       Shlomo Kofman                  the-starbusters-
## 637        Shreeram Modi                      cosmic-yoyo-
## 641        Shreeram Modi                     in-the-garden-
## 647        Shreeram Modi          peggy-finds-the-theatre-
## 648        Shreeram Modi         phone-me-in-central-park-
```

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## 658      Shreeram Modi               the-man-who-was-six-
## 677 Vishakh Padmakumar                stalemate-in-space-
## 679 Vishakh Padmakumar             the-air-of-castor-oil-
## 680 Vishakh Padmakumar          the-desert-and-the-stars-
## 683 Vishakh Padmakumar                 the-monster-maker-
##                             Room name Room start time  Role Is turn Is over
## 21                         monopoly-1   1680552464768 Judge   FALSE    TRUE
## 43                  tollivers-orbit-1   1681765942714 Judge   FALSE    TRUE
## 78                               rx-3   1683298141840 Judge   FALSE    TRUE
## 81                stranger-from-space-0   1683298716462 Judge   FALSE    TRUE
## 91        the-long-remembered-thunder-1   1689876270711 Judge   FALSE    TRUE
## 94     the-princess-and-the-physicist-4   1682112300045 Judge   FALSE    TRUE
## 99                the-starsent-knaves-2   1688757372245 Judge   FALSE    TRUE
## 113                       cosmic-yoyo-0   1681159027164 Judge   FALSE    TRUE
## 136             out-of-the-iron-womb-0   1689876275997 Judge   FALSE    TRUE
## 140                  planet-of-dread-2   1680829456935 Judge   FALSE    TRUE
## 149            the-air-of-castor-oil-5   1680552962919 Judge   FALSE    TRUE
## 177                         monopoly-2   1680552464768 Judge   FALSE    TRUE
## 179          peggy-finds-the-theatre-4   1682110072206 Judge   FALSE    TRUE
## 185               stalemate-in-space-0   1677532762430 Judge   FALSE    TRUE
## 186              stranger-from-space-4   1683298716462 Judge   FALSE    TRUE
## 191            the-great-nebraska-sea-1   1683321454611 Judge   FALSE    TRUE
## 202                      cosmic-yoyo-3   1681159027164 Judge   FALSE    TRUE
## 211              stranger-from-space-5   1683298716462 Judge   FALSE    TRUE
## 215              the-man-who-was-six-1   1676313105423 Judge   FALSE    TRUE
## 216                the-monster-maker-4   1681159292566 Judge   FALSE    TRUE
## 219 atom-mystery-young-atom-detective-0   1689949095893 Judge   FALSE    TRUE
## 236                         muck-man-5   1687546720669 Judge   FALSE    TRUE
## 240                               rx-4   1683298141840 Judge   FALSE    TRUE
## 241                 silence-isdeadly-3   1688157095546 Judge   FALSE    TRUE
## 254    the-princess-and-the-physicist-0   1682112300045 Judge   FALSE    TRUE
## 270                  doctor-universe-0   1680206097221 Judge   FALSE    TRUE
## 276              how-to-make-friends-11   1681724583153 Judge   FALSE    TRUE
## 290                 silence-isdeadly-2   1688157095546 Judge   FALSE    TRUE
## 306    the-princess-and-the-physicist-2   1682112300045 Judge   FALSE    TRUE
## 324                         monopoly-0   1680552464768 Judge   FALSE    TRUE
## 331              stranger-from-space-1   1683298716462 Judge   FALSE    TRUE
## 332                    survival-type-4   1681159356736 Judge   FALSE    TRUE
## 338                the-monster-maker-3   1681159292566 Judge   FALSE    TRUE
## 342        the-spicy-sound-of-success-4   1679607458871 Judge   FALSE    TRUE
## 348              manners-and-customs-1   1676043334730 Judge   FALSE    TRUE
## 356                  doctor-universe-5   1680206097221 Judge   FALSE    TRUE
## 366                           volpla-2   1680205817615 Judge   FALSE    TRUE
## 378              how-to-make-friends-0   1681724583153 Judge   FALSE    TRUE
## 387                         muck-man-7   1687546765239 Judge   FALSE    TRUE
## 401                the-monster-maker-1   1681159292566 Judge   FALSE    TRUE
## 411                      break-a-leg-5   1682110823449 Judge   FALSE    TRUE
## 414                      cosmic-yoyo-2   1681159027164 Judge   FALSE    TRUE
## 421              manners-and-customs-0   1676043281654 Judge   FALSE    TRUE
## 424                         muck-man-4   1687546720669 Judge   FALSE    TRUE
## 425                  planet-of-dread-1   1680829456935 Judge   FALSE    TRUE
## 429                 silence-isdeadly-6   1688157095546 Judge   FALSE    TRUE
## 431              stranger-from-space-2   1683298716462 Judge   FALSE    TRUE
## 433               the-happy-castaway-2   1679606564549 Judge   FALSE    TRUE
```

```
## 436              the-reluctant-heroes-2   1682965111772 Judge   FALSE    TRUE
## 439               the-starsent-knaves-0   1688757372245 Judge   FALSE    TRUE
## 448                coming-of-the-gods-2   1689020073883 Judge   FALSE    TRUE
## 510             venus-is-a-mans-world-0   1691058680973 Judge   FALSE    TRUE
## 533               lost-in-translation-3   1678404069200 Judge   FALSE    TRUE
## 538           peggy-finds-the-theatre-0   1682090000149 Judge   FALSE    TRUE
## 544                     survival-type-0   1681159356736 Judge   FALSE    TRUE
## 550                      the-cool-war-0   1689949097911 Judge   FALSE    TRUE
## 561                            volpla-3   1680205817615 Judge   FALSE    TRUE
## 598              out-of-the-iron-womb-1   1689876275999 Judge   FALSE    TRUE
## 602                pied-piper-of-mars-8   1689278492513 Judge   FALSE    TRUE
## 606                                rx-5   1683298141840 Judge   FALSE    TRUE
## 626                   the-starbusters-3   1689371609880 Judge   FALSE    TRUE
## 637                     cosmic-yoyo-1   1681159027164 Judge   FALSE    TRUE
## 641                     in-the-garden-6   1680206043370 Judge   FALSE    TRUE
## 647           peggy-finds-the-theatre-2   1682090000149 Judge   FALSE    TRUE
## 648          phone-me-in-central-park-5   1678684819928 Judge   FALSE    TRUE
## 658               the-man-who-was-six-5   1676645924826 Judge   FALSE    TRUE
## 677                stalemate-in-space-2   1677792427135 Judge   FALSE    TRUE
## 679             the-air-of-castor-oil-4   1680552962919 Judge   FALSE    TRUE
## 680          the-desert-and-the-stars-2   1677792315334 Judge   FALSE    TRUE
## 683                 the-monster-maker-5   1681159292566 Judge   FALSE    TRUE
##     Number of judge continues Final probability correct
## 21                          4                      0.70
## 43                          2                      0.90
## 78                          1                      0.99
## 81                          4                      0.99
## 91                          3                      0.98
## 94                          4                      0.99
## 99                          4                      0.85
## 113                         4                      0.99
## 136                         4                      0.99
## 140                         2                      0.99
## 149                         3                      0.85
## 177                         3                      0.85
## 179                         4                      0.90
## 185                         2                      0.99
## 186                         4                      0.95
## 191                         3                      0.95
## 202                         2                      0.90
## 211                         2                      0.95
## 215                         2                      0.80
## 216                         2                      0.99
## 219                         6                      0.80
## 236                         7                      0.99
## 240                         3                      0.90
## 241                         3                      0.99
## 254                         4                      0.95
## 270                         2                      0.70
## 276                         2                      0.99
## 290                         1                      0.99
## 306                         2                      0.99
## 324                         3                      0.99
## 331                         2                      0.99
```

```
## 332                          2                          0.99
## 338                          3                          0.99
## 342                          4                          0.99
## 348                          3                          0.85
## 356                          4                          0.85
## 366                          3                          0.95
## 378                          3                          0.98
## 387                          4                          0.88
## 401                          2                          0.96
## 411                          2                          0.99
## 414                          2                          0.99
## 421                          3                          0.99
## 424                          3                          0.99
## 425                          3                          0.99
## 429                          4                          0.99
## 431                          2                          0.99
## 433                          3                          0.99
## 436                          4                          0.99
## 439                          6                          0.95
## 448                          3                          0.99
## 510                          3                          0.99
## 533                          2                          0.98
## 538                          2                          0.90
## 544                          1                          0.98
## 550                          3                          0.99
## 561                          2                          0.95
## 598                          1                          0.94
## 602                          4                          0.91
## 606                          4                          0.86
## 626                          3                          0.97
## 637                          4                          0.95
## 641                          2                          0.99
## 647                          1                          0.99
## 648                          2                          0.99
## 658                          3                          0.99
## 677                          3                          0.80
## 679                          2                          0.75
## 680                          3                          0.75
## 683                          5                          0.80
##     Offline judging start time Offline judging end time
## 21                         NaN                      NaN
## 43                         NaN                      NaN
## 78                         NaN                      NaN
## 81                         NaN                      NaN
## 91                         NaN                      NaN
## 94                         NaN                      NaN
## 99                         NaN                      NaN
## 113                        NaN                      NaN
## 136                        NaN                      NaN
## 140                        NaN                      NaN
## 149                        NaN                      NaN
## 177                        NaN                      NaN
## 179                        NaN                      NaN
## 185                        NaN                      NaN
```

```
## 186                     NaN                     NaN
## 191                     NaN                     NaN
## 202                     NaN                     NaN
## 211                     NaN                     NaN
## 215                     NaN                     NaN
## 216                     NaN                     NaN
## 219                     NaN                     NaN
## 236                     NaN                     NaN
## 240                     NaN                     NaN
## 241                     NaN                     NaN
## 254                     NaN                     NaN
## 270                     NaN                     NaN
## 276                     NaN                     NaN
## 290                     NaN                     NaN
## 306                     NaN                     NaN
## 324                     NaN                     NaN
## 331                     NaN                     NaN
## 332                     NaN                     NaN
## 338                     NaN                     NaN
## 342                     NaN                     NaN
## 348                     NaN                     NaN
## 356                     NaN                     NaN
## 366                     NaN                     NaN
## 378                     NaN                     NaN
## 387                     NaN                     NaN
## 401                     NaN                     NaN
## 411                     NaN                     NaN
## 414                     NaN                     NaN
## 421                     NaN                     NaN
## 424                     NaN                     NaN
## 425                     NaN                     NaN
## 429                     NaN                     NaN
## 431                     NaN                     NaN
## 433                     NaN                     NaN
## 436                     NaN                     NaN
## 439                     NaN                     NaN
## 448                     NaN                     NaN
## 510                     NaN                     NaN
## 533                     NaN                     NaN
## 538                     NaN                     NaN
## 544                     NaN                     NaN
## 550                     NaN                     NaN
## 561                     NaN                     NaN
## 598                     NaN                     NaN
## 602                     NaN                     NaN
## 606                     NaN                     NaN
## 626                     NaN                     NaN
## 637                     NaN                     NaN
## 641                     NaN                     NaN
## 647                     NaN                     NaN
## 648           1682713008576           1682713141741
## 658                     NaN                     NaN
## 677                     NaN                     NaN
## 679                     NaN                     NaN
```

```
## 680                         NaN                      NaN
## 683                         NaN                      NaN
##                                                                          other
## 21                                                                        <NA>
## 43                                                                        <NA>
## 78                                                                        <NA>
## 81                                                                        <NA>
## 91                                                                        <NA>
## 94                                                                        <NA>
## 99                                                                        <NA>
## 113                                                                       <NA>
## 136                                                                       <NA>
## 140                                                                       <NA>
## 149                                                                       <NA>
## 177                                                                       <NA>
## 179                                                                       <NA>
## 185                                                                       <NA>
## 186                                                                       <NA>
## 191                                                                       <NA>
## 202                                                                       <NA>
## 211                                                                       <NA>
## 215                                                                      nope.
## 216                                                                       <NA>
## 219                                                                       <NA>
## 236                                                                       <NA>
## 240                                                                       <NA>
## 241                                                                       <NA>
## 254                                                                       <NA>
## 270                                                                       <NA>
## 276                                                                       <NA>
## 290                                                                       <NA>
## 306                                                                       <NA>
## 324                                                                       <NA>
## 331                                                                       <NA>
## 332 Maybe I could have decided sooner, even. but first round is a lot to go for.
## 338                                                                       <NA>
## 342                                                                       <NA>
## 348                                                                       <NA>
## 356                                                                       <NA>
## 366                                                                       <NA>
## 378                                                                       <NA>
## 387                                                                       <NA>
## 401                                                                       <NA>
## 411                                                                       <NA>
## 414                                                                       <NA>
## 421                                                                       <NA>
## 424                                                                       <NA>
## 425                                                                       <NA>
## 429                                                                       <NA>
## 431                                                                       <NA>
## 433                                                                       <NA>
## 436                                                                       <NA>
## 439                                                                       <NA>
## 448                                                                       <NA>
```

```
## 510                                                                                   <NA>
## 533                                                                                   <NA>
## 538                                                                                   <NA>
## 544                                                                                   <NA>
## 550                                                                                   <NA>
## 561                                                                                   <NA>
## 598                                                                                   <NA>
## 602                                                                                   <NA>
## 606                                                                                   <NA>
## 626                                                                                   <NA>
## 637                                                                                   <NA>
## 641                                                                                   <NA>
## 647                                                                                   <NA>
## 648                                                                                   <NA>
## 658                                                                                   <NA>
## 677                                                                                   <NA>
## 679                                                                                   <NA>
## 680                                                                                   <NA>
## 683                                                                                   <NA>
##     factual informativeness (comparative).1
## 21                                        2
## 43                                        2
## 78                                        3
## 81                                        3
## 91                                        1
## 94                                        4
## 99                                        1
## 113                                       2
## 136                                       4
## 140                                       4
## 149                                       1
## 177                                       3
## 179                                     NaN
## 185                                       2
## 186                                       1
## 191                                       1
## 202                                       3
## 211                                       4
## 215                                       3
## 216                                       2
## 219                                       3
## 236                                       3
## 240                                       3
## 241                                       4
## 254                                       3
## 270                                       2
## 276                                       2
## 290                                       2
## 306                                       1
## 324                                       2
## 331                                       2
## 332                                       1
## 338                                       1
## 342                                       3
```

```
## 348                                            4
## 356                                            2
## 366                                            1
## 378                                            4
## 387                                            3
## 401                                            4
## 411                                            3
## 414                                            3
## 421                                            1
## 424                                            3
## 425                                            2
## 429                                            3
## 431                                            3
## 433                                            3
## 436                                            3
## 439                                            3
## 448                                          NaN
## 510                                          NaN
## 533                                            3
## 538                                            4
## 544                                            2
## 550                                            3
## 561                                            3
## 598                                            4
## 602                                            2
## 606                                            2
## 626                                            2
## 637                                            3
## 641                                            3
## 647                                            3
## 648                                            1
## 658                                            2
## 677                                            2
## 679                                            2
## 680                                            2
## 683                                            0
##     factual informativeness (comparative).2 facts versus semantics (single)
## 21                                         2                            NaN
## 43                                         2                            NaN
## 78                                         4                            NaN
## 81                                         3                            NaN
## 91                                         3                            NaN
## 94                                         2                            NaN
## 99                                         3                            NaN
## 113                                        2                            NaN
## 136                                        3                            NaN
## 140                                        3                            NaN
## 149                                        3                            NaN
## 177                                        3                            NaN
## 179                                      NaN                            NaN
## 185                                        2                            NaN
## 186                                        1                            NaN
## 191                                        1                            NaN
## 202                                        4                            NaN
```

```
## 211                            2                              NaN
## 215                            2                              NaN
## 216                            2                              NaN
## 219                            3                              NaN
## 236                            3                              NaN
## 240                            3                              NaN
## 241                            4                              NaN
## 254                            3                              NaN
## 270                            3                              NaN
## 276                            3                              NaN
## 290                            4                              NaN
## 306                            0                              NaN
## 324                            4                              NaN
## 331                            3                              NaN
## 332                            4                              NaN
## 338                            4                              NaN
## 342                            4                              NaN
## 348                            4                              NaN
## 356                            1                              NaN
## 366                            2                              NaN
## 378                            4                              NaN
## 387                            4                              NaN
## 401                            4                              NaN
## 411                            3                              NaN
## 414                            3                              NaN
## 421                            3                              NaN
## 424                            3                              NaN
## 425                            2                              NaN
## 429                            2                              NaN
## 431                            3                              NaN
## 433                            3                              NaN
## 436                            3                              NaN
## 439                            3                              NaN
## 448                          NaN                              NaN
## 510                          NaN                              NaN
## 533                            2                              NaN
## 538                            4                              NaN
## 544                            2                              NaN
## 550                            3                              NaN
## 561                            3                              NaN
## 598                            2                              NaN
## 602                            2                              NaN
## 606                            3                              NaN
## 626                            4                              NaN
## 637                            3                              NaN
## 641                            1                              NaN
## 647                            3                              NaN
## 648                            3                              NaN
## 658                            3                              NaN
## 677                            2                              NaN
## 679                            2                              NaN
## 680                            1                              NaN
## 683                            3                              NaN
##     factual accuracy (single) clarity.1 clarity.2 factual accuracy.1
```

```
## 21                        NaN         1         1                NaN
## 43                        NaN         2         3                NaN
## 78                        NaN         3         4                NaN
## 81                        NaN         3         3                NaN
## 91                        NaN         1         3                NaN
## 94                        NaN         2         4                NaN
## 99                        NaN         1         3                NaN
## 113                       NaN         2         2                NaN
## 136                       NaN         4         3                NaN
## 140                       NaN         3         3                NaN
## 149                       NaN         1         2                NaN
## 177                       NaN         2         2                NaN
## 179                       NaN       NaN       NaN                NaN
## 185                       NaN         3         4                NaN
## 186                       NaN         3         3                NaN
## 191                       NaN         2         2                NaN
## 202                       NaN         4         4                NaN
## 211                       NaN         4         1                NaN
## 215                       NaN         4         4                NaN
## 216                       NaN         4         4                NaN
## 219                       NaN         3         3                NaN
## 236                       NaN         2         3                NaN
## 240                       NaN         3         3                NaN
## 241                       NaN         4         4                NaN
## 254                       NaN         3         2                NaN
## 270                       NaN         4         4                NaN
## 276                       NaN         3         4                NaN
## 290                       NaN         3         4                NaN
## 306                       NaN         1         0                NaN
## 324                       NaN         0         3                NaN
## 331                       NaN         3         4                NaN
## 332                       NaN         3         4                NaN
## 338                       NaN         1         4                NaN
## 342                       NaN         1         2                NaN
## 348                       NaN         4         4                NaN
## 356                       NaN         1         1                NaN
## 366                       NaN         2         2                NaN
## 378                       NaN         4         4                NaN
## 387                       NaN         4         4                NaN
## 401                       NaN         4         4                NaN
## 411                       NaN         3         3                NaN
## 414                       NaN         3         3                NaN
## 421                       NaN         2         3                NaN
## 424                       NaN         3         3                NaN
## 425                       NaN         3         3                NaN
## 429                       NaN         3         3                NaN
## 431                       NaN         3         3                NaN
## 433                       NaN         3         3                NaN
## 436                       NaN         3         3                NaN
## 439                       NaN         3         3                NaN
## 448                       NaN       NaN       NaN                NaN
## 510                       NaN       NaN       NaN                NaN
## 533                       NaN         2         3                NaN
## 538                       NaN         4         4                NaN
```

```
## 544                      NaN         4         4                NaN
## 550                      NaN         4         4                NaN
## 561                      NaN         3         3                NaN
## 598                      NaN         1         4                NaN
## 602                      NaN         3         2                NaN
## 606                      NaN         2         3                NaN
## 626                      NaN         1         4                NaN
## 637                      NaN         2         2                NaN
## 641                      NaN         2         1                NaN
## 647                      NaN         3         3                NaN
## 648                      NaN         2         3                NaN
## 658                      NaN         2         2                NaN
## 677                      NaN         3         2                NaN
## 679                      NaN         3         2                NaN
## 680                      NaN         3         1                NaN
## 683                      NaN         0         3                NaN
##     factual accuracy.2 judge reasoning
## 21                 NaN               3
## 43                 NaN               3
## 78                 NaN               4
## 81                 NaN               3
## 91                 NaN               4
## 94                 NaN               4
## 99                 NaN               4
## 113                NaN               2
## 136                NaN               4
## 140                NaN               4
## 149                NaN               4
## 177                NaN               3
## 179                NaN             NaN
## 185                NaN               4
## 186                NaN               4
## 191                NaN               4
## 202                NaN               4
## 211                NaN               4
## 215                NaN               4
## 216                NaN               4
## 219                NaN               3
## 236                NaN               4
## 240                NaN               4
## 241                NaN               4
## 254                NaN               3
## 270                NaN               4
## 276                NaN               4
## 290                NaN               4
## 306                NaN               4
## 324                NaN               4
## 331                NaN               4
## 332                NaN               4
## 338                NaN               4
## 342                NaN               4
## 348                NaN               4
## 356                NaN               4
## 366                NaN               3
```

```
## 378                  NaN              4
## 387                  NaN              4
## 401                  NaN              4
## 411                  NaN              3
## 414                  NaN              3
## 421                  NaN            NaN
## 424                  NaN              3
## 425                  NaN              3
## 429                  NaN              3
## 431                  NaN              3
## 433                  NaN              3
## 436                  NaN              4
## 439                  NaN              3
## 448                  NaN            NaN
## 510                  NaN            NaN
## 533                  NaN              3
## 538                  NaN              4
## 544                  NaN              4
## 550                  NaN              4
## 561                  NaN              4
## 598                  NaN              4
## 602                  NaN              3
## 606                  NaN              4
## 626                  NaN              4
## 637                  NaN              3
## 641                  NaN              3
## 647                  NaN              3
## 648                  NaN              3
## 658                  NaN              2
## 677                  NaN              3
## 679                  NaN              2
## 680                  NaN              4
## 683                  NaN              3
##
## 21
## 43
## 78
## 81
## 91
## 94
## 99
## 113
## 136
## 140
## 149
## 177
## 179
## 185
## 186
## 191
## 202
## 211
## 215
## 216
```

```
## 219
## 236
## 240
## 241
## 254
## 270
## 276
## 290
## 306
## 324
## 331
## 332
## 338
## 342
## 348
## 356
## 366
## 378                              I think I continued the debate for an extra round just to see if any
## 387
## 401                                                                                                   Accidentally voted
## 411
## 414
## 421
## 424
## 425
## 429
## 431
## 433
## 436
## 439
## 448
## 510
## 533
## 538
## 544
## 550
## 561
## 598
## 602
## 606
## 626
## 637
## 641
## 647
## 648
## 658
## 677
## 679
## 680
## 683 I think the factor which convinces me is that the evidence presented seems compelling that the m
##     protocol evidence use.1 evidence use.2 evidence in story.1
## 21      <NA>            NaN            NaN                NaN
## 43      <NA>            NaN            NaN                NaN
## 78      <NA>            NaN            NaN                NaN
```

```
## 81      <NA>            NaN            NaN                NaN
## 91      <NA>            NaN            NaN                NaN
## 94      <NA>            NaN            NaN                NaN
## 99      <NA>            NaN            NaN                NaN
## 113     <NA>            NaN            NaN                NaN
## 136     <NA>            NaN            NaN                NaN
## 140     <NA>            NaN            NaN                NaN
## 149     <NA>            NaN            NaN                NaN
## 177     <NA>            NaN            NaN                NaN
## 179     <NA>            NaN            NaN                NaN
## 185     <NA>            NaN            NaN                NaN
## 186     <NA>            NaN            NaN                NaN
## 191     <NA>            NaN            NaN                NaN
## 202     <NA>            NaN            NaN                NaN
## 211     <NA>            NaN            NaN                NaN
## 215    nope.            NaN            NaN                NaN
## 216     <NA>            NaN            NaN                NaN
## 219     <NA>            NaN            NaN                NaN
## 236     <NA>            NaN            NaN                NaN
## 240     <NA>            NaN            NaN                NaN
## 241     <NA>            NaN            NaN                NaN
## 254     <NA>            NaN            NaN                NaN
## 270     <NA>            NaN            NaN                NaN
## 276     <NA>            NaN            NaN                NaN
## 290     <NA>            NaN            NaN                NaN
## 306     <NA>            NaN            NaN                NaN
## 324     <NA>            NaN            NaN                NaN
## 331     <NA>            NaN            NaN                NaN
## 332     <NA>            NaN            NaN                NaN
## 338     <NA>            NaN            NaN                NaN
## 342     <NA>            NaN            NaN                NaN
## 348     <NA>            NaN            NaN                NaN
## 356     <NA>            NaN            NaN                NaN
## 366     <NA>            NaN            NaN                NaN
## 378     <NA>            NaN            NaN                NaN
## 387     <NA>            NaN            NaN                NaN
## 401     <NA>            NaN            NaN                NaN
## 411     <NA>            NaN            NaN                NaN
## 414     <NA>            NaN            NaN                NaN
## 421     <NA>            NaN            NaN                NaN
## 424     <NA>            NaN            NaN                NaN
## 425     <NA>            NaN            NaN                NaN
## 429     <NA>            NaN            NaN                NaN
## 431     <NA>            NaN            NaN                NaN
## 433     <NA>            NaN            NaN                NaN
## 436     <NA>            NaN            NaN                NaN
## 439     <NA>            NaN            NaN                NaN
## 448     <NA>            NaN            NaN                NaN
## 510     <NA>            NaN            NaN                NaN
## 533     <NA>            NaN            NaN                NaN
## 538     <NA>            NaN            NaN                NaN
## 544     <NA>            NaN            NaN                NaN
## 550     <NA>            NaN            NaN                NaN
## 561     <NA>            NaN            NaN                NaN
```

```
## 598     <NA>             NaN             NaN                 NaN
## 602     <NA>             NaN             NaN                 NaN
## 606     <NA>             NaN             NaN                 NaN
## 626     <NA>             NaN             NaN                 NaN
## 637     <NA>             NaN             NaN                 NaN
## 641     <NA>             NaN             NaN                 NaN
## 647     <NA>             NaN             NaN                 NaN
## 648     <NA>             NaN             NaN                 NaN
## 658     <NA>             NaN             NaN                 NaN
## 677     <NA>             NaN             NaN                 NaN
## 679     <NA>             NaN             NaN                 NaN
## 680     <NA>             NaN             NaN                 NaN
## 683     <NA>             NaN             NaN                 NaN
##     evidence in story.2
## 21                  NaN
## 43                  NaN
## 78                  NaN
## 81                  NaN
## 91                  NaN
## 94                  NaN
## 99                  NaN
## 113                 NaN
## 136                 NaN
## 140                 NaN
## 149                 NaN
## 177                 NaN
## 179                 NaN
## 185                 NaN
## 186                 NaN
## 191                 NaN
## 202                 NaN
## 211                 NaN
## 215                 NaN
## 216                 NaN
## 219                 NaN
## 236                 NaN
## 240                 NaN
## 241                 NaN
## 254                 NaN
## 270                 NaN
## 276                 NaN
## 290                 NaN
## 306                 NaN
## 324                 NaN
## 331                 NaN
## 332                 NaN
## 338                 NaN
## 342                 NaN
## 348                 NaN
## 356                 NaN
## 366                 NaN
## 378                 NaN
## 387                 NaN
## 401                 NaN
```

```
## 411                              NaN
## 414                              NaN
## 421                              NaN
## 424                              NaN
## 425                              NaN
## 429                              NaN
## 431                              NaN
## 433                              NaN
## 436                              NaN
## 439                              NaN
## 448                              NaN
## 510                              NaN
## 533                              NaN
## 538                              NaN
## 544                              NaN
## 550                              NaN
## 561                              NaN
## 598                              NaN
## 602                              NaN
## 606                              NaN
## 626                              NaN
## 637                              NaN
## 641                              NaN
## 647                              NaN
## 648                              NaN
## 658                              NaN
## 677                              NaN
## 679                              NaN
## 680                              NaN
## 683                              NaN
##
## 21
## 43
## 78
## 81
## 91
## 94
## 99
## 113
## 136
## 140
## 149
## 177
## 179
## 185
## 186
## 191
## 202
## 211
## 215
## 216
## 219
## 236
## 240
```

```
## 241
## 254
## 270
## 276
## 290
## 306
## 324
## 331
## 332
## 338
## 342
## 348
## 356
## 366
## 378
## 387
## 401
## 411
## 414
## 421
## 424
## 425
## 429
## 431
## 433
## 436
## 439
## 448
## 510
## 533
## 538
## 544
## 550
## 561
## 598
## 602
## 606
## 626
## 637
## 641
## 647
## 648
## 658
## 677
## 679 I definitely dropped the ball here and got back to judging the debate after a few weeks. I think
## 680                                              I sensed towards the end that the dishonest debate
## 683
##     judge adaptation (single) evidence in debate.1 evidence in debate.2
## 21                        NaN                    2                    2
## 43                        NaN                    2                    3
## 78                        NaN                    1                    4
## 81                        NaN                    3                    3
## 91                        NaN                    2                    3
## 94                        NaN                    1                    3
```

```
## 99                          NaN                    1                    4
## 113                         NaN                    2                    2
## 136                         NaN                    4                    3
## 140                         NaN                    4                    3
## 149                         NaN                    2                    3
## 177                         NaN                    3                    2
## 179                         NaN                  NaN                  NaN
## 185                         NaN                    0                    3
## 186                         NaN                    3                    2
## 191                         NaN                    2                    3
## 202                         NaN                    3                    4
## 211                         NaN                    4                    0
## 215                         NaN                    4                    1
## 216                         NaN                    0                    4
## 219                         NaN                    3                    2
## 236                         NaN                    2                    4
## 240                         NaN                    4                    2
## 241                         NaN                    2                    4
## 254                         NaN                    3                    2
## 270                         NaN                    2                    4
## 276                         NaN                    2                    4
## 290                         NaN                    2                    4
## 306                         NaN                    2                    0
## 324                         NaN                    0                    3
## 331                         NaN                    1                    4
## 332                         NaN                    0                    3
## 338                         NaN                    0                    3
## 342                         NaN                    3                    4
## 348                         NaN                    2                    4
## 356                         NaN                    2                    1
## 366                         NaN                    1                    3
## 378                         NaN                    4                    4
## 387                         NaN                    2                    4
## 401                         NaN                    4                    4
## 411                         NaN                    3                    3
## 414                         NaN                    3                    2
## 421                         NaN                    1                    3
## 424                         NaN                    2                    3
## 425                         NaN                    3                    3
## 429                         NaN                    3                    3
## 431                         NaN                    4                    3
## 433                         NaN                    3                    2
## 436                         NaN                    3                    3
## 439                         NaN                    2                    3
## 448                         NaN                  NaN                  NaN
## 510                         NaN                  NaN                  NaN
## 533                         NaN                    3                    1
## 538                         NaN                    1                    4
## 544                         NaN                    0                    3
## 550                         NaN                    4                    3
## 561                         NaN                    2                    4
## 598                         NaN                    4                    2
## 602                         NaN                    2                    2
## 606                         NaN                    1                    4
```

```
## 626                     NaN                    1                    4
## 637                     NaN                    2                    2
## 641                     NaN                    3                    1
## 647                     NaN                    1                    3
## 648                     NaN                    2                    4
## 658                     NaN                    2                    2
## 677                     NaN                    4                    1
## 679                     NaN                    3                    1
## 680                     NaN                    3                    1
## 683                     NaN                    4                    2
##                                                             interface
## 21                                                               <NA>
## 43                                                               <NA>
## 78                                                               <NA>
## 81                                                               <NA>
## 91                                                               <NA>
## 94                                                               <NA>
## 99                                                               <NA>
## 113                                                              <NA>
## 136                                                              <NA>
## 140                                                              <NA>
## 149                                                              <NA>
## 177                                                              <NA>
## 179                                                              <NA>
## 185                 I accidentally entered the probabilities backwards
## 186                                                              <NA>
## 191                                                              <NA>
## 202                                                              <NA>
## 211                                                              <NA>
## 215                                           The interface is great!
## 216                                                              <NA>
## 219                                                              <NA>
## 236                                                              <NA>
## 240                                                              <NA>
## 241                                                              <NA>
## 254                                                              <NA>
## 270                                                              <NA>
## 276                                                              <NA>
## 290                                                              <NA>
## 306                                                              <NA>
## 324                                                              <NA>
## 331                                                              <NA>
## 332                                                              <NA>
## 338                                                              <NA>
## 342                                                              <NA>
## 348                                                              <NA>
## 356                                                              <NA>
## 366                                                              <NA>
## 378                                                              <NA>
## 387                                                              <NA>
## 401                                                              <NA>
## 411                                                              <NA>
## 414                                                              <NA>
## 421                                                              <NA>
```

```
## 424                                                                    <NA>
## 425                                                                    <NA>
## 429                                                                    <NA>
## 431                                                                    <NA>
## 433                                                                    <NA>
## 436                                                                    <NA>
## 439                                                                    <NA>
## 448                                                                    <NA>
## 510                                                                    <NA>
## 533                                                                    <NA>
## 538                                                                    <NA>
## 544                                                                    <NA>
## 550                                                                    <NA>
## 561                                                                    <NA>
## 598                                                                    <NA>
## 602                                                                    <NA>
## 606                                                                    <NA>
## 626                                                                    <NA>
## 637                                                                    <NA>
## 641                                                                    <NA>
## 647                                                                    <NA>
## 648                                                                    <NA>
## 658                                                                    <NA>
## 677 Quote limits seemed to hamper both debaters? Unclear if they agree
## 679                                                                    <NA>
## 680                                                                    <NA>
## 683                                                                    <NA>
##     evidence in debate (single) facts versus semantics.1
## 21                         NaN                         3
## 43                         NaN                         3
## 78                         NaN                         2
## 81                         NaN                         1
## 91                         NaN                         3
## 94                         NaN                         2
## 99                         NaN                         2
## 113                        NaN                         2
## 136                        NaN                         4
## 140                        NaN                         1
## 149                        NaN                         3
## 177                        NaN                         1
## 179                        NaN                       NaN
## 185                        NaN                         2
## 186                        NaN                         2
## 191                        NaN                         3
## 202                        NaN                         0
## 211                        NaN                         0
## 215                        NaN                         0
## 216                        NaN                         0
## 219                        NaN                         2
## 236                        NaN                         1
## 240                        NaN                         1
## 241                        NaN                         0
## 254                        NaN                         1
## 270                        NaN                         2
```

```
## 276                          NaN                          2
## 290                          NaN                          3
## 306                          NaN                          4
## 324                          NaN                          0
## 331                          NaN                          0
## 332                          NaN                          0
## 338                          NaN                          0
## 342                          NaN                          0
## 348                          NaN                          3
## 356                          NaN                          1
## 366                          NaN                          2
## 378                          NaN                          3
## 387                          NaN                          4
## 401                          NaN                          1
## 411                          NaN                          3
## 414                          NaN                          1
## 421                          NaN                          1
## 424                          NaN                          1
## 425                          NaN                          2
## 429                          NaN                          1
## 431                          NaN                          1
## 433                          NaN                          1
## 436                          NaN                          2
## 439                          NaN                          2
## 448                          NaN                        NaN
## 510                          NaN                        NaN
## 533                          NaN                          2
## 538                          NaN                          3
## 544                          NaN                          3
## 550                          NaN                          2
## 561                          NaN                          2
## 598                          NaN                          2
## 602                          NaN                          2
## 606                          NaN                          2
## 626                          NaN                          0
## 637                          NaN                          1
## 641                          NaN                          1
## 647                          NaN                          3
## 648                          NaN                          2
## 658                          NaN                          3
## 677                          NaN                          1
## 679                          NaN                          2
## 680                          NaN                          2
## 683                          NaN                          1
##     facts versus semantics.2 clash.1 clash.2 identity guesses.Judge
## 21                         3       1       2                   <NA>
## 43                         2       2       2                   <NA>
## 78                         1       1       4                   <NA>
## 81                         1       3       3                   <NA>
## 91                         1       0       3                   <NA>
## 94                         1       1       4                   <NA>
## 99                         3       1       3                   <NA>
## 113                        2       2       2                   <NA>
## 136                        3       4       3                   <NA>
```

```
## 140                        3       3       2                  <NA>
## 149                        1       2       2                  <NA>
## 177                        3       2       2                  <NA>
## 179                      NaN     NaN     NaN                  <NA>
## 185                        1       2       3                  <NA>
## 186                        1       4       2                  <NA>
## 191                        3       3       3                  <NA>
## 202                        0       3       4                  <NA>
## 211                        4       4       1                  <NA>
## 215                        1       3       2                  <NA>
## 216                        0       0       4                  <NA>
## 219                        2       3       2                  <NA>
## 236                        1       3       3                  <NA>
## 240                        1       4       3                  <NA>
## 241                        0       3       4                  <NA>
## 254                        3       3       2                  <NA>
## 270                        0       2       2                  <NA>
## 276                        0       2       4                  <NA>
## 290                        0       1       2                  <NA>
## 306                        3       1       0                  <NA>
## 324                        0       1       4                  <NA>
## 331                        0       1       4                  <NA>
## 332                        0       0       4                  <NA>
## 338                        0       0       4                  <NA>
## 342                        0       2       4                  <NA>
## 348                        1       4       4                  <NA>
## 356                        2       1       1                  <NA>
## 366                        1       2       3                  <NA>
## 378                        0       4       4                  <NA>
## 387                        4       4       4                  <NA>
## 401                        0       4       4                  <NA>
## 411                        2       3       3                  <NA>
## 414                        2       3       3                  <NA>
## 421                        1       2       3                  <NA>
## 424                        1       3       3                  <NA>
## 425                        2       3       3                  <NA>
## 429                        1       3       2                  <NA>
## 431                        2       3       2                  <NA>
## 433                        1       3       3                  <NA>
## 436                        2       3       3                  <NA>
## 439                        1       2       2                  <NA>
## 448                      NaN     NaN     NaN                  <NA>
## 510                      NaN     NaN     NaN                  <NA>
## 533                        1       3       3                  <NA>
## 538                        3       4       2                  <NA>
## 544                        0       0       0                  <NA>
## 550                        1       4       2                  <NA>
## 561                        0       4       4                  <NA>
## 598                        1       2       2                  <NA>
## 602                        2       3       3                  <NA>
## 606                        2       3       2                  <NA>
## 626                        0       0       4                  <NA>
## 637                        3       3       3                  <NA>
## 641                        3       2       0                  <NA>
```

```
## 647                        2       2       3                   <NA>
## 648                        1       2       4                   <NA>
## 658                        3       1       3                   <NA>
## 677                        3       4       2                   <NA>
## 679                        3       3       2                   <NA>
## 680                        3       4       2                   <NA>
## 683                        3       1       3                   <NA>
##     identity guesses.Debater A identity guesses.Debater B judge adaptation.1
## 21                        <NA>                       <NA>                  1
## 43                        <NA>                       <NA>                  2
## 78                        <NA>                       <NA>                  2
## 81                        <NA>                       <NA>                  3
## 91                        <NA>                       <NA>                  2
## 94                        <NA>                       <NA>                  1
## 99                        <NA>                       <NA>                  0
## 113                       <NA>                       <NA>                  2
## 136                       <NA>                       <NA>                  4
## 140                       <NA>                       <NA>                  3
## 149           Emmanuel Makinde                       <NA>                  1
## 177                       <NA>                       <NA>                  1
## 179                       <NA>                       <NA>                NaN
## 185                       <NA>                       <NA>                  2
## 186                       <NA>                       <NA>                  2
## 191                       <NA>                       <NA>                  4
## 202                       <NA>                       <NA>                  2
## 211                       <NA>                       <NA>                  4
## 215                       <NA>                       <NA>                  4
## 216                       <NA>                       <NA>                  2
## 219                       <NA>                       <NA>                  3
## 236                       <NA>                       <NA>                  3
## 240                       <NA>                       <NA>                  4
## 241                       <NA>                       <NA>                  2
## 254                       <NA>                       <NA>                  3
## 270                       <NA>                       <NA>                  3
## 276                       <NA>                       <NA>                  2
## 290                       <NA>                       <NA>                  2
## 306                       <NA>                       <NA>                  1
## 324               Reeya Kansra                  Sean Wang                  2
## 331               Reeya Kansra                  Sean Wang                  0
## 332                       <NA>                       <NA>                  4
## 338                       <NA>                       <NA>                  0
## 342                       <NA>                       <NA>                  2
## 348                       <NA>                       <NA>                  3
## 356                       <NA>                       <NA>                  2
## 366                       <NA>                       <NA>                  3
## 378                 Jessica Li            Adelle Fernando                  4
## 387              Julien Dirani                Ethan Rosen                  4
## 401           Emmanuel Makinde            Adelle Fernando                  4
## 411                       <NA>                       <NA>                  3
## 414                       <NA>                       <NA>                  2
## 421                       <NA>                       <NA>                  3
## 424              Shlomo Kofman                    Sam Jin                  3
## 425                 Jessica Li                  Anuj Jain                  3
## 429                 Jessica Li              Shreeram Modi                  3
```

```
## 431                      <NA>                 <NA>                    3
## 433                      <NA>                 <NA>                    3
## 436                      <NA>                 <NA>                    4
## 439                 Sean Wang          Reeya Kansra                    3
## 448                      <NA>                 <NA>                  NaN
## 510                      <NA>                 <NA>                  NaN
## 533                      <NA>                 <NA>                    2
## 538                      <NA>                 <NA>                    4
## 544                      <NA>                 <NA>                    2
## 550                      <NA>                 <NA>                    3
## 561                      <NA>                 <NA>                    3
## 598                      <NA>                 <NA>                    2
## 602                      <NA>                 <NA>                    3
## 606                      <NA>                 <NA>                    2
## 626                      <NA>                 <NA>                    0
## 637                      <NA>                 <NA>                    3
## 641                      <NA>                 <NA>                    2
## 647                      <NA>                 <NA>                    2
## 648                      <NA>                 <NA>                    1
## 658                      <NA>                 <NA>                    1
## 677                      <NA>                 <NA>                    4
## 679                      <NA>                 <NA>                    3
## 680                      <NA>                 <NA>                    4
## 683                      <NA>                 <NA>                    1
##     judge adaptation.2 subjective correctness evidence use (single)
## 21                   1                    NaN                  NaN
## 43                   3                    NaN                  NaN
## 78                   4                    NaN                  NaN
## 81                   3                    NaN                  NaN
## 91                   3                    NaN                  NaN
## 94                   4                    NaN                  NaN
## 99                   4                    NaN                  NaN
## 113                  2                    NaN                  NaN
## 136                  3                    NaN                  NaN
## 140                  2                    NaN                  NaN
## 149                  2                    NaN                  NaN
## 177                  1                    NaN                  NaN
## 179                NaN                    NaN                  NaN
## 185                  2                    NaN                  NaN
## 186                  2                    NaN                  NaN
## 191                  4                    NaN                  NaN
## 202                  4                    NaN                  NaN
## 211                  1                    NaN                  NaN
## 215                  4                    NaN                  NaN
## 216                  4                    NaN                  NaN
## 219                  2                    NaN                  NaN
## 236                  4                    NaN                  NaN
## 240                  2                    NaN                  NaN
## 241                  4                    NaN                  NaN
## 254                  1                    NaN                  NaN
## 270                  4                    NaN                  NaN
## 276                  4                    NaN                  NaN
## 290                  2                    NaN                  NaN
## 306                  0                    NaN                  NaN
```

```
## 324                 4                    NaN                    NaN
## 331                 4                    NaN                    NaN
## 332                 4                    NaN                    NaN
## 338                 4                    NaN                    NaN
## 342                 3                    NaN                    NaN
## 348                 3                    NaN                    NaN
## 356                 2                    NaN                    NaN
## 366                 3                    NaN                    NaN
## 378                 4                    NaN                    NaN
## 387                 4                    NaN                    NaN
## 401                 4                    NaN                    NaN
## 411                 3                    NaN                    NaN
## 414                 3                    NaN                    NaN
## 421                 4                    NaN                    NaN
## 424                 3                    NaN                    NaN
## 425                 3                    NaN                    NaN
## 429                 2                    NaN                    NaN
## 431                 3                    NaN                    NaN
## 433                 2                    NaN                    NaN
## 436                 3                    NaN                    NaN
## 439                 3                    NaN                    NaN
## 448               NaN                    NaN                    NaN
## 510               NaN                    NaN                    NaN
## 533                 3                    NaN                    NaN
## 538                 4                    NaN                    NaN
## 544                 2                    NaN                    NaN
## 550                 3                    NaN                    NaN
## 561                 3                    NaN                    NaN
## 598                 2                    NaN                    NaN
## 602                 3                    NaN                    NaN
## 606                 3                    NaN                    NaN
## 626                 4                    NaN                    NaN
## 637                 3                    NaN                    NaN
## 641                 1                    NaN                    NaN
## 647                 2                    NaN                    NaN
## 648                 4                    NaN                    NaN
## 658                 3                    NaN                    NaN
## 677                 1                    NaN                    NaN
## 679                 0                    NaN                    NaN
## 680                 2                    NaN                    NaN
## 683                 3                    NaN                    NaN
##     factual informativeness (total)
## 21                                1
## 43                                2
## 78                                3
## 81                                3
## 91                                3
## 94                                3
## 99                                3
## 113                               2
## 136                               4
## 140                               3
## 149                               3
## 177                               1
```

```
## 179                                            NaN
## 185                                              1
## 186                                              1
## 191                                              1
## 202                                              4
## 211                                              3
## 215                                              2
## 216                                              0
## 219                                              3
## 236                                              4
## 240                                              4
## 241                                              4
## 254                                              3
## 270                                              3
## 276                                              4
## 290                                              3
## 306                                              0
## 324                                              4
## 331                                              3
## 332                                              4
## 338                                              3
## 342                                              3
## 348                                              3
## 356                                              2
## 366                                              2
## 378                                              4
## 387                                              4
## 401                                              4
## 411                                              3
## 414                                              3
## 421                                              3
## 424                                              3
## 425                                              3
## 429                                              3
## 431                                              3
## 433                                              3
## 436                                              4
## 439                                              3
## 448                                            NaN
## 510                                            NaN
## 533                                              3
## 538                                              4
## 544                                              0
## 550                                              3
## 561                                              4
## 598                                              4
## 602                                              3
## 606                                              3
## 626                                              4
## 637                                              3
## 641                                              2
## 647                                              3
## 648                                              3
## 658                                              3
```

```
## 677                              1
## 679                              2
## 680                              3
## 683                              3
##
## 21
## 43
## 78
## 81
## 91
## 94
## 99
## 113
## 136
## 140
## 149
## 177
## 179
## 185                  I said this to debater A: Are there any other resources mentioned, or context
## 186
## 191
## 202
## 211
## 215
## 216
## 219
## 236
## 240
## 241
## 254
## 270
## 276
## 290
## 306
## 324
## 331
## 332
## 338
## 342
## 348
## 356
## 366
## 378
## 387
## 401
## 411
## 414
## 421
## 424
## 425
## 429
## 431
## 433
## 436
```

```
## 439
## 448
## 510
## 533
## 538
## 544
## 550
## 561
## 598
## 602
## 606
## 626
## 637
## 641
## 647
## 648
## 658 Yes. I indicated particular pieces of evidence that both were missing and that would help me grea
## 677
## 679
## 680
## 683
##     clarity (single)          Debater A          Debater B     Honest debater
## 21               NaN        Ethan Rosen          Sean Wang        Ethan Rosen
## 43               NaN         Jessica Li        Ethan Rosen        Ethan Rosen
## 78               NaN       Reeya Kansra     Julian Michael     Julian Michael
## 81               NaN      Shreeram Modi          Sean Wang      Shreeram Modi
## 91               NaN      Shlomo Kofman          Sean Wang          Sean Wang
## 94               NaN          Sean Wang          Anuj Jain          Anuj Jain
## 99               NaN    Adelle Fernando      Shreeram Modi      Shreeram Modi
## 113              NaN  Noor Mirza-Rashid          Sean Wang  Noor Mirza-Rashid
## 136              NaN      Shreeram Modi    Adelle Fernando      Shreeram Modi
## 140              NaN       Reeya Kansra         Jessica Li       Reeya Kansra
## 149              NaN    Salsabila Mahdi         Jessica Li         Jessica Li
## 177              NaN        Ethan Rosen       Reeya Kansra        Ethan Rosen
## 179              NaN       Reeya Kansra      Jackson Petty      Jackson Petty
## 185              NaN      Shreeram Modi        Ethan Rosen        Ethan Rosen
## 186              NaN      Shreeram Modi    Adelle Fernando      Shreeram Modi
## 191              NaN          Sean Wang    Salsabila Mahdi    Salsabila Mahdi
## 202              NaN    Adelle Fernando          Sean Wang          Sean Wang
## 211              NaN          Sean Wang      Shreeram Modi          Sean Wang
## 215              NaN         David Rein          Sean Wang         David Rein
## 216              NaN  Noor Mirza-Rashid      Shreeram Modi      Shreeram Modi
## 219              NaN          Anuj Jain            Sam Jin          Anuj Jain
## 236              NaN            Sam Jin      Shlomo Kofman      Shlomo Kofman
## 240              NaN    Adelle Fernando       Reeya Kansra    Adelle Fernando
## 241              NaN            Sam Jin          Anuj Jain          Anuj Jain
## 254              NaN          Anuj Jain       Reeya Kansra          Anuj Jain
## 270              NaN       Reeya Kansra          Anuj Jain          Anuj Jain
## 276              NaN    Adelle Fernando        Ethan Rosen        Ethan Rosen
## 290              NaN    Adelle Fernando            Sam Jin            Sam Jin
## 306              NaN          Anuj Jain          Sean Wang          Anuj Jain
## 324              NaN       Reeya Kansra          Sean Wang          Sean Wang
## 331              NaN      Shreeram Modi          Sean Wang          Sean Wang
## 332              NaN    Adelle Fernando        Ethan Rosen        Ethan Rosen
```

```
## 338              NaN      Shreeram Modi          Anuj Jain          Anuj Jain
## 342              NaN         Jessica Li          Anuj Jain          Anuj Jain
## 348              NaN          Sean Wang         Jessica Li         Jessica Li
## 356              NaN       Reeya Kansra      Shreeram Modi       Reeya Kansra
## 366              NaN      Shreeram Modi    Salsabila Mahdi    Salsabila Mahdi
## 378              NaN    Salsabila Mahdi        Ethan Rosen        Ethan Rosen
## 387              NaN            Sam Jin      Shlomo Kofman      Shlomo Kofman
## 401              NaN          Anuj Jain  Noor Mirza-Rashid          Anuj Jain
## 411              NaN          Sean Wang          Anuj Jain          Anuj Jain
## 414              NaN          Sean Wang    Adelle Fernando    Adelle Fernando
## 421              NaN      Shreeram Modi     Julian Michael     Julian Michael
## 424              NaN      Shlomo Kofman            Sam Jin            Sam Jin
## 425              NaN         Jessica Li      Shreeram Modi         Jessica Li
## 429              NaN            Sam Jin    Adelle Fernando            Sam Jin
## 431              NaN      Shreeram Modi    Adelle Fernando      Shreeram Modi
## 433              NaN  Aliyaah Toussaint    Adelle Fernando  Aliyaah Toussaint
## 436              NaN Vishakh Padmakumar      Shreeram Modi Vishakh Padmakumar
## 439              NaN            Sam Jin    Adelle Fernando    Adelle Fernando
## 448              NaN    Adelle Fernando         Jessica Li    Adelle Fernando
## 510              NaN          Anuj Jain      Shlomo Kofman          Anuj Jain
## 533              NaN      Shreeram Modi    Salsabila Mahdi    Salsabila Mahdi
## 538              NaN    Salsabila Mahdi Vishakh Padmakumar Vishakh Padmakumar
## 544              NaN    Adelle Fernando      Jackson Petty      Jackson Petty
## 550              NaN         Jessica Li      Shlomo Kofman         Jessica Li
## 561              NaN      Shreeram Modi  Aliyaah Toussaint  Aliyaah Toussaint
## 598              NaN      Shreeram Modi    Adelle Fernando    Adelle Fernando
## 602              NaN         Jessica Li          Sean Wang         Jessica Li
## 606              NaN    Adelle Fernando       Reeya Kansra       Reeya Kansra
## 626              NaN            Sam Jin    Adelle Fernando    Adelle Fernando
## 637              NaN          Sean Wang    Adelle Fernando          Sean Wang
## 641              NaN         David Rein         Jessica Li         David Rein
## 647              NaN    Salsabila Mahdi Vishakh Padmakumar Vishakh Padmakumar
## 648              NaN          Sean Wang        Ethan Rosen        Ethan Rosen
## 658              NaN          Sean Wang     Julian Michael     Julian Michael
## 677              NaN     Julian Michael         Jessica Li     Julian Michael
## 679              NaN         Jessica Li    Salsabila Mahdi    Salsabila Mahdi
## 680              NaN     Julian Michael    Salsabila Mahdi     Julian Michael
## 683              NaN          Anuj Jain      Shreeram Modi          Anuj Jain
##     Dishonest debater Is single debater Has honest debater Final_Setting
## 21          Sean Wang             FALSE               TRUE  Human Debate
## 43         Jessica Li             FALSE               TRUE  Human Debate
## 78       Reeya Kansra             FALSE               TRUE  Human Debate
## 81          Sean Wang             FALSE               TRUE  Human Debate
## 91      Shlomo Kofman             FALSE               TRUE  Human Debate
## 94          Sean Wang             FALSE               TRUE  Human Debate
## 99    Adelle Fernando             FALSE               TRUE  Human Debate
## 113         Sean Wang             FALSE               TRUE  Human Debate
## 136   Adelle Fernando             FALSE               TRUE  Human Debate
## 140        Jessica Li             FALSE               TRUE  Human Debate
## 149   Salsabila Mahdi             FALSE               TRUE  Human Debate
## 177      Reeya Kansra             FALSE               TRUE  Human Debate
## 179      Reeya Kansra             FALSE               TRUE  Human Debate
## 185     Shreeram Modi             FALSE               TRUE  Human Debate
## 186   Adelle Fernando             FALSE               TRUE  Human Debate
```

```
## 191          Sean Wang             FALSE                TRUE  Human Debate
## 202   Adelle Fernando             FALSE                TRUE  Human Debate
## 211     Shreeram Modi             FALSE                TRUE  Human Debate
## 215          Sean Wang             FALSE                TRUE  Human Debate
## 216 Noor Mirza-Rashid             FALSE                TRUE  Human Debate
## 219            Sam Jin             FALSE                TRUE  Human Debate
## 236            Sam Jin             FALSE                TRUE  Human Debate
## 240      Reeya Kansra             FALSE                TRUE  Human Debate
## 241            Sam Jin             FALSE                TRUE  Human Debate
## 254      Reeya Kansra             FALSE                TRUE  Human Debate
## 270      Reeya Kansra             FALSE                TRUE  Human Debate
## 276   Adelle Fernando             FALSE                TRUE  Human Debate
## 290   Adelle Fernando             FALSE                TRUE  Human Debate
## 306          Sean Wang             FALSE                TRUE  Human Debate
## 324      Reeya Kansra             FALSE                TRUE  Human Debate
## 331     Shreeram Modi             FALSE                TRUE  Human Debate
## 332   Adelle Fernando             FALSE                TRUE  Human Debate
## 338     Shreeram Modi             FALSE                TRUE  Human Debate
## 342        Jessica Li             FALSE                TRUE  Human Debate
## 348          Sean Wang             FALSE                TRUE  Human Debate
## 356     Shreeram Modi             FALSE                TRUE  Human Debate
## 366     Shreeram Modi             FALSE                TRUE  Human Debate
## 378   Salsabila Mahdi             FALSE                TRUE  Human Debate
## 387            Sam Jin             FALSE                TRUE  Human Debate
## 401 Noor Mirza-Rashid             FALSE                TRUE  Human Debate
## 411          Sean Wang             FALSE                TRUE  Human Debate
## 414          Sean Wang             FALSE                TRUE  Human Debate
## 421     Shreeram Modi             FALSE                TRUE  Human Debate
## 424     Shlomo Kofman             FALSE                TRUE  Human Debate
## 425     Shreeram Modi             FALSE                TRUE  Human Debate
## 429   Adelle Fernando             FALSE                TRUE  Human Debate
## 431   Adelle Fernando             FALSE                TRUE  Human Debate
## 433   Adelle Fernando             FALSE                TRUE  Human Debate
## 436     Shreeram Modi             FALSE                TRUE  Human Debate
## 439            Sam Jin             FALSE                TRUE  Human Debate
## 448        Jessica Li             FALSE                TRUE  Human Debate
## 510     Shlomo Kofman             FALSE                TRUE  Human Debate
## 533     Shreeram Modi             FALSE                TRUE  Human Debate
## 538   Salsabila Mahdi             FALSE                TRUE  Human Debate
## 544   Adelle Fernando             FALSE                TRUE  Human Debate
## 550     Shlomo Kofman             FALSE                TRUE  Human Debate
## 561     Shreeram Modi             FALSE                TRUE  Human Debate
## 598     Shreeram Modi             FALSE                TRUE  Human Debate
## 602          Sean Wang             FALSE                TRUE  Human Debate
## 606   Adelle Fernando             FALSE                TRUE  Human Debate
## 626            Sam Jin             FALSE                TRUE  Human Debate
## 637   Adelle Fernando             FALSE                TRUE  Human Debate
## 641        Jessica Li             FALSE                TRUE  Human Debate
## 647   Salsabila Mahdi             FALSE                TRUE  Human Debate
## 648          Sean Wang             FALSE                TRUE  Human Debate
## 658          Sean Wang             FALSE                TRUE  Human Debate
## 677        Jessica Li             FALSE                TRUE  Human Debate
## 679        Jessica Li             FALSE                TRUE  Human Debate
## 680   Salsabila Mahdi             FALSE                TRUE  Human Debate
```

```
## 683     Shreeram Modi              FALSE               TRUE  Human Debate
##          Setting
## 21  Human Debate
## 43  Human Debate
## 78  Human Debate
## 81  Human Debate
## 91  Human Debate
## 94  Human Debate
## 99  Human Debate
## 113 Human Debate
## 136 Human Debate
## 140 Human Debate
## 149 Human Debate
## 177 Human Debate
## 179 Human Debate
## 185 Human Debate
## 186 Human Debate
## 191 Human Debate
## 202 Human Debate
## 211 Human Debate
## 215 Human Debate
## 216 Human Debate
## 219 Human Debate
## 236 Human Debate
## 240 Human Debate
## 241 Human Debate
## 254 Human Debate
## 270 Human Debate
## 276 Human Debate
## 290 Human Debate
## 306 Human Debate
## 324 Human Debate
## 331 Human Debate
## 332 Human Debate
## 338 Human Debate
## 342 Human Debate
## 348 Human Debate
## 356 Human Debate
## 366 Human Debate
## 378 Human Debate
## 387 Human Debate
## 401 Human Debate
## 411 Human Debate
## 414 Human Debate
## 421 Human Debate
## 424 Human Debate
## 425 Human Debate
## 429 Human Debate
## 431 Human Debate
## 433 Human Debate
## 436 Human Debate
## 439 Human Debate
## 448 Human Debate
## 510 Human Debate
```

```
## 533 Human Debate
## 538 Human Debate
## 544 Human Debate
## 550 Human Debate
## 561 Human Debate
## 598 Human Debate
## 602 Human Debate
## 606 Human Debate
## 626 Human Debate
## 637 Human Debate
## 641 Human Debate
## 647 Human Debate
## 648 Human Debate
## 658 Human Debate
## 677 Human Debate
## 679 Human Debate
## 680 Human Debate
## 683 Human Debate
##
## 21                                                                          Which is
## 43                                                                             Which
## 78                                                                      How did Earth
## 81                                                                  Why does Koroby i
## 91                                                         Did the questions Tremaine
## 94                                                           Why did the physicist an
## 99                                                                 What was the blu
## 113                                                                     What is li
## 136                                                                        Why was
## 140
## 149                                                    Why was the main character daydreami
## 177                                                    Generally, which of the following bo
## 179                                                              Which of these sets of de
## 185                                                                     What was the
## 186
## 191
## 202                                                            Why do Bob and Quezy ha
## 211
## 215                                                             Why was Dr. Crander so p
## 216                                                            What is not a type techno
## 219                                      What best describes how the overall tone changed fr
## 236                                                       What would best describe Asa's m
## 240                                                                   Why did the Earth c
## 241                                                            Who are the four to blame
## 254                                                     What did Zen think of the plan the re
## 270                                                   Why is Grannie Annie so concerned abou
## 276                                                                 How many compani
## 290                                                            Who are the four to blame
## 306                                                            What was the population of
## 324                                                                         Which is
## 331                                                                  Why does Koroby i
## 332                                                 How did the planet of Niobe compare to
## 338                                                         Which best describes the relati
## 342                                                      What is the relationship between C
## 348                                                                     What is the c
```

```
## 356                                                                              Why is 
## 366                                                                     What does the narrat
## 378
## 387                                                              What happens to a changelin
## 401                                             What makes the protagonists become less concerned a
## 411                                                  Why was the approach that Charlie took to eng
## 414                                                                   Why do Bob and Quezy h
## 421                                                                             Why is Jor
## 424                                                            What would best describe Asa’s 
## 425
## 429                                                             What is Androka’s motivation 
## 431                              Which of the following is not a reason why Koroby is impressed by the s
## 433 Johnathan doesn’t tell the Interstellar Cosmography Society about the twenty-seven women who are
## 436                                                                        How many people 
## 439                                                                         What was the bl
## 448
## 510                                                       What was the relationship like between 
## 533                                                            Why did Korvin have to word his 
## 538                                                                   How would you describe
## 544
## 550                                                                          Why did Pashk
## 561                                                                     What does the narrat
## 598                                                                              Why wa
## 602                                         What would be the main reason Mr. Ranson wants to find t
## 606                                                                       Why did the Earth 
## 626                                                                            How did H
## 637                                                                            What is l
## 641                                                          What is likely to happen to the crew
## 647                                                                                 Wh
## 648                                                        What is the true explanation for Charles 
## 658                                  If Dan and Erica had been seen together before the accident, what 
## 677                                                       Of the following situations, what was t
## 679                                                          Why was the main character daydream
## 680                                                                     What is the style of
## 683                                                                  What is not a type techn
##     Article ID Speed annotator accuracy bins Untimed annotator context bins
## 21       61499                             0                              4
## 43       61053                             0                              4
## 78       60412                             0                              2
## 81       62314                           0.2                              3
## 91       52844                           0.2                              4
## 94       51126                           0.2                              2
## 99       52855                           0.2                              3
## 113      63527                             0                              3
## 136      63633                           0.2                              4
## 140      43046                           0.4                              2
## 149      51688                           0.2                              2
## 177      61499                           0.2                              3
## 179      55933                           0.4                              3
## 185      63862                           0.2                              2
## 186      62314                           0.2                              3
## 191      50893                           0.2                              3
## 202      63527                           0.2                              2
## 211      62314                           0.2                              3
```

```
## 215      51295                           0.4                              3
## 216      62569                           0.4                              3
## 219      53269                           0.2                              4
## 236      61467                           0.4                              2
## 240      60412                           0.2                              3
## 241      61481                           0.2                              3
## 254      51126                             0                              2
## 270      63109                           0.2                              2
## 276      50818                           0.2                              3
## 290      61481                           0.2                              3
## 306      51126                           0.2                              2
## 324      61499                             0                              4
## 331      62314                           0.2                              3
## 332      51395                           0.2                              3
## 338      62569                           0.2                              3
## 342      51351                           0.2                              3
## 348      61430                             0                              2
## 356      63109                           0.2                              3
## 366      51201                             0                              3
## 378      50818                           0.4                              4
## 387      61467                           0.4                              2
## 401      62569                             0                              2
## 411      51320                           0.2                              2
## 414      63527                           0.2                              2
## 421      61430                           0.4                              2
## 424      61467                           0.4                              2
## 425      43046                           0.4                              3
## 429      61481                             0                              3
## 431      62314                           0.2                              2
## 433      63401                           0.2                              2
## 436      51483                           0.2                              2
## 439      52855                           0.2                              3
## 448      63523                           0.2                              3
## 510      51150                           0.2                              3
## 533      30029                           0.4                              2
## 538      55933                             0                              4
## 544      51395                           0.2                              2
## 550      51256                           0.4                              3
## 561      51201                             0                              3
## 598      63633                           0.2                              4
## 602      62085                           0.2                              2
## 606      60412                           0.2                              3
## 626      63855                             0                              2
## 637      63527                             0                              3
## 641      61007                           0.2                              2
## 647      55933                           0.2                              2
## 648      63631                           0.2                              3
## 658      51295                           0.4                              4
## 677      63862                           0.4                              3
## 679      51688                           0.2                              2
## 680      61285                           0.4                              2
## 683      62569                           0.4                              3
##     Speed annotator accuracy Untimed annotator context Is offline
## 21                 0.0000000                  3.666667      FALSE
```

```
## 43                    0.0000000                    3.666667     FALSE
## 78                    0.0000000                    2.000000     FALSE
## 81                    0.2000000                    3.000000     FALSE
## 91                    0.2000000                    4.000000     FALSE
## 94                    0.2000000                    1.800000     FALSE
## 99                    0.2000000                    2.600000     FALSE
## 113                   0.0000000                    3.000000     FALSE
## 136                   0.2000000                    4.000000     FALSE
## 140                   0.4000000                    1.600000     FALSE
## 149                   0.2000000                    2.333333     FALSE
## 177                   0.2000000                    3.333333     FALSE
## 179                   0.4000000                    3.333333     FALSE
## 185                   0.2000000                    2.000000     FALSE
## 186                   0.2000000                    2.600000     FALSE
## 191                   0.2000000                    3.333333     FALSE
## 202                   0.2000000                    1.666667     FALSE
## 211                   0.2000000                    2.600000     FALSE
## 215                   0.4000000                    3.000000     FALSE
## 216                   0.4000000                    3.000000     FALSE
## 219                   0.2000000                    3.666667     FALSE
## 236                   0.4000000                    2.333333     FALSE
## 240                   0.2000000                    2.600000     FALSE
## 241                   0.2000000                    3.333333     FALSE
## 254                   0.0000000                    2.200000     FALSE
## 270                   0.2000000                    1.666667     FALSE
## 276                   0.2000000                    3.400000     FALSE
## 290                   0.2000000                    3.333333     FALSE
## 306                   0.2000000                    2.200000     FALSE
## 324                   0.0000000                    3.666667     FALSE
## 331                   0.2000000                    3.000000     FALSE
## 332                   0.1666667                    2.750000     FALSE
## 338                   0.2000000                    3.000000     FALSE
## 342                   0.1666667                    2.800000     FALSE
## 348                   0.0000000                    1.600000     FALSE
## 356                   0.2000000                    2.666667     FALSE
## 366                   0.0000000                    2.600000     FALSE
## 378                   0.4000000                    3.600000     FALSE
## 387                   0.4000000                    2.000000     FALSE
## 401                   0.0000000                    2.000000     FALSE
## 411                   0.1666667                    2.400000     FALSE
## 414                   0.2000000                    1.666667     FALSE
## 421                   0.4000000                    2.200000     FALSE
## 424                   0.4000000                    2.333333     FALSE
## 425                   0.4000000                    3.200000     FALSE
## 429                   0.0000000                    3.333333     FALSE
## 431                   0.2000000                    2.200000     FALSE
## 433                   0.2000000                    2.200000     FALSE
## 436                   0.2000000                    2.200000     FALSE
## 439                   0.2000000                    2.600000     FALSE
## 448                   0.2000000                    3.400000     FALSE
## 510                   0.2000000                    3.000000     FALSE
## 533                   0.4000000                    1.800000     FALSE
## 538                   0.0000000                    4.000000     FALSE
## 544                   0.2000000                    2.250000     FALSE
```

```
## 550                0.4000000                   3.000000      FALSE
## 561                0.0000000                   2.600000      FALSE
## 598                0.2000000                   4.000000      FALSE
## 602                0.2000000                   2.333333      FALSE
## 606                0.2000000                   2.600000      FALSE
## 626                0.0000000                   2.000000      FALSE
## 637                0.0000000                   3.000000      FALSE
## 641                0.2000000                   1.666667      FALSE
## 647                0.2000000                   2.000000      FALSE
## 648                0.2000000                   2.666667      FALSE
## 658                0.4000000                   3.666667      FALSE
## 677                0.4000000                   3.400000      FALSE
## 679                0.2000000                   2.333333      FALSE
## 680                0.4000000                   2.000000      FALSE
## 683                0.4000000                   3.000000      FALSE
##                End time  Last modified time Final_Accuracy
## 21  2023-04-10 16:16:41 2023-04-28 11:30:24           TRUE
## 43  2023-05-21 14:03:16 2023-05-26 10:54:34           TRUE
## 78  2023-05-19 15:40:18 2023-05-19 16:20:39           TRUE
## 81  2023-06-22 17:38:01 2023-06-23 11:56:33           TRUE
## 91  2023-07-27 16:36:48 2023-07-27 16:36:48           TRUE
## 94  2023-06-29 18:36:11 2023-06-29 18:41:52           TRUE
## 99  2023-07-13 17:57:20 2023-07-31 15:39:55           TRUE
## 113 2023-04-21 16:43:34 2023-04-21 16:48:05           TRUE
## 136 2023-07-24 15:45:08 2023-07-24 15:45:08           TRUE
## 140 2023-04-17 16:40:55 2023-06-12 16:25:09           TRUE
## 149 2023-04-10 17:33:21 2023-04-12 17:18:09           TRUE
## 177 2023-04-18 15:05:57 2023-04-28 10:25:57           TRUE
## 179 2023-07-20 15:41:51 2023-07-20 15:41:51           TRUE
## 185 2023-02-27 17:02:34 2023-04-28 16:44:08           TRUE
## 186 2023-05-12 16:09:16 2023-05-12 16:09:16           TRUE
## 191 2023-05-09 16:15:12 2023-05-19 16:52:53           TRUE
## 202 2023-04-14 18:04:29 2023-04-29 18:16:46           TRUE
## 211 2023-05-12 16:15:12 2023-05-18 11:38:29           TRUE
## 215 2023-02-13 16:41:56 2023-02-13 16:41:56           TRUE
## 216 2023-04-14 16:31:19 2023-05-01 16:31:54           TRUE
## 219 2023-07-28 15:39:59 2023-07-28 15:39:59           TRUE
## 236 2023-06-26 17:15:36 2023-06-26 17:15:36           TRUE
## 240 2023-06-16 16:50:59 2023-06-23 23:14:19           TRUE
## 241 2023-07-17 16:33:07 2023-07-17 16:33:07           TRUE
## 254 2023-07-17 15:04:00 2023-07-17 15:04:00           TRUE
## 270 2023-04-14 17:10:57 2023-04-28 16:50:44           TRUE
## 276 2023-05-15 16:10:35 2023-05-15 16:10:35           TRUE
## 290 2023-07-06 15:47:04 2023-07-06 15:47:04           TRUE
## 306 2023-06-29 17:10:29 2023-07-17 18:30:49           TRUE
## 324 2023-05-01 17:55:02 2023-05-11 16:49:22           TRUE
## 331 2023-05-05 11:55:03 2023-05-11 15:50:12           TRUE
## 332 2023-04-15 06:30:53 2023-04-29 17:56:08           TRUE
## 338 2023-06-22 18:58:39 2023-06-22 18:58:39           TRUE
## 342 2023-06-26 15:43:46 2023-06-26 15:57:14           TRUE
## 348 2023-02-24 11:44:11 2023-04-28 16:45:16           TRUE
## 356 2023-04-21 16:49:20 2023-04-21 16:49:20           TRUE
## 366 2023-05-12 10:15:53 2023-05-12 10:15:53           TRUE
## 378 2023-05-12 11:42:59 2023-06-12 16:33:57           TRUE
```

```
## 387 2023-07-07 17:37:10 2023-07-07 17:37:10           TRUE
## 401 2023-04-21 16:27:51 2023-04-21 16:27:51           TRUE
## 411 2023-04-28 13:51:32 2023-05-12 10:49:32           TRUE
## 414 2023-04-14 16:42:51 2023-06-12 16:48:26           TRUE
## 421 2023-02-17 11:51:02 2023-05-15 17:10:36           TRUE
## 424 2023-06-26 18:59:34 2023-06-26 18:59:34           TRUE
## 425 2023-04-14 17:20:04 2023-04-28 10:10:59           TRUE
## 429 2023-07-06 17:58:47 2023-07-06 17:58:47           TRUE
## 431 2023-05-12 11:47:45 2023-06-12 16:01:09           TRUE
## 433 2023-04-07 16:34:58 2023-04-07 16:34:58           TRUE
## 436 2023-05-11 14:57:46 2023-05-11 14:57:46           TRUE
## 439 2023-07-13 13:02:18 2023-07-13 13:02:18           TRUE
## 448 2023-07-14 16:51:09 2023-07-14 16:51:09           TRUE
## 510 2023-08-04 16:36:03 2023-08-04 16:36:03           TRUE
## 533 2023-03-10 11:53:42 2023-04-13 16:46:04           TRUE
## 538 2023-04-28 10:13:44 2023-06-12 16:24:31           TRUE
## 544 2023-04-17 17:06:13 2023-04-18 13:42:45           TRUE
## 550 2023-08-03 16:36:15 2023-08-03 16:36:15           TRUE
## 561 2023-04-17 17:45:31 2023-04-29 22:45:31           TRUE
## 598 2023-07-24 17:40:02 2023-07-24 17:40:02           TRUE
## 602 2023-07-17 19:39:59 2023-07-17 19:39:59           TRUE
## 606 2023-07-07 18:12:21 2023-07-07 21:30:24           TRUE
## 626 2023-07-17 19:00:09 2023-07-17 19:00:09           TRUE
## 637 2023-04-17 18:48:16 2023-04-18 14:26:39           TRUE
## 641 2023-05-12 10:16:04 2023-05-12 10:16:04           TRUE
## 647 2023-04-24 17:33:24 2023-05-24 16:28:55           TRUE
## 648 2023-03-20 17:06:51 2023-04-28 16:39:55           TRUE
## 658 2023-02-22 17:30:45 2023-02-22 17:30:45           TRUE
## 677 2023-03-07 21:04:25 2023-04-28 17:01:26           TRUE
## 679 2023-06-22 21:37:32 2023-06-22 21:37:32           TRUE
## 680 2023-03-07 17:00:26 2023-04-28 17:38:19           TRUE
## 683 2023-04-21 11:01:01 2023-06-12 16:05:11           TRUE
##     Human Consultancy Sample AI Consultancy Sample Human Debate Sample
## 21                     FALSE                 FALSE               FALSE
## 43                     FALSE                 FALSE               FALSE
## 78                     FALSE                 FALSE               FALSE
## 81                     FALSE                 FALSE               FALSE
## 91                     FALSE                 FALSE                TRUE
## 94                     FALSE                 FALSE               FALSE
## 99                     FALSE                 FALSE               FALSE
## 113                    FALSE                 FALSE               FALSE
## 136                    FALSE                 FALSE               FALSE
## 140                    FALSE                 FALSE                TRUE
## 149                    FALSE                 FALSE               FALSE
## 177                    FALSE                 FALSE               FALSE
## 179                    FALSE                 FALSE               FALSE
## 185                    FALSE                 FALSE                TRUE
## 186                    FALSE                 FALSE               FALSE
## 191                    FALSE                 FALSE               FALSE
## 202                    FALSE                 FALSE               FALSE
## 211                    FALSE                 FALSE                TRUE
## 215                    FALSE                 FALSE                TRUE
## 216                    FALSE                 FALSE               FALSE
## 219                    FALSE                 FALSE                TRUE
```

```
## 236                    FALSE                 FALSE                 FALSE
## 240                    FALSE                 FALSE                 FALSE
## 241                    FALSE                 FALSE                 FALSE
## 254                    FALSE                 FALSE                 FALSE
## 270                    FALSE                 FALSE                  TRUE
## 276                    FALSE                 FALSE                  TRUE
## 290                    FALSE                 FALSE                  TRUE
## 306                    FALSE                 FALSE                 FALSE
## 324                    FALSE                 FALSE                  TRUE
## 331                    FALSE                 FALSE                  TRUE
## 332                    FALSE                 FALSE                  TRUE
## 338                    FALSE                 FALSE                  TRUE
## 342                    FALSE                 FALSE                 FALSE
## 348                    FALSE                 FALSE                  TRUE
## 356                    FALSE                 FALSE                  TRUE
## 366                    FALSE                 FALSE                 FALSE
## 378                    FALSE                 FALSE                  TRUE
## 387                    FALSE                 FALSE                 FALSE
## 401                    FALSE                 FALSE                 FALSE
## 411                    FALSE                 FALSE                 FALSE
## 414                    FALSE                 FALSE                  TRUE
## 421                    FALSE                 FALSE                  TRUE
## 424                    FALSE                 FALSE                  TRUE
## 425                    FALSE                 FALSE                  TRUE
## 429                    FALSE                 FALSE                 FALSE
## 431                    FALSE                 FALSE                  TRUE
## 433                    FALSE                 FALSE                  TRUE
## 436                    FALSE                 FALSE                  TRUE
## 439                    FALSE                 FALSE                  TRUE
## 448                    FALSE                 FALSE                  TRUE
## 510                    FALSE                 FALSE                  TRUE
## 533                    FALSE                 FALSE                  TRUE
## 538                    FALSE                 FALSE                  TRUE
## 544                    FALSE                 FALSE                  TRUE
## 550                    FALSE                 FALSE                  TRUE
## 561                    FALSE                 FALSE                  TRUE
## 598                    FALSE                 FALSE                  TRUE
## 602                    FALSE                 FALSE                  TRUE
## 606                    FALSE                 FALSE                  TRUE
## 626                    FALSE                 FALSE                  TRUE
## 637                    FALSE                 FALSE                  TRUE
## 641                    FALSE                 FALSE                  TRUE
## 647                    FALSE                 FALSE                  TRUE
## 648                    FALSE                 FALSE                  TRUE
## 658                    FALSE                 FALSE                  TRUE
## 677                    FALSE                 FALSE                  TRUE
## 679                    FALSE                 FALSE                  TRUE
## 680                    FALSE                 FALSE                  TRUE
## 683                    FALSE                 FALSE                  TRUE
##     AI Debate Sample Sample Consultancy Sample initial_question_weights
## 21             FALSE  FALSE              FALSE                0.5000000
## 43             FALSE  FALSE              FALSE                0.5000000
## 78             FALSE  FALSE              FALSE                0.5000000
## 81             FALSE  FALSE              FALSE                0.2500000
```

```
## 91             FALSE   TRUE               TRUE                0.1666667
## 94             FALSE  FALSE              FALSE                0.5000000
## 99             FALSE  FALSE              FALSE                0.2500000
## 113            FALSE  FALSE              FALSE                0.3333333
## 136            FALSE  FALSE              FALSE                0.1428571
## 140            FALSE   TRUE               TRUE                1.0000000
## 149            FALSE  FALSE              FALSE                0.2500000
## 177            FALSE  FALSE              FALSE                0.5000000
## 179            FALSE  FALSE              FALSE                0.5000000
## 185            FALSE   TRUE               TRUE                1.0000000
## 186            FALSE  FALSE              FALSE                0.5000000
## 191            FALSE  FALSE              FALSE                0.2000000
## 202            FALSE  FALSE              FALSE                0.5000000
## 211            FALSE   TRUE               TRUE                0.5000000
## 215            FALSE   TRUE               TRUE                1.0000000
## 216            FALSE  FALSE              FALSE                0.5000000
## 219            FALSE   TRUE               TRUE                0.1666667
## 236            FALSE  FALSE              FALSE                0.5000000
## 240            FALSE  FALSE              FALSE                0.5000000
## 241            FALSE  FALSE              FALSE                0.2500000
## 254            FALSE  FALSE              FALSE                0.5000000
## 270            FALSE   TRUE               TRUE                1.0000000
## 276            FALSE   TRUE               TRUE                0.5000000
## 290            FALSE   TRUE               TRUE                0.2500000
## 306            FALSE  FALSE              FALSE                0.5000000
## 324            FALSE   TRUE               TRUE                0.5000000
## 331            FALSE   TRUE               TRUE                0.2500000
## 332            FALSE   TRUE               TRUE                0.5000000
## 338            FALSE   TRUE               TRUE                0.5000000
## 342            FALSE  FALSE              FALSE                0.5000000
## 348            FALSE   TRUE               TRUE                1.0000000
## 356            FALSE   TRUE               TRUE                0.3333333
## 366            FALSE  FALSE              FALSE                0.2500000
## 378            FALSE   TRUE               TRUE                0.3333333
## 387            FALSE  FALSE              FALSE                0.5000000
## 401            FALSE  FALSE              FALSE                0.2500000
## 411            FALSE  FALSE              FALSE                0.5000000
## 414            FALSE   TRUE               TRUE                0.5000000
## 421            FALSE   TRUE               TRUE                1.0000000
## 424            FALSE   TRUE               TRUE                0.5000000
## 425            FALSE   TRUE               TRUE                0.3333333
## 429            FALSE  FALSE              FALSE                0.2000000
## 431            FALSE   TRUE               TRUE                1.0000000
## 433            FALSE   TRUE               TRUE                0.3333333
## 436            FALSE   TRUE               TRUE                1.0000000
## 439            FALSE   TRUE               TRUE                0.2500000
## 448            FALSE   TRUE               TRUE                0.2000000
## 510            FALSE   TRUE               TRUE                0.1666667
## 533            FALSE   TRUE               TRUE                0.5000000
## 538            FALSE   TRUE               TRUE                0.5000000
## 544            FALSE   TRUE               TRUE                1.0000000
## 550            FALSE   TRUE               TRUE                0.2500000
## 561            FALSE   TRUE               TRUE                0.2500000
## 598            FALSE   TRUE               TRUE                0.1428571
```

```
## 602           FALSE   TRUE               TRUE                  0.5000000
## 606           FALSE   TRUE               TRUE                  0.5000000
## 626           FALSE   TRUE               TRUE                  0.2500000
## 637           FALSE   TRUE               TRUE                  0.3333333
## 641           FALSE   TRUE               TRUE                  0.3333333
## 647           FALSE   TRUE               TRUE                  0.5000000
## 648           FALSE   TRUE               TRUE                  0.2000000
## 658           FALSE   TRUE               TRUE                  0.3333333
## 677           FALSE   TRUE               TRUE                  0.3333333
## 679           FALSE   TRUE               TRUE                  0.2500000
## 680           FALSE   TRUE               TRUE                  1.0000000
## 683           FALSE   TRUE               TRUE                  0.5000000
##     initial_question_weights_grouped_setting
## 21                                       0.5
## 43                                       0.5
## 78                                       0.5
## 81                                       0.5
## 91                                       1.0
## 94                                       0.5
## 99                                       0.5
## 113                                      0.5
## 136                                      0.5
## 140                                      1.0
## 149                                      0.5
## 177                                      0.5
## 179                                      0.5
## 185                                      1.0
## 186                                      0.5
## 191                                      0.5
## 202                                      0.5
## 211                                      0.5
## 215                                      1.0
## 216                                      0.5
## 219                                      1.0
## 236                                      0.5
## 240                                      0.5
## 241                                      0.5
## 254                                      0.5
## 270                                      1.0
## 276                                      0.5
## 290                                      0.5
## 306                                      0.5
## 324                                      0.5
## 331                                      0.5
## 332                                      0.5
## 338                                      0.5
## 342                                      0.5
## 348                                      1.0
## 356                                      1.0
## 366                                      0.5
## 378                                      0.5
## 387                                      0.5
## 401                                      0.5
## 411                                      0.5
```

```
## 414                                          0.5
## 421                                          1.0
## 424                                          0.5
## 425                                          0.5
## 429                                          0.5
## 431                                          1.0
## 433                                          1.0
## 436                                          1.0
## 439                                          0.5
## 448                                          1.0
## 510                                          1.0
## 533                                          1.0
## 538                                          0.5
## 544                                          1.0
## 550                                          1.0
## 561                                          0.5
## 598                                          0.5
## 602                                          1.0
## 606                                          0.5
## 626                                          0.5
## 637                                          0.5
## 641                                          0.5
## 647                                          0.5
## 648                                          0.5
## 658                                          1.0
## 677                                          1.0
## 679                                          0.5
## 680                                          1.0
## 683                                          0.5
##     sampled_consultancies_all_debates_weights
## 21                                    0.5000000
## 43                                    0.5000000
## 78                                    0.5000000
## 81                                    0.3333333
## 91                                    0.2000000
## 94                                    0.5000000
## 99                                    0.2500000
## 113                                   0.3333333
## 136                                   0.1666667
## 140                                   1.0000000
## 149                                   0.2500000
## 177                                   0.5000000
## 179                                   0.5000000
## 185                                   1.0000000
## 186                                   0.5000000
## 191                                   0.2500000
## 202                                   0.5000000
## 211                                   0.5000000
## 215                                   1.0000000
## 216                                   0.5000000
## 219                                   0.2000000
## 236                                   0.5000000
## 240                                   0.5000000
## 241                                   0.2500000
```

```
## 254                                  0.5000000
## 270                                  1.0000000
## 276                                  0.5000000
## 290                                  0.2500000
## 306                                  0.5000000
## 324                                  0.5000000
## 331                                  0.3333333
## 332                                  0.5000000
## 338                                  0.5000000
## 342                                  0.5000000
## 348                                  1.0000000
## 356                                  0.5000000
## 366                                  0.3333333
## 378                                  0.3333333
## 387                                  0.5000000
## 401                                  0.2500000
## 411                                  0.5000000
## 414                                  0.5000000
## 421                                  1.0000000
## 424                                  0.5000000
## 425                                  0.3333333
## 429                                  0.3333333
## 431                                  1.0000000
## 433                                  0.5000000
## 436                                  1.0000000
## 439                                  0.2500000
## 448                                  0.3333333
## 510                                  0.2000000
## 533                                  0.5000000
## 538                                  0.5000000
## 544                                  1.0000000
## 550                                  0.2500000
## 561                                  0.3333333
## 598                                  0.1666667
## 602                                  0.5000000
## 606                                  0.5000000
## 626                                  0.2500000
## 637                                  0.3333333
## 641                                  0.3333333
## 647                                  0.5000000
## 648                                  0.2500000
## 658                                  0.5000000
## 677                                  0.5000000
## 679                                  0.2500000
## 680                                  1.0000000
## 683                                  0.5000000
##     sampled_consultancies_all_debates_weights_grouped_setting
## 21                                                        0.5
## 43                                                        0.5
## 78                                                        0.5
## 81                                                        0.5
## 91                                                        1.0
## 94                                                        0.5
## 99                                                        0.5
```

```
## 113                                                          0.5
## 136                                                          0.5
## 140                                                          1.0
## 149                                                          0.5
## 177                                                          0.5
## 179                                                          0.5
## 185                                                          1.0
## 186                                                          0.5
## 191                                                          0.5
## 202                                                          0.5
## 211                                                          0.5
## 215                                                          1.0
## 216                                                          0.5
## 219                                                          1.0
## 236                                                          0.5
## 240                                                          0.5
## 241                                                          0.5
## 254                                                          0.5
## 270                                                          1.0
## 276                                                          0.5
## 290                                                          0.5
## 306                                                          0.5
## 324                                                          0.5
## 331                                                          0.5
## 332                                                          0.5
## 338                                                          0.5
## 342                                                          0.5
## 348                                                          1.0
## 356                                                          1.0
## 366                                                          0.5
## 378                                                          0.5
## 387                                                          0.5
## 401                                                          0.5
## 411                                                          0.5
## 414                                                          0.5
## 421                                                          1.0
## 424                                                          0.5
## 425                                                          0.5
## 429                                                          0.5
## 431                                                          1.0
## 433                                                          1.0
## 436                                                          1.0
## 439                                                          0.5
## 448                                                          1.0
## 510                                                          1.0
## 533                                                          1.0
## 538                                                          0.5
## 544                                                          1.0
## 550                                                          1.0
## 561                                                          0.5
## 598                                                          0.5
## 602                                                          1.0
## 606                                                          0.5
## 626                                                          0.5
```

```
## 637                                                          0.5
## 641                                                          0.5
## 647                                                          0.5
## 648                                                          0.5
## 658                                                          1.0
## 677                                                          1.0
## 679                                                          0.5
## 680                                                          1.0
## 683                                                          0.5
##     sampled_consultancies_all_debates_weights_setting
## 21                                                 0.5
## 43                                                 0.5
## 78                                                 0.5
## 81                                                 0.5
## 91                                                 1.0
## 94                                                 0.5
## 99                                                 0.5
## 113                                                0.5
## 136                                                0.5
## 140                                                1.0
## 149                                                0.5
## 177                                                0.5
## 179                                                0.5
## 185                                                1.0
## 186                                                0.5
## 191                                                0.5
## 202                                                0.5
## 211                                                0.5
## 215                                                1.0
## 216                                                0.5
## 219                                                1.0
## 236                                                0.5
## 240                                                0.5
## 241                                                0.5
## 254                                                0.5
## 270                                                1.0
## 276                                                0.5
## 290                                                0.5
## 306                                                0.5
## 324                                                0.5
## 331                                                0.5
## 332                                                0.5
## 338                                                0.5
## 342                                                0.5
## 348                                                1.0
## 356                                                1.0
## 366                                                0.5
## 378                                                0.5
## 387                                                0.5
## 401                                                0.5
## 411                                                0.5
## 414                                                0.5
## 421                                                1.0
## 424                                                0.5
```

```
## 425                                            0.5
## 429                                            0.5
## 431                                            1.0
## 433                                            1.0
## 436                                            1.0
## 439                                            0.5
## 448                                            1.0
## 510                                            1.0
## 533                                            1.0
## 538                                            0.5
## 544                                            1.0
## 550                                            1.0
## 561                                            0.5
## 598                                            0.5
## 602                                            1.0
## 606                                            0.5
## 626                                            0.5
## 637                                            0.5
## 641                                            0.5
## 647                                            0.5
## 648                                            0.5
## 658                                            1.0
## 677                                            1.0
## 679                                            0.5
## 680                                            1.0
## 683                                            0.5
##     sampled_consultancies_debates_weights_grouped_setting
## 21                                                     0
## 43                                                     0
## 78                                                     0
## 81                                                     0
## 91                                                     1
## 94                                                     0
## 99                                                     0
## 113                                                    0
## 136                                                    0
## 140                                                    1
## 149                                                    0
## 177                                                    0
## 179                                                    0
## 185                                                    1
## 186                                                    0
## 191                                                    0
## 202                                                    0
## 211                                                    1
## 215                                                    1
## 216                                                    0
## 219                                                    1
## 236                                                    0
## 240                                                    0
## 241                                                    0
## 254                                                    0
## 270                                                    1
## 276                                                    1
```

```
## 290                                                 1
## 306                                                 0
## 324                                                 1
## 331                                                 1
## 332                                                 1
## 338                                                 1
## 342                                                 0
## 348                                                 1
## 356                                                 1
## 366                                                 0
## 378                                                 1
## 387                                                 0
## 401                                                 0
## 411                                                 0
## 414                                                 1
## 421                                                 1
## 424                                                 1
## 425                                                 1
## 429                                                 0
## 431                                                 1
## 433                                                 1
## 436                                                 1
## 439                                                 1
## 448                                                 1
## 510                                                 1
## 533                                                 1
## 538                                                 1
## 544                                                 1
## 550                                                 1
## 561                                                 1
## 598                                                 1
## 602                                                 1
## 606                                                 1
## 626                                                 1
## 637                                                 1
## 641                                                 1
## 647                                                 1
## 648                                                 1
## 658                                                 1
## 677                                                 1
## 679                                                 1
## 680                                                 1
## 683                                                 1
##     sampled_consultancies_debates_weights Final_Accuracy_char  fpc  fpcw
## 21                              0.0000000                  NA 0.70 0.350
## 43                              0.0000000                  NA 0.90 0.450
## 78                              0.0000000                  NA 0.99 0.495
## 81                              0.0000000                  NA 0.99 0.495
## 91                              0.2500000                  NA 0.98 0.980
## 94                              0.0000000                  NA 0.99 0.495
## 99                              0.0000000                  NA 0.85 0.425
## 113                             0.0000000                  NA 0.99 0.495
## 136                             0.0000000                  NA 0.99 0.495
## 140                             1.0000000                  NA 0.99 0.990
```

```
## 149                                    0.0000000                             NA 0.85 0.425
## 177                                    0.0000000                             NA 0.85 0.425
## 179                                    0.0000000                             NA 0.90 0.450
## 185                                    1.0000000                             NA 0.99 0.990
## 186                                    0.0000000                             NA 0.95 0.475
## 191                                    0.0000000                             NA 0.95 0.475
## 202                                    0.0000000                             NA 0.90 0.450
## 211                                    1.0000000                             NA 0.95 0.475
## 215                                    1.0000000                             NA 0.80 0.800
## 216                                    0.0000000                             NA 0.99 0.495
## 219                                    0.2500000                             NA 0.80 0.800
## 236                                    0.0000000                             NA 0.99 0.495
## 240                                    0.0000000                             NA 0.90 0.450
## 241                                    0.0000000                             NA 0.99 0.495
## 254                                    0.0000000                             NA 0.95 0.475
## 270                                    1.0000000                             NA 0.70 0.700
## 276                                    1.0000000                             NA 0.99 0.495
## 290                                    0.3333333                             NA 0.99 0.495
## 306                                    0.0000000                             NA 0.99 0.495
## 324                                    1.0000000                             NA 0.99 0.495
## 331                                    0.5000000                             NA 0.99 0.495
## 332                                    1.0000000                             NA 0.99 0.495
## 338                                    1.0000000                             NA 0.99 0.495
## 342                                    0.0000000                             NA 0.99 0.495
## 348                                    1.0000000                             NA 0.85 0.850
## 356                                    0.5000000                             NA 0.85 0.850
## 366                                    0.0000000                             NA 0.95 0.475
## 378                                    0.5000000                             NA 0.98 0.490
## 387                                    0.0000000                             NA 0.88 0.440
## 401                                    0.0000000                             NA 0.96 0.480
## 411                                    0.0000000                             NA 0.99 0.495
## 414                                    1.0000000                             NA 0.99 0.495
## 421                                    1.0000000                             NA 0.99 0.990
## 424                                    1.0000000                             NA 0.99 0.495
## 425                                    0.5000000                             NA 0.99 0.495
## 429                                    0.0000000                             NA 0.99 0.495
## 431                                    1.0000000                             NA 0.99 0.990
## 433                                    0.5000000                             NA 0.99 0.990
## 436                                    1.0000000                             NA 0.99 0.990
## 439                                    0.3333333                             NA 0.95 0.475
## 448                                    0.3333333                             NA 0.99 0.990
## 510                                    0.2500000                             NA 0.99 0.990
## 533                                    0.5000000                             NA 0.98 0.980
## 538                                    1.0000000                             NA 0.90 0.450
## 544                                    1.0000000                             NA 0.98 0.980
## 550                                    0.2500000                             NA 0.99 0.990
## 561                                    0.5000000                             NA 0.95 0.475
## 598                                    0.2500000                             NA 0.94 0.470
## 602                                    0.5000000                             NA 0.91 0.910
## 606                                    1.0000000                             NA 0.86 0.430
## 626                                    0.3333333                             NA 0.97 0.485
## 637                                    0.5000000                             NA 0.95 0.475
## 641                                    0.5000000                             NA 0.99 0.495
## 647                                    1.0000000                             NA 0.99 0.495
```

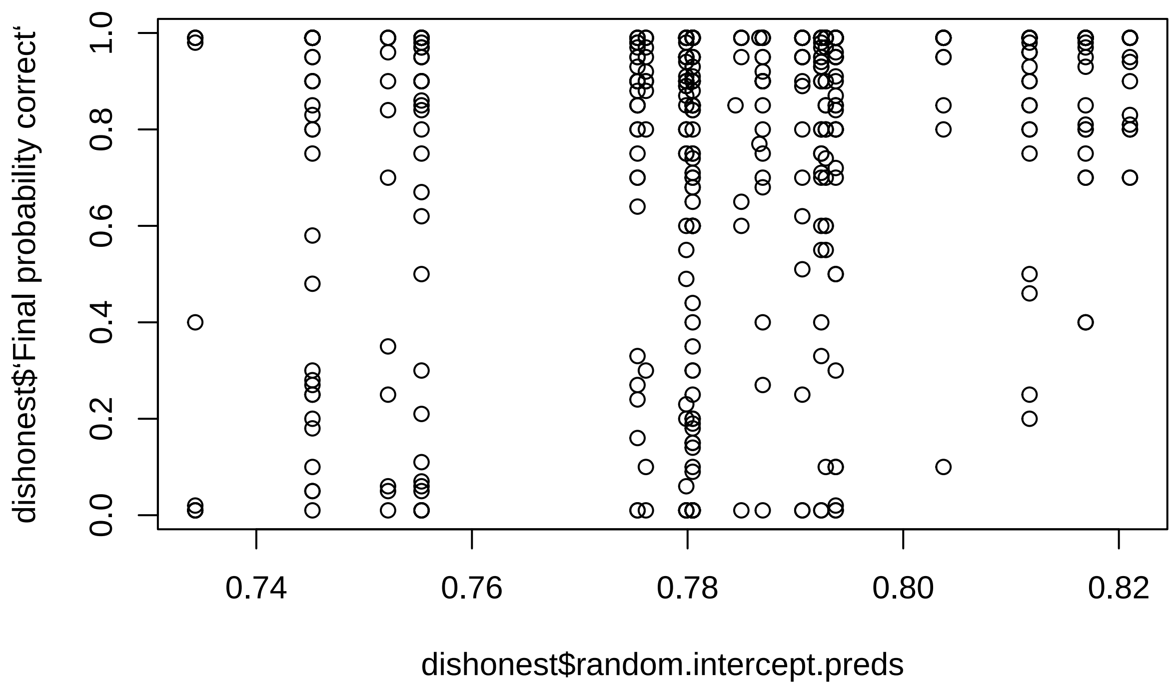
```
## 648                            0.3333333                       NA 0.99 0.495
## 658                            0.5000000                       NA 0.99 0.990
## 677                            0.5000000                       NA 0.80 0.800
## 679                            0.3333333                       NA 0.75 0.375
## 680                            1.0000000                       NA 0.75 0.750
## 683                            1.0000000                       NA 0.80 0.400
```

```r
# Fit the random intercept model and only remove missing values for 'Dishonest debater'
random_intercept_model <- lmer(`Final probability correct` ~ (1|`Dishonest debater`),
                               data = dishonest,
                               REML = TRUE)

# Summary of the model
summary(random_intercept_model)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: `Final probability correct` ~ (1 | `Dishonest debater`)
##    Data: dishonest
##
## REML criterion at convergence: 302.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5213 -0.1985  0.5027  0.6588  0.8225
##
## Random effects:
##  Groups            Name        Variance Std.Dev.
##  Dishonest debater (Intercept) 0.001765 0.04201
##  Residual                      0.096628 0.31085
## Number of obs: 577, groups:  Dishonest debater, 20
##
## Fixed effects:
##             Estimate Std. Error      df t value       Pr(>|t|)
## (Intercept)  0.78325    0.01719 7.54926   45.58 0.000000000172 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
dishonest$random.intercept.preds = predict(random_intercept_model)
plot(dishonest$random.intercept.preds, dishonest$`Final probability correct`)
```



Debater "Experience", ratings - how many wins?

AI vs Humans

Old vs New

possibly unnessary

Finally, these are how many we get correct in each setting

```
judgments_online <- py$judgments_online
table(judgments_online$Final_Accuracy, judgments_online$Final_Setting)
```

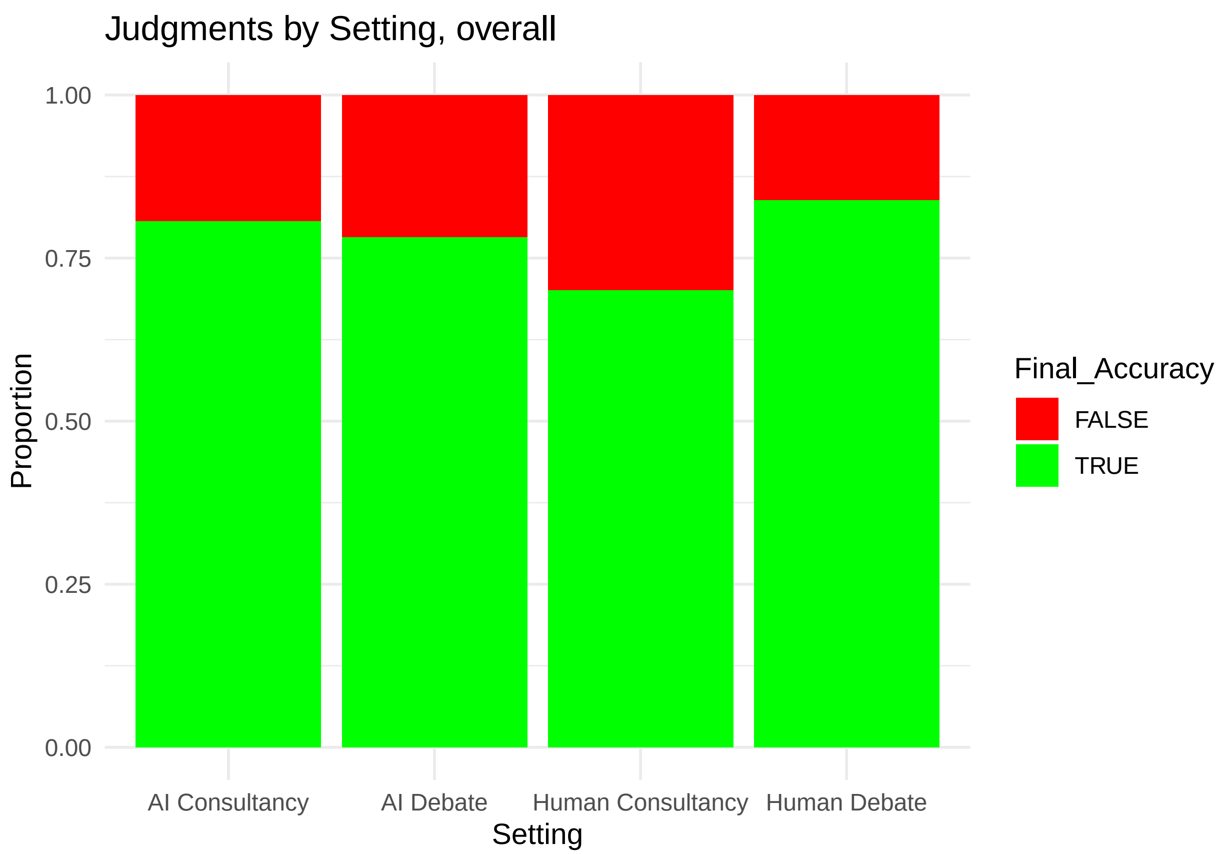
```
##
##          AI Consultancy AI Debate Human Consultancy Human Debate
##    FALSE             18        19                32           25
##    TRUE              75        68                75          130
```

```
table(judgments_online$Final_Accuracy, judgments_online$Setting)
```

```
##
##          AI Consultancy Dishonest AI Consultancy Honest AI Debate
##    FALSE                        5                    13        19
##    TRUE                        33                    42        68
```

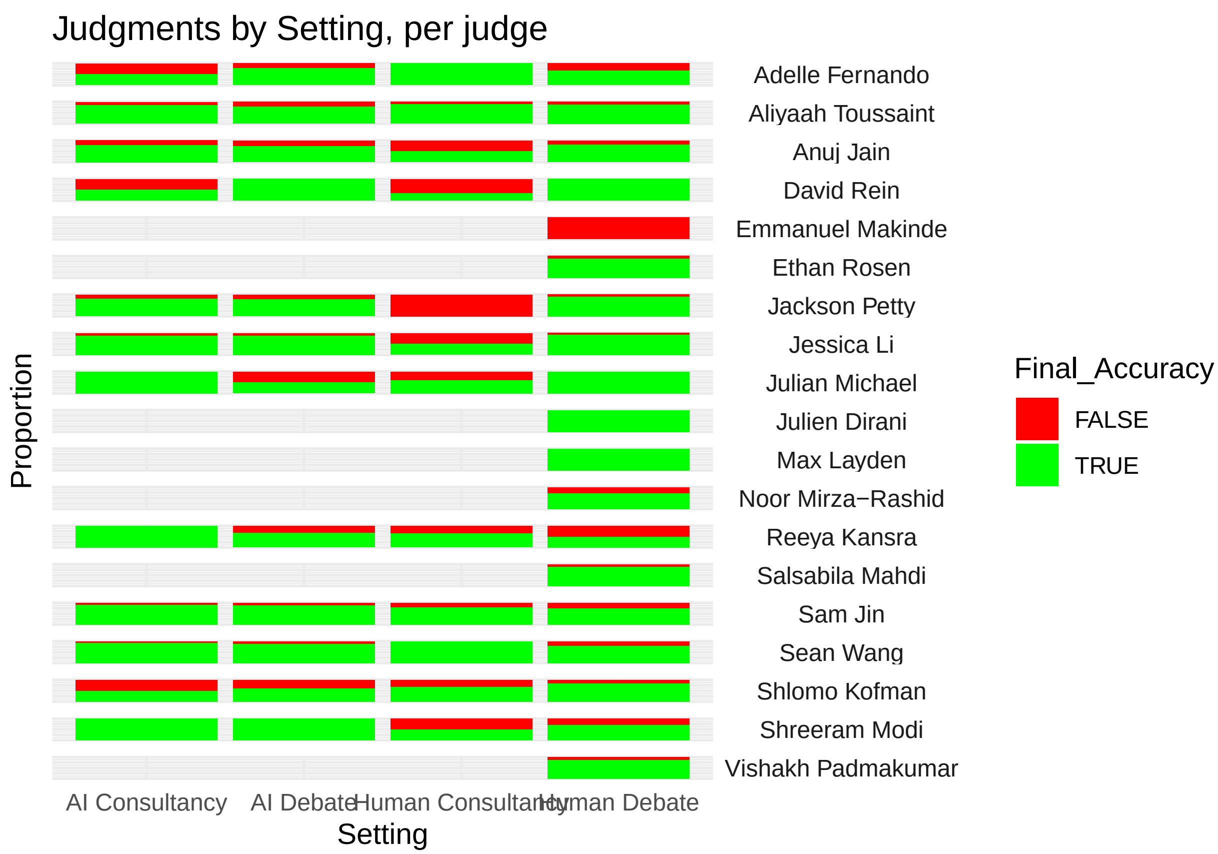
```
##
##         Human Consultancy Dishonest Human Consultancy Honest Human Debate
##   FALSE                          26                        6           25
##   TRUE                           33                       42          130
```

```
ggplot(judgments_online, aes(x = Final_Setting, fill = Final_Accuracy)) +
  geom_bar(position = "fill") +
  scale_fill_manual(values = c("TRUE" = "green", "FALSE" = "red")) +
  labs(title = "Judgments by Setting, overall", x = "Setting", y = "Proportion", fill = "Final_Accuracy
  theme_minimal() +
  theme(axis.text.x = element_text())
```



Sneak peak of accuracy differences between judges, but we won't get to that again until models

```
ggplot(judgments_online, aes(x = Final_Setting, fill = Final_Accuracy)) +
  geom_bar(position = "fill") +
  scale_fill_manual(values = c("TRUE" = "green", "FALSE" = "red")) +
  labs(title = "Judgments by Setting, per judge", x = "Setting", y = "Proportion", fill = "Final_Accura
  theme_minimal() +
  theme(axis.text.x = element_text(),#angle = 90, hjust = 1),
        axis.text.y = element_blank(),
        strip.text.y.right = element_text(angle = 0)) +
  facet_grid(rows = "Participant")
```


Judgments by Setting, per judge
Proportion
Adelle Fernando
Aliyaah Toussaint
Anuj Jain
David Rein
Emmanuel Makinde
Ethan Rosen
Jackson Petty
Jessica Li
Julian Michael
Julien Dirani
Max Layden
Noor Mirza−Rashid
Reeya Kansra
Salsabila Mahdi
Sam Jin
Sean Wang
Shlomo Kofman
Shreeram Modi
Vishakh Padmakumar
AI Consultancy
AI Debate
Human Consultancy
Human Debate
Setting
Final_Accuracy
FALSE
TRUE