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/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 altair as alt
import math as math
import matplotlib.pyplot as plt
import re
pd.options.mode.chained_assignment = None  # default='warn'

# Load summaries that can be downloaded from the interface
data_path = "/Users/bila/git/for-debate/debate/save/official/summaries/"
debates = pd.read_csv(data_path + "debates.csv", keep_default_na=True)
sessions = pd.read_csv(data_path + "sessions.csv", keep_default_na=True)
turns = pd.read_csv(data_path + "turns.csv", keep_default_na=True)
print(f' {debates.shape} - Debates') ;
```

```
##  (632, 29) - Debates
```

```
print(f'{sessions.shape} - Sessions, which has multiple rows (of participants) for each debate') ;
```

```
## (1863, 46) - Sessions, which has multiple rows (of participants) for each debate
```

```
print(f'{turns.shape} - and Turns, which has multiple rows (of participant turns) 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
```

```
# Secondary analysis: Question Difficulty
# Create new columns with bin labels
debates['Untimed annotator context bins'] = pd.cut(debates['Untimed annotator context'].round(), bins=[(
#print(debates['Untimed annotator context'].round().value_counts()) #check
#print(debates['Untimed annotator context bins'].value_counts()) #check
debates['Speed annotator accuracy bins'] = pd.cut(debates['Speed annotator accuracy'].round(1), bins=[0
## respectively, those speed annotator accuracies probably mean 0 right, 1 right, 2 right
#print(debates['Speed annotator accuracy'].round(1).value_counts().sort_index()) #check #0.5 acc?
#print(debates['Speed annotator accuracy bins'].value_counts().sort_index()) #check

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
## Overall accuracy goes down the more context is required
##
## <string>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True i
```

```
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
## 0.1                                        NaN            0
## 0.2                                   0.697509          281
## 0.3                                   0.666667            3
## 0.4                                   0.694611          167
## 0.5                                   0.666667            3
```

```
## 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 i
```

```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

```python
# 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
```

```python
#[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.
```

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

```
## 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
```

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

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
```

```
# 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_n

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
```

```
# 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
```

```
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
```

```
## 3. We then filter to judgments which require more than a sentence or two, and now we have this much
##                      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
## This is where debate accuracy drops
```

```
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"], observed=False).
    Proportion_True=pd.NamedAgg(column='Final_Accuracy', aggfunc=lambda x: x.mean()),
    Count=pd.NamedAgg(column='Final_Accuracy', aggfunc='size'),
    Proportion_Count=pd.NamedAgg(column='Final_Setting', aggfunc=lambda x: len(x) / total_counts_for_se
)
print(f'Are the difficult questions equally enough distributed amongst settings?:\n{result}')
```

```
## Are the difficult questions equally enough distributed amongst settings?:
##                                                      Proportion_True  Count  \
## Final_Setting     Untimed annotator context bins
## AI Consultancy    1                                              NaN      0
##                   2                                         0.823529     51
##                   3                                         0.826087     23
##                   4                                         0.736842     19
## AI Debate         1                                              NaN      0
##                   2                                         0.777778     45
##                   3                                         0.772727     22
##                   4                                         0.800000     20
## Human Consultancy 1                                              NaN      0
##                   2                                         0.634146     41
##                   3                                         0.708333     48
##                   4                                         0.833333     18
## Human Debate      1                                              NaN      0
##                   2                                         0.890411     73
##                   3                                         0.816667     60
##                   4                                         0.727273     22
##
##                                                      Proportion_Count
## 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** We might at least want to ratio it better for AI settings…

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):
            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', 'Quest
    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=Fa
#    result = judgments_online[consultancy_balanced].groupby(["Final_Setting"])["Final_Accuracy"].agg(P
#    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? (not actually used)

```
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)
```

Question weights

```
# 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[consultancy_sample_columns].any(axis=1)
consultancy_balanced = (~judgments_online['Setting'].str.contains('Consultancy', case=False, na=False))

print(f'Accuracy per setting (aggregated) after balancing:\n{judgments_online[consultancy_balanced].grou
```

```
## Accuracy per setting (aggregated) after balancing:
##                      Proportion_True  Total_Count
## Final_Setting
## AI Consultancy              0.815789           76
## AI Debate                   0.781609           87
## Human Consultancy           0.707317           82
## Human Debate                0.838710          155
## Accuracies remain pretty similar
```

```
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(quest
    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['Consultancy Sample'] == consultancy_sample)
    for setting in sorted(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 consultancies/debates (initial) weights, by group setting')
```

```
## Unsampled consultancies/debates (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 AI Consultancy Honest: 49.50
## 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 Human Debate: 107.00
```

```
# 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', 'Setting'],
    weight_column_name='sampled_consultancies_all_debates_weights_setting',
    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
)
print('Consultancy balanced weights, not grouped - (not balanced, would have to change balancing functi
```

```
## Consultancy balanced weights, not grouped - (not balanced, would have to change balancing function..
```

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

```
print('Consultancy balanced weights, grouped by Setting - see that the consultancies are balanced betwe
```

```
## Consultancy balanced weights, grouped by Setting - see that the consultancies are balanced between th
```

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

```
print('Consultancy balanced weights, grouped by Final Setting')
```

```
## Consultancy balanced weights, grouped by Final Setting
```

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

```


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

```
)
judgments_online = question_weights(
    data=judgments_online,
    columns=['Article ID', 'Question', 'Setting'],
    weight_column_name='sampled_consultancies_debates_weights_setting',
    consultancy_sample=True,
    debate_sample=True
)
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
)
```

Note: we are not balancing between settings(?), and more counts of the human debate settings are on the same questions..?

Load into R environment

```
set.seed(123)
# Read in objects from Python with py$
judgments <- py$judgments
judgments_online <- py$judgments_online
# Change type into factor so it is read as categories which can be manipulated instead of characters
judgments_online$Participant <- as.factor(judgments_online$Participant)
judgments_online$Setting <- as.factor(judgments_online$Setting)

# Doing some sanity checks
subset_dishonest <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & judgments_onl
subset_honest <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & judgments_onlin
#Are the question weights equal for human consultancies?"
table(subset_dishonest$sampled_consultancies_all_debates_weights_grouped_setting) ; table(subset_honest$
```

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

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

```
#What does the accuracy look like for those question weights?
#table(subset_dishonest$sampled_consultancies_all_debates_weights_grouped_setting, subset_dishonest$Fin
#table(subset_honest$sampled_consultancies_all_debates_weights_grouped_setting, subset_honest$Final_Acc




#subset_human_consultancies <- judgments_online[judgments_online$`Human Consultancy Sample` == TRUE & j
```

```r
#table(subset_human_consultancies$sampled_consultancies_all_debates_weights_grouped_setting, subset_hum
#Difference between grouping and not grouping question weights
table(judgments_online$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
```

```
##
##                       0 0.166666666666667 0.2 0.25 0.333333333333333 0.5  1
##   AI Consultancy     17                 2   7    5                 0   1 61
##   AI Debate           0                 4  13    7                 0   3 60
##   Human Consultancy 25                 2   8   21                22  22  7
##   Human Debate        0                 4   7   19                26  64 35
```

```r
# Balanced consultancies difference between grouping and not grouping question weights
consultancy_condition <- (judgments_online$Sample == TRUE) | (!grepl("Consultancy", judgments_online$Fi
table(judgments_online[consultancy_condition, ]$Final_Setting, judgments_online[consultancy_condition, ]
```

```
## , ,  = FALSE
##
##
##                      0.5  1
##   AI Consultancy      0 14
##   AI Debate           7 12
##   Human Consultancy  16  8
##   Human Debate       17  8
##
## , ,  = TRUE
##
##
##                      0.5  1
##   AI Consultancy      0 62
##   AI Debate          17 51
##   Human Consultancy  26 32
##   Human Debate       79 51
```

```r
table(judgments_online[consultancy_condition, ]$Final_Setting, judgments_online[consultancy_condition, ]
```

```
## , ,  = FALSE
##
##
##                      0.166666666666667 0.2 0.25 0.333333333333333 0.5  1
##   AI Consultancy                     0   1    0                 0   0 13
##   AI Debate                          1   3    1                 0   2 12
##   Human Consultancy                  0   1    8                 5   8  2
##   Human Debate                       1   3    3                 7   8  3
##
```

```
## , ,  = TRUE
##
##
##                      0.166666666666667 0.2 0.25 0.333333333333333 0.5  1
##   AI Consultancy                     2   6    5                 0   1 48
##   AI Debate                          3  10    6                 0   1 48
##   Human Consultancy                  2   7   13                17  14  5
##   Human Debate                       3   4   16                19  56 32
```

```r
# Sampled data (balanced consultancies and sampled debates) difference between grouping and not groupin
table(judgments_online[judgments_online$Sample == TRUE, ]$Final_Setting, judgments_online[judgments_onl
```

```
##
##                      0.5   1
##   AI Consultancy       0  76
##   AI Debate            0  75
##   Human Consultancy   42  40
##   Human Debate         0 107
```

```r
table(judgments_online[judgments_online$Sample == TRUE, ]$Final_Setting, judgments_online[judgments_onl
```

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

Results

Accuracy

Difference in proportions

```r
# Make a function to easily try out different weights
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
```

```
print("Balanced consultancies, NO weights") # still sig
```

```
## [1] "Balanced consultancies, NO weights"
```

```
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
```

```
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
```

```r
print("Balanced # consultancies, question weights")
```

```
## [1] "Balanced # consultancies, question weights"
```

```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 = 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, NO weights")
```

```
## [1] "Balanced consultancies sampled debates, NO weights"
```

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

```
## Warning in svydesign.default(ids = ~1, data = subset(judgments_online, 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 = 6.1384, df = 3, p-value = 0.1059
##
##
##  Pairwise comparisons using Pairwise comparison of proportions
##
## data:  freq_table
##
##                   AI Consultancy AI Debate Human Consultancy
## AI Debate         0.968          -         -
## Human Consultancy 0.159          0.247     -
## Human Debate      0.673          0.489     0.027
##
## P value adjustment method: none
##                   FALSE TRUE Accuracy
## AI Consultancy       14   62 81.57895
## AI Debate            15   60 80.00000
## Human Consultancy    24   58 70.73171
## Human Debate         16   91 85.04673
```

```
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
```

```
svytable(~Final_Setting+Final_Accuracy, svydesign(ids = ~1, data = subset(judgments_online, `Sample` ==
```

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

```
##                     Final_Accuracy
## Final_Setting        FALSE TRUE
##   AI Consultancy        14   62
##   AI Debate             15   60
##   Human Consultancy     24   58
##   Human Debate          16   91
```

```
svytable(~Final_Setting+Final_Accuracy, svydesign(ids = ~1, data = subset(judgments_online, `Sample` ==
```

```
##                     Final_Accuracy
## Final_Setting        FALSE TRUE
##   AI Consultancy        14   62
##   AI Debate             15   60
##   Human Consultancy     16   45
##   Human Debate          16   91
```

```
print("Now trying manually tests that aren't pairwise + cobfidence intervals for the table")
```

```
## [1] "Now trying manually tests that aren't pairwise + cobfidence intervals for the table"
```

```
process_table <- function(svy_table, round_by) {
  # Ensure that the input is a svytable object
  if (!inherits(svy_table, "svytable")) {
    stop("Input must be a svytable object")
  }
```

```
  # Add accuracy
  svy_table <- cbind(svy_table, Accuracy = (svy_table[,2] / (svy_table[,1] + svy_table[,2])) * 100)
  # Calculate the difference in accuracy for each row compared to "Human Debate"
  difference_with_debate <- svy_table[,"Accuracy"] - svy_table["Human Debate", "Accuracy"]
  # Bind the difference column to the svy_table
  svy_table <- cbind(svy_table, `Difference with Debate` = difference_with_debate)
  # Initialize vectors to store confidence interval bounds and p-values
  ci_lowers <- c() ; ci_uppers <- c() ; p_values <- c()
  # Loop through each setting
  for (setting in rownames(svy_table)) {
    # Use prop.test to compare the setting's accuracy with "Human Debate"
    results <- prop.test(
      x = c(svy_table["Human Debate", "TRUE"], svy_table[setting, "TRUE"]),
      n = c((svy_table["Human Debate", "TRUE"] + svy_table["Human Debate", "FALSE"]), (svy_table[setting
    )
    # Extract the confidence interval and store it as a string in the format "lower - upper"
    ci_lower <- round(results$conf.int[1] * 100,round_by)  # Multiply by 100 to convert to percentage
    ci_upper <- round(results$conf.int[2] * 100,round_by)  # 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)
  }
  # Change to wanted format (judgments summed, split counts removed)
  svy_table <- cbind("n Judgments (weighted)" = (svy_table[,"FALSE"] + svy_table[,"TRUE"]), svy_table)
  svy_table <- svy_table[ , !(colnames(svy_table) %in% c("FALSE", "TRUE"))]
  # Concatenate the CI bounds into a single string
  ci_strings <- paste0("[", ci_lowers, ", ", ci_uppers, "]")
  # Convert svy_table to a data.frame so adding the strings doesn't change the data type for entire mat
  svy_table <- as.data.frame(svy_table)
  # Bind the confidence interval bounds and p-values to the svy_table
  svy_table <- cbind(svy_table, `95% CI [lower, upper]` = ci_strings, `p val` = p_values)
  return(svy_table)
}

# First table, all data accuracy
svy_table_input <- svytable(
  ~Setting + Final_Accuracy,
  design = svydesign(
    ids = ~1,
    data = subset(judgments_online, `Consultancy Sample` == TRUE | !grepl("Consultancy", Final_Setting)
    weights = ~sampled_consultancies_all_debates_weights_grouped_setting
  )
)

# Call the function
final_table <- process_table(svy_table_input, round_by = 1)
```

```
## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect
```

```
final_table
```

```
##                              n Judgments (weighted) Accuracy
```

```
## AI Consultancy Dishonest                      38.0 86.84211
## AI Consultancy Honest                         38.0 76.31579
## AI Debate                                     75.0 79.33333
## Human Consultancy Dishonest                   30.5 59.01639
## Human Consultancy Honest                      30.5 88.52459
## Human Debate                                 107.0 84.57944
##                             Difference with Debate 95% CI [lower, upper]
## AI Consultancy Dishonest                  2.262666         [-16.8, 12.3]
## AI Consultancy Honest                    -8.263650          [-8.7, 25.2]
## AI Debate                                -5.246106          [-7.3, 17.8]
## Human Consultancy Dishonest             -25.563046           [4.7, 46.4]
## Human Consultancy Honest                  3.945151         [-19.3, 11.4]
## Human Debate                              0.000000           [-9.7, 9.7]
##                                   p val
## AI Consultancy Dishonest    0.943029144
## AI Consultancy Honest       0.367365381
## AI Debate                   0.473183236
## Human Consultancy Dishonest 0.005091626
## Human Consultancy Honest    0.799453469
## Human Debate                1.000000000
```

```
knitr::kable(final_table, booktab = TRUE, digits = c(rep(1,3),NA,3))
```

	n Judgments (weighted)	Accuracy	Difference with Debate	95% CI [lower, upper]	p val
AI Consultancy Dishonest	38.0	86.8	2.3	[-16.8, 12.3]	0.943
AI Consultancy Honest	38.0	76.3	-8.3	[-8.7, 25.2]	0.367
AI Debate	75.0	79.3	-5.2	[-7.3, 17.8]	0.473
Human Consultancy Dishonest	30.5	59.0	-25.6	[4.7, 46.4]	0.005
Human Consultancy Honest	30.5	88.5	3.9	[-19.3, 11.4]	0.799
Human Debate	107.0	84.6	0.0	[-9.7, 9.7]	1.000

```
# Possible table?, high confidence accuracy
high_conf_data <- subset(judgments_online,
                        `Final probability correct` <= 0.01 | `Final probability correct` >= 0.99)

# Create the svytable object for high confidence accuracy
svy_table_high_conf <- svytable(
  ~Final_Setting + Final_Accuracy,
  design = svydesign(
    ids = ~1,
    data = subset(high_conf_data, `Consultancy Sample` == TRUE | !grepl("Consultancy", Final_Setting)),
    weights = ~sampled_consultancies_all_debates_weights_grouped_setting
  )
)

# Call the function for high confidence accuracy
high_conf_table <- process_table(svy_table_high_conf, round_by = 1)
```

```
## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect
```

```r
high_conf_table
```

```
##                     n Judgments (weighted) Accuracy Difference with Debate
## AI Consultancy                        48.0 85.41667              -4.057018
## AI Debate                             50.5 85.14851              -4.325169
## Human Consultancy                     17.5 80.00000              -9.473684
## Human Debate                          47.5 89.47368               0.000000
##                     95% CI [lower, upper]     p val
## AI Consultancy              [-11.3, 19.4] 0.7723289
## AI Debate                   [-10.8, 19.5] 0.7349818
## Human Consultancy           [-15.1, 34.1] 0.5550842
## Human Debate                [-12.3, 12.3] 1.0000000
```

```r
# Render the high confidence accuracy table
knitr::kable(high_conf_table, booktab = TRUE, digits = c(rep(1,3),NA,3))
```

	n Judgments (weighted)	Accuracy	Difference with Debate	95% CI [lower, upper]	p val
AI Consultancy	48.0	85.4	-4.1	[-11.3, 19.4]	0.772
AI Debate	50.5	85.1	-4.3	[-10.8, 19.5]	0.735
Human Consultancy	17.5	80.0	-9.5	[-15.1, 34.1]	0.555
Human Debate	47.5	89.5	0.0	[-12.3, 12.3]	1.000

```r
# Possible table?, high confidence accuracy
low_conf_data <- subset(judgments_online,
                        `Final probability correct` >= 0.30 & `Final probability correct` <= 0.70)

# Create the svytable object for high confidence accuracy
svy_table_low_conf <- svytable(
  ~Final_Setting + Final_Accuracy,
  design = svydesign(
    ids = ~1,
    data = subset(low_conf_data, `Consultancy Sample` == TRUE | !grepl("Consultancy", Final_Setting)),
    weights = ~sampled_consultancies_all_debates_weights_grouped_setting
  )
)

# Call the function for high confidence accuracy
low_conf_table <- process_table(svy_table_low_conf, round_by = 1)
```

```
## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect

## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect
```

```
## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect

## Warning in prop.test(x = c(svy_table["Human Debate", "TRUE"],
## svy_table[setting, : Chi-squared approximation may be incorrect
```

```
low_conf_table
```

```
##                    n Judgments (weighted) Accuracy Difference with Debate
## AI Consultancy                        9.0 66.66667               0.000000
## AI Debate                             7.0 64.28571              -2.380952
## Human Consultancy                     8.5 58.82353              -7.843137
## Human Debate                         10.5 66.66667               0.000000
##                    95% CI [lower, upper] p val
## AI Consultancy               [-42, 42]     1
## AI Debate                [-45.5, 50.3]     1
## Human Consultancy        [-43.7, 59.4]     1
## Human Debate             [-40.3, 40.3]     1
```

```
# Render the high confidence accuracy table
knitr::kable(low_conf_table, booktab = TRUE, digits = c(rep(1,3),NA,3))
```

	n Judgments (weighted)	Accuracy	Difference with Debate	95% CI [lower, upper]	p val
AI Consultancy	9.0	66.7	0.0	[-42, 42]	1
AI Debate	7.0	64.3	-2.4	[-45.5, 50.3]	1
Human Consultancy	8.5	58.8	-7.8	[-43.7, 59.4]	1
Human Debate	10.5	66.7	0.0	[-40.3, 40.3]	1

```
judgments_online$fpc <- judgments_online$`Final probability correct`

# Weighted Kruskal-Wallis
svyranktest(fpc~Final_Setting, svydesign(ids = ~1, data = subset(judgments_online, `Consultancy Sample`
```

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

```
# Test Human Settings only
svyranktest(fpc~Final_Setting,
            svydesign(ids = ~1, data = subset(judgments_online, `Human Consultancy Sample` == TRUE | !g
            test = "wilcoxon")
```

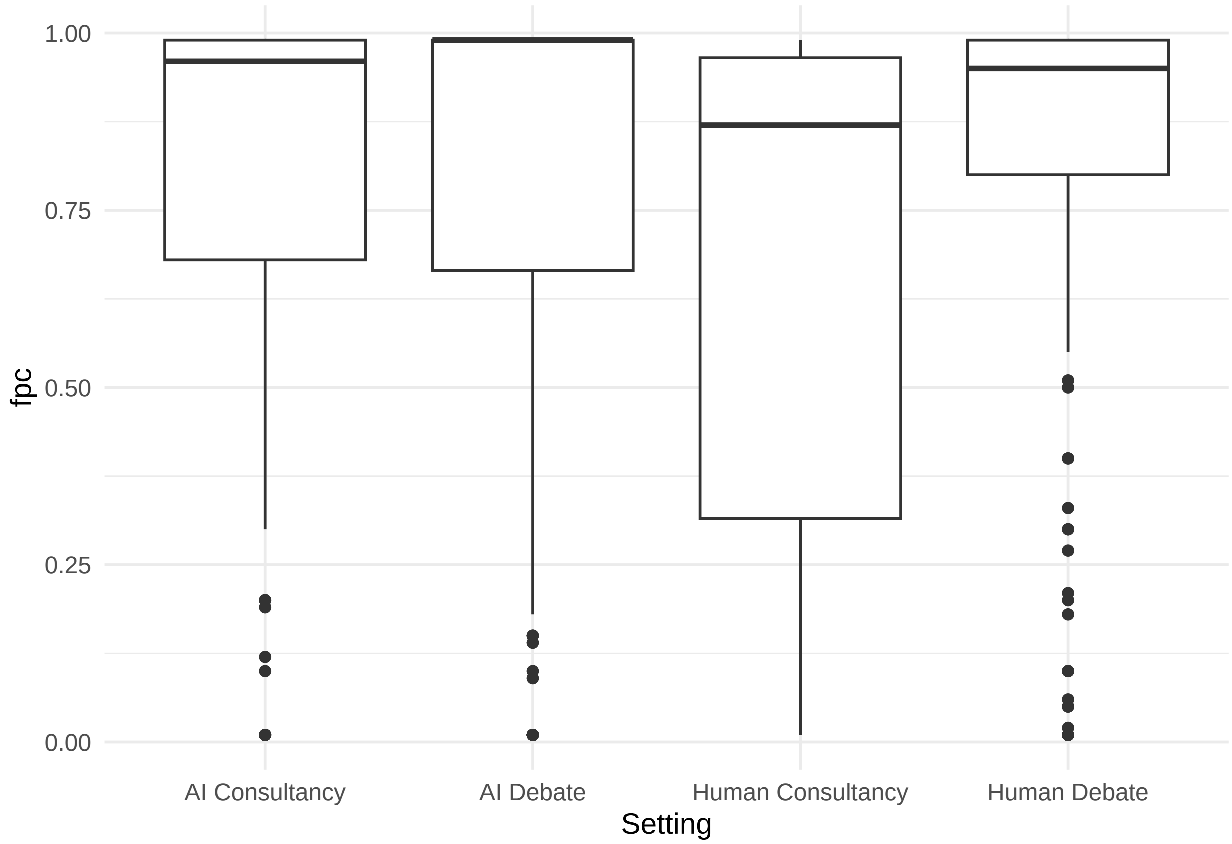
```
##
##  Design-based KruskalWallis test
##
## data:  fpc ~ Final_Setting
```

```
## 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
```

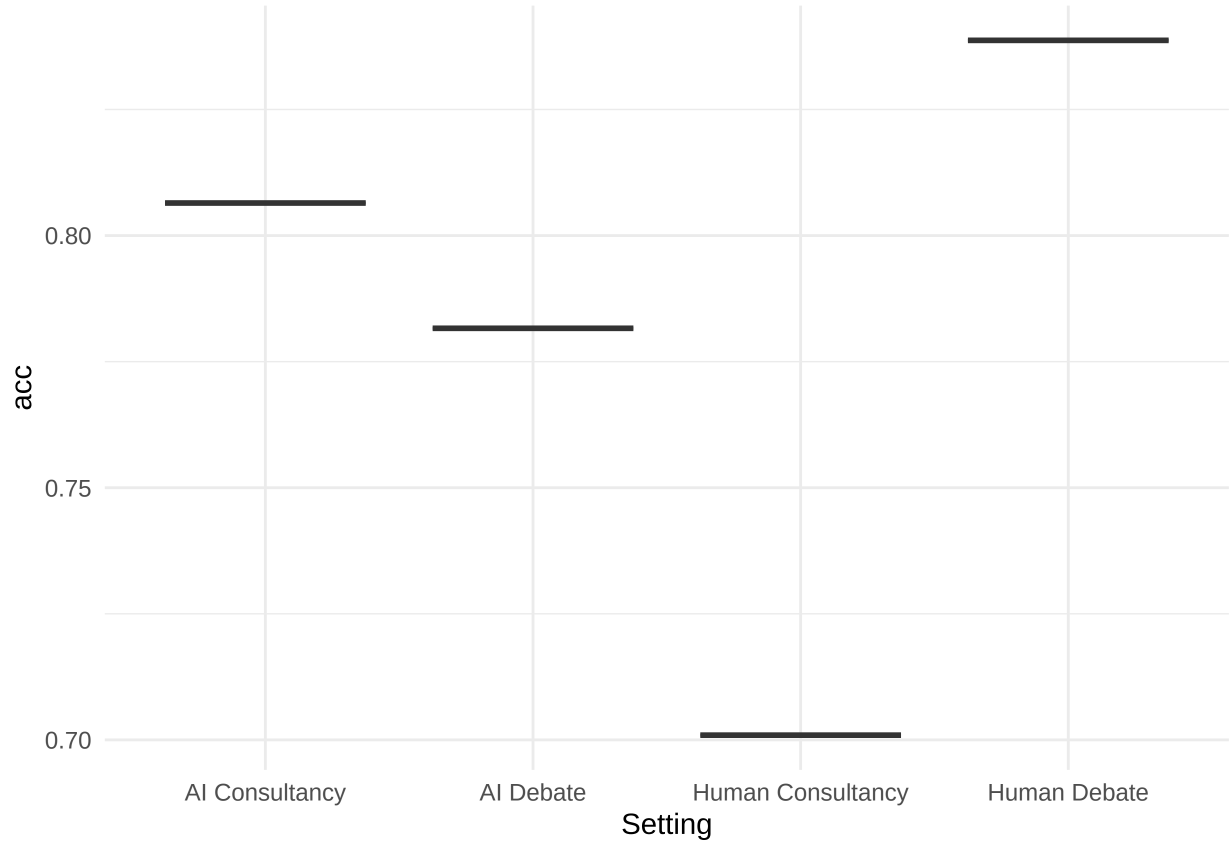
```
svyranktest(fpc~Final_Setting,
            svydesign(ids = ~1, data = subset(judgments_online, `Human Consultancy Sample` == TRUE | !g
            test = "median")
```

```
##
##  Design-based median test
##
## data:  fpc ~ Final_Setting
## t = 2.7708, df = 235, p-value = 0.00604
## alternative hypothesis: true difference in mean rank score is not equal to 0
## sample estimates:
## difference in mean rank score
##                       0.19427
```

```
# TODO: check test for human consultancy & human debate, make table. Might have to rebuild package to g
# see calibration for confident mistakes
# Note: see publication in help page for more



# The rest is stuff i tried
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()
```




```
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
```

```
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, ju
```

```
## 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
weighted_mannwhitney(fpc ~ Final_Setting + sampled_consultancies_all_debates_weights_grouped_setting, ju
```

```
## 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
```

Logistic regression

```r
#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
```

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

```
##
```

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

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

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

```r
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

```
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"
```

```r
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

```
debater_turns = 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
debater_turns = debater_turns[debater_turns['Role (honest/dishonest)'].isin(['Honest debater', 'Dishones

# 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
```

```python
    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 debater_turns dataframe
questions_with_multi_settings = debater_turns.groupby("Question").filter(lambda x: len(x["Setting"].uniq
debater_turns_filtered = debater_turns[debater_turns["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
debater_turns_filtered_by_room = debater_turns_filtered.groupby('Room name').agg(aggregates).reset_inde

# Merging the aggregated results with the original data to reintroduce the desired columns
debater_turns_agg = debater_turns_filtered_by_room.merge(
    debater_turns_filtered[['Room name', 'Setting', 'Final_Setting', 'Question', 'Untimed annotator con
    on='Room name'
)

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

# 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

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

#print((debater_turns_agg['quote_length'].fillna(0)/debater_turns_agg['Story length'].fillna(0)).descri


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
        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(debater_turns_agg)

#print(span_differences_all.keys())
```

```python
#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 1

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

```
## 28         Human Debate - Human Consultancy Dishonest  ...               163.956522
## 29            Human Debate - Human Consultancy Honest  ...               147.880952
##
## [30 rows x 3 columns]
```

```
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  ...     75%    max
## Setting 2                  Acc_1 Acc_2                      ...
## Human Consultancy Dishonest False False    5.0  187.200000  ...  275.00  293.0
##                                  True     8.0  149.625000  ...  236.25  275.0
##                            True  False   16.0  148.687500  ...  182.00  358.0
##                                  True    17.0  178.235294  ...  233.00  526.0
## Human Consultancy Honest    False False    4.0  144.750000  ...  257.25  267.0
##                                  True    12.0  122.416667  ...  164.75  325.0
##                            True  False    4.0  197.000000  ...  224.25  273.0
##                                  True    22.0  153.409091  ...  195.00  394.0
##
## [8 rows x 8 columns]
```

```
# 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
```

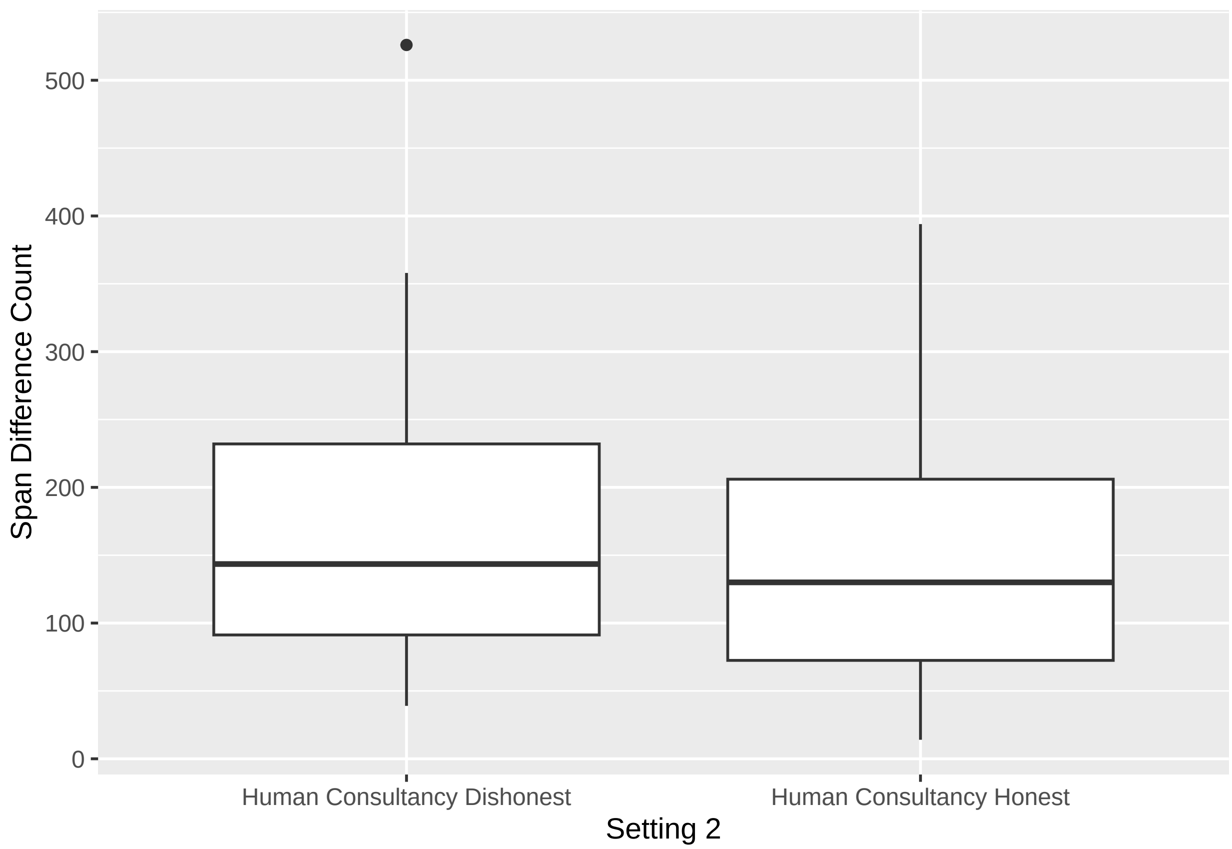
```
##                                                Question  ...                                   Setti
## 0    By the end of the passage. what can we underst...  ...     Human Debate - Human Consultancy Hone
## 2    By the end of the passage. what can we underst...  ...  Human Debate - Human Consultancy 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]
```

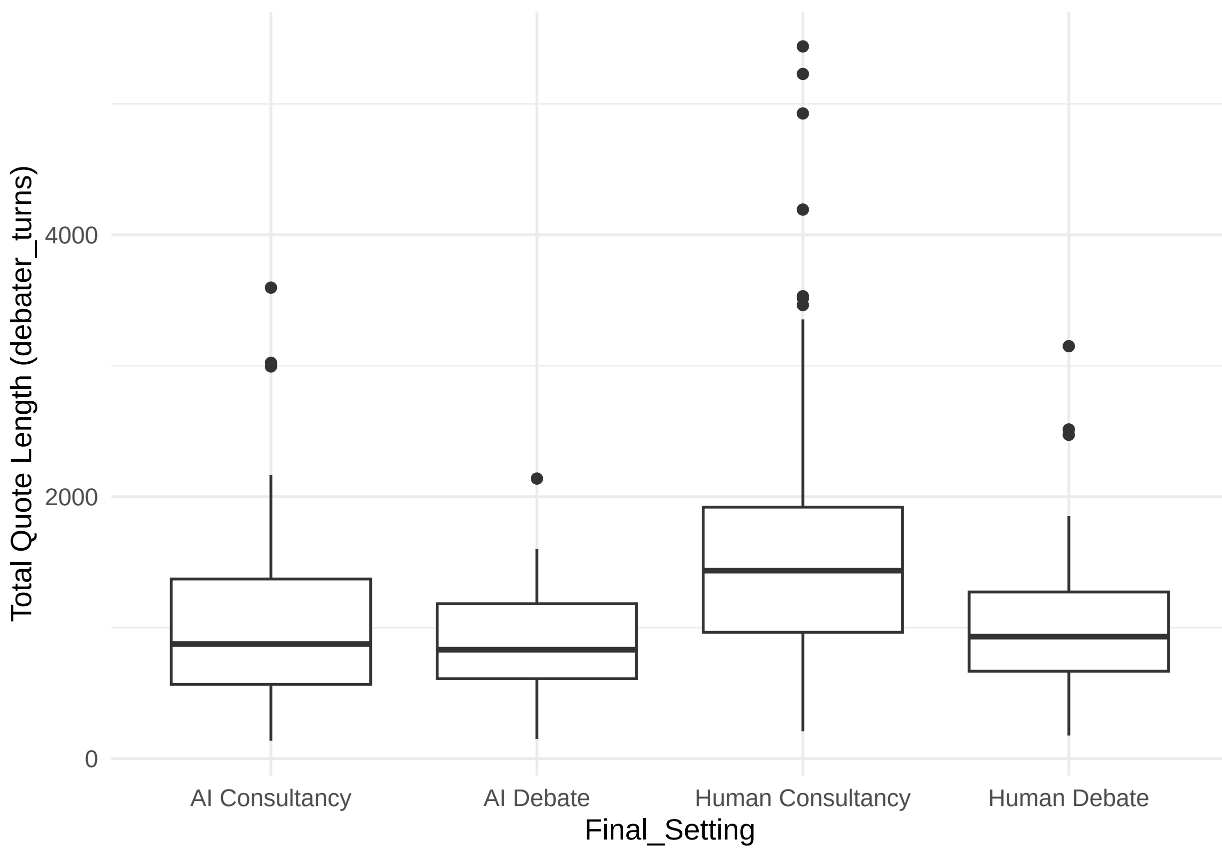
```
print(filtered_no_outliers.groupby(['Setting 2','Acc_1','Acc_2'])['Span Difference Count'].describe())
```

```
##                                           count        mean  ...     75%    max
## Setting 2                   Acc_1 Acc_2                      ...
## Human Consultancy Dishonest False False    5.0  187.200000  ...  275.00  293.0
##                                   True     8.0  149.625000  ...  236.25  275.0
##                             True  False   16.0  148.687500  ...  182.00  358.0
##                                   True    16.0  156.500000  ...  220.25  289.0
## Human Consultancy Honest    False False    4.0  144.750000  ...  257.25  267.0
##                                   True    12.0  122.416667  ...  164.75  325.0
##                             True  False    4.0  197.000000  ...  224.25  273.0
##                                   True    22.0  153.409091  ...  195.00  394.0
##
## [8 rows x 8 columns]
```

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

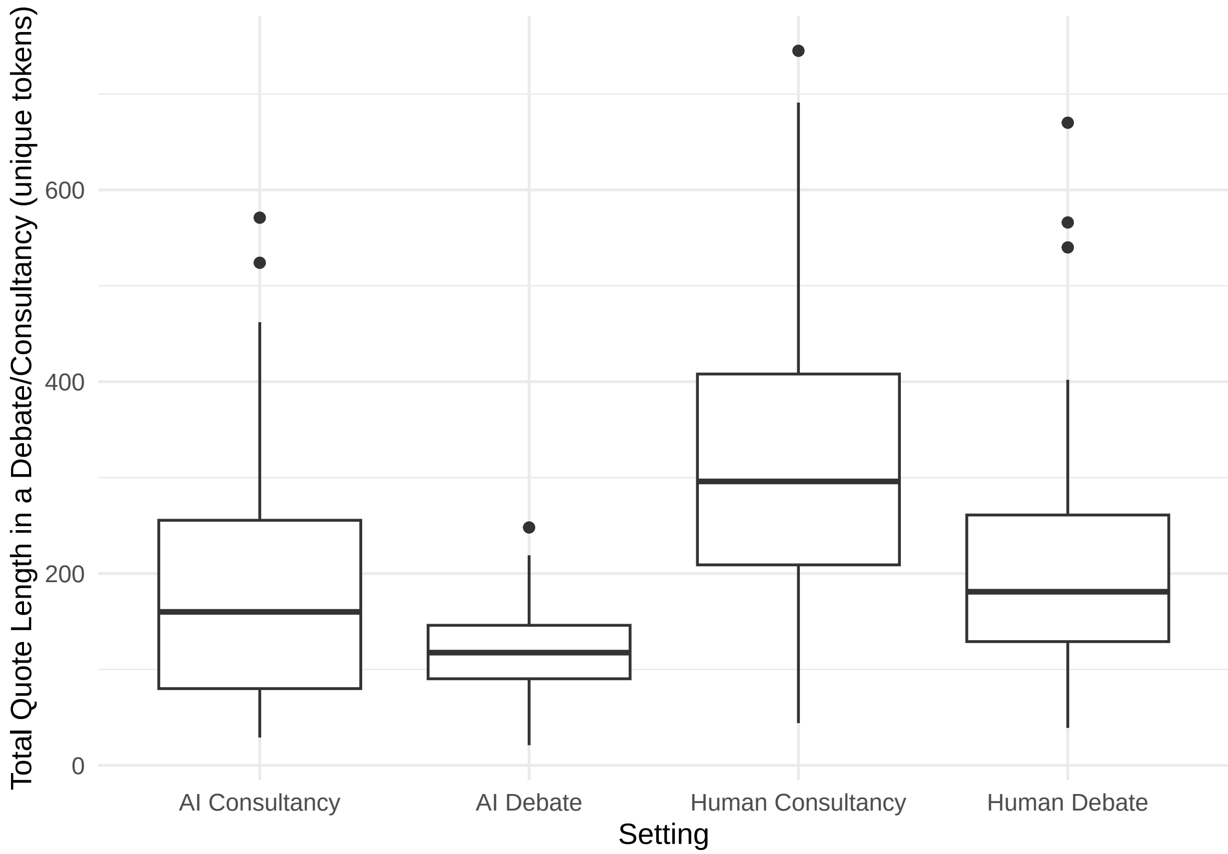


```r
filtered_outliers <- debater_turns %>%
  group_by(Final_Setting) %>%
  mutate(Q1 = quantile(quote_length, 0.25),
         Q3 = quantile(quote_length, 0.75),
         IQR = Q3 - Q1,
         lower_bound = Q1 - 1.5 * IQR,
         upper_bound = Q3 + 1.5 * IQR)

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

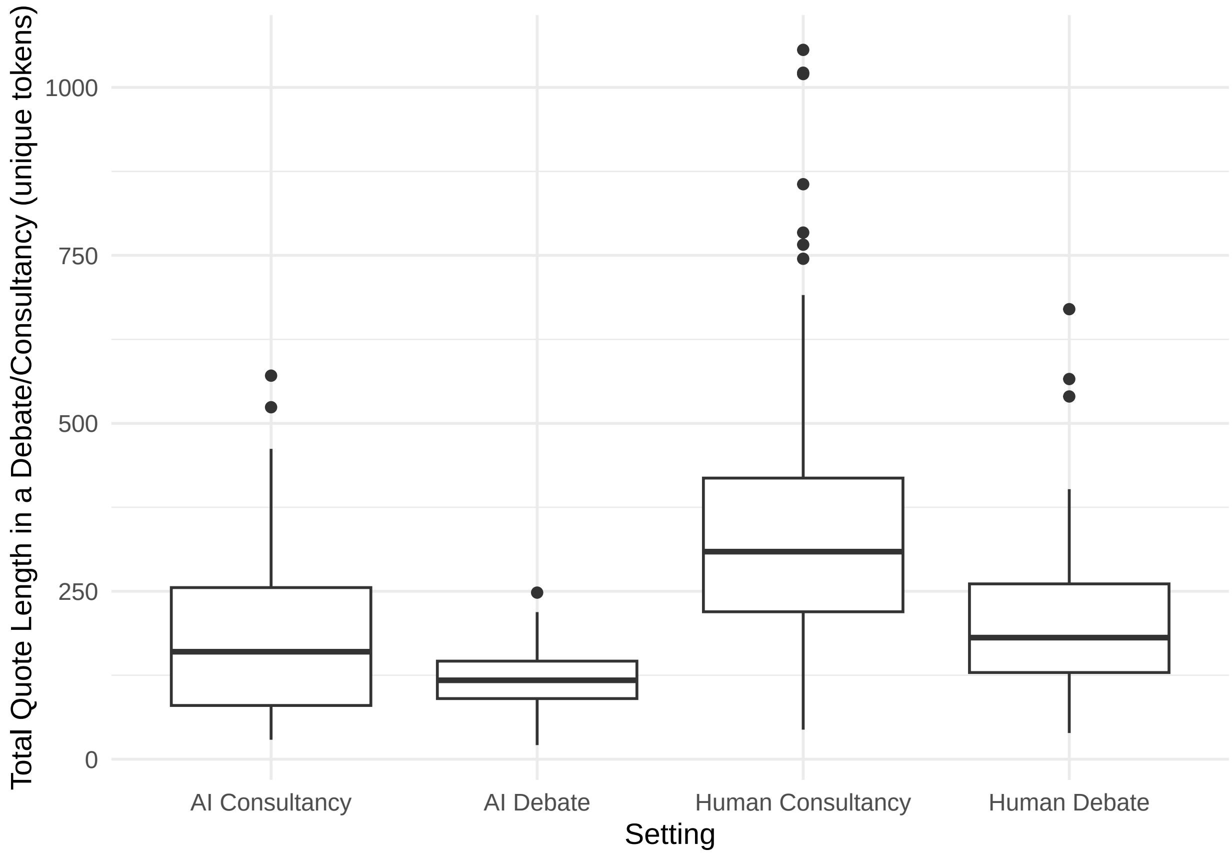



```r
filtered <- debater_turns %>%
  group_by(Final_Setting) %>%
  mutate(Q1 = quantile(quote_length, 0.25),
         Q3 = quantile(quote_length, 0.75),
         IQR = Q3 - Q1,
         lower_bound = Q1 - 1.5 * IQR,
         upper_bound = Q3 + 1.5 * IQR) %>%
  filter(quote_length > 0 & quote_length < 750) %>%
  select(-Q1, -Q3, -IQR, -lower_bound, -upper_bound)
filtered %>%
  ggplot() +
  geom_boxplot(aes(x = Final_Setting, y = quote_length)) +
```

```r
  labs(y = "Total Quote Length in a Debate/Consultancy (unique tokens)", x = "Setting")+
  theme_minimal()
```




```r
debater_turns %>%
  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
```

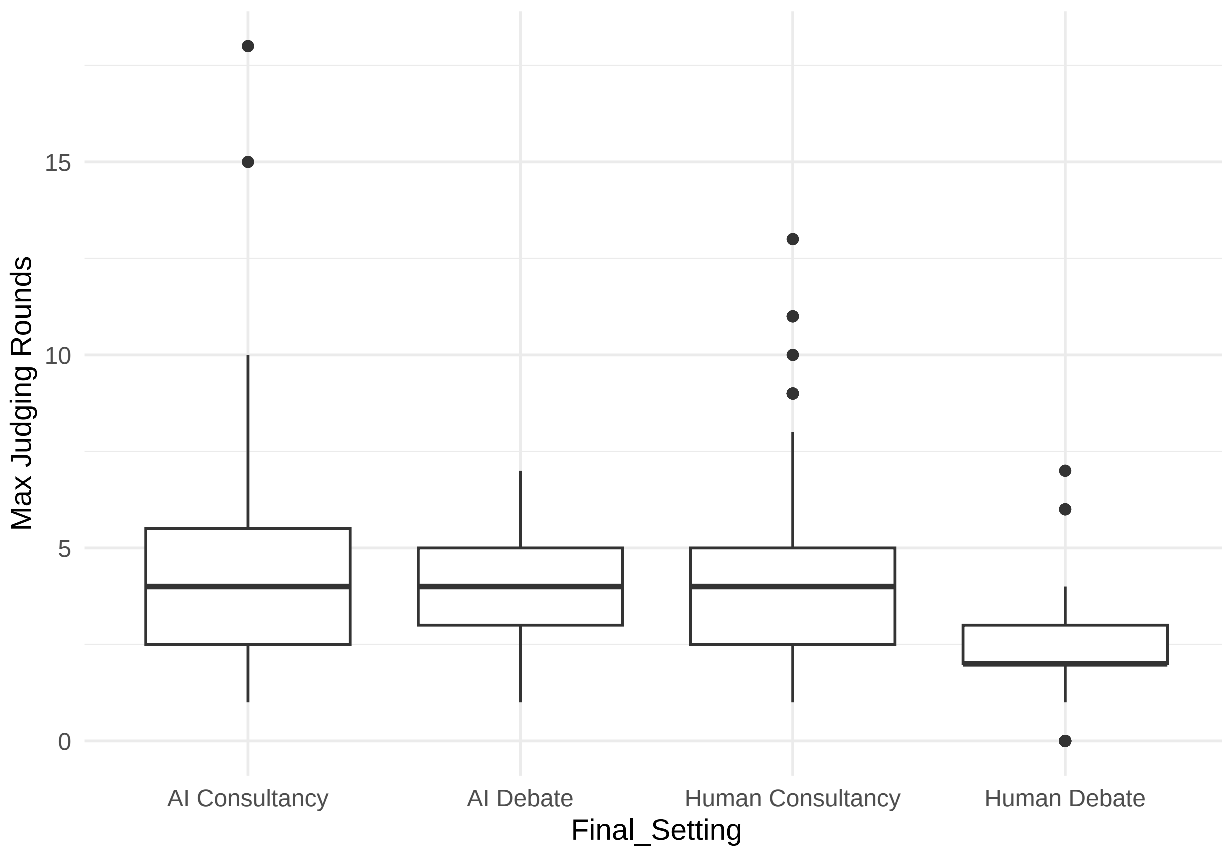
```
filtered %>% group_by(Final_Setting) %>% summarise(avground = median(quote_length))
```

```
## # 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
```

```
debater_turns %>% 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
```

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

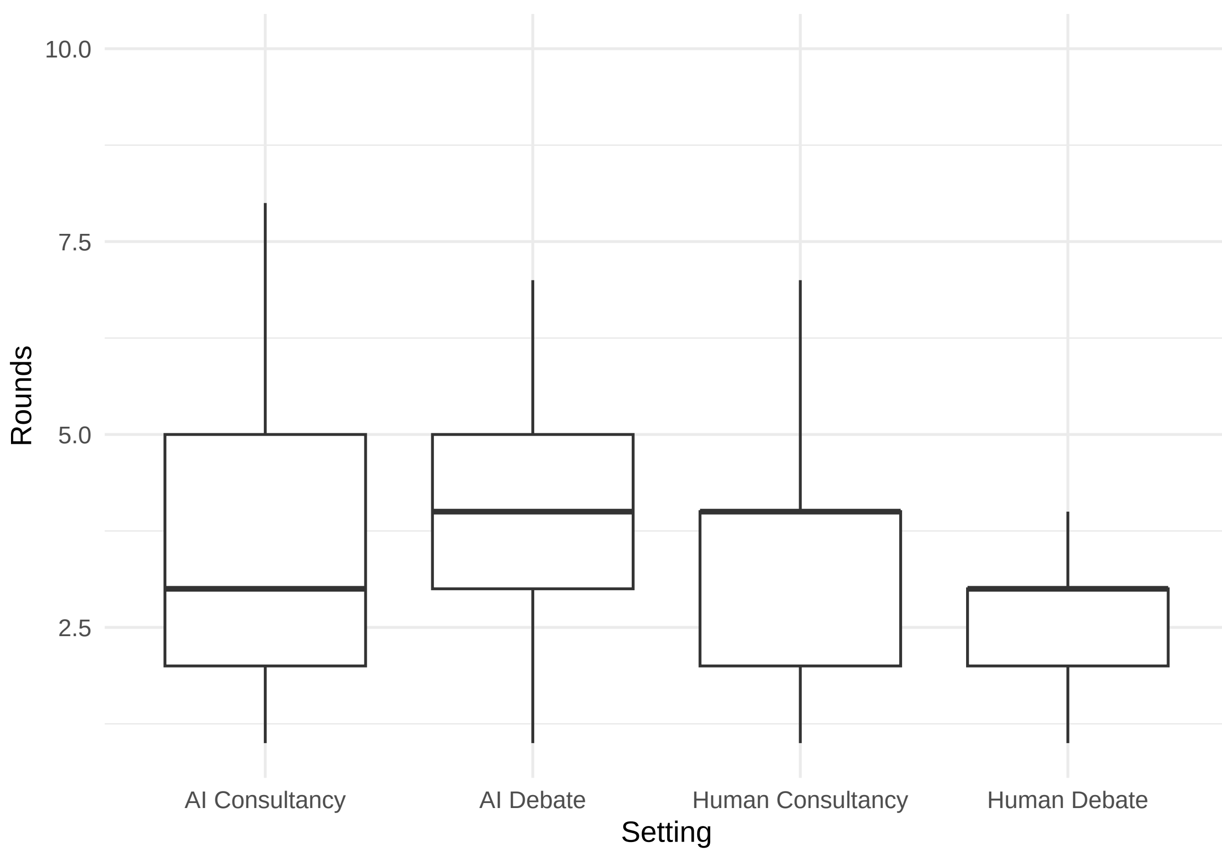



```
pairwise.t.test(debater_turns$`Max judge rounds by room`, debater_turns$Final_Setting)
```

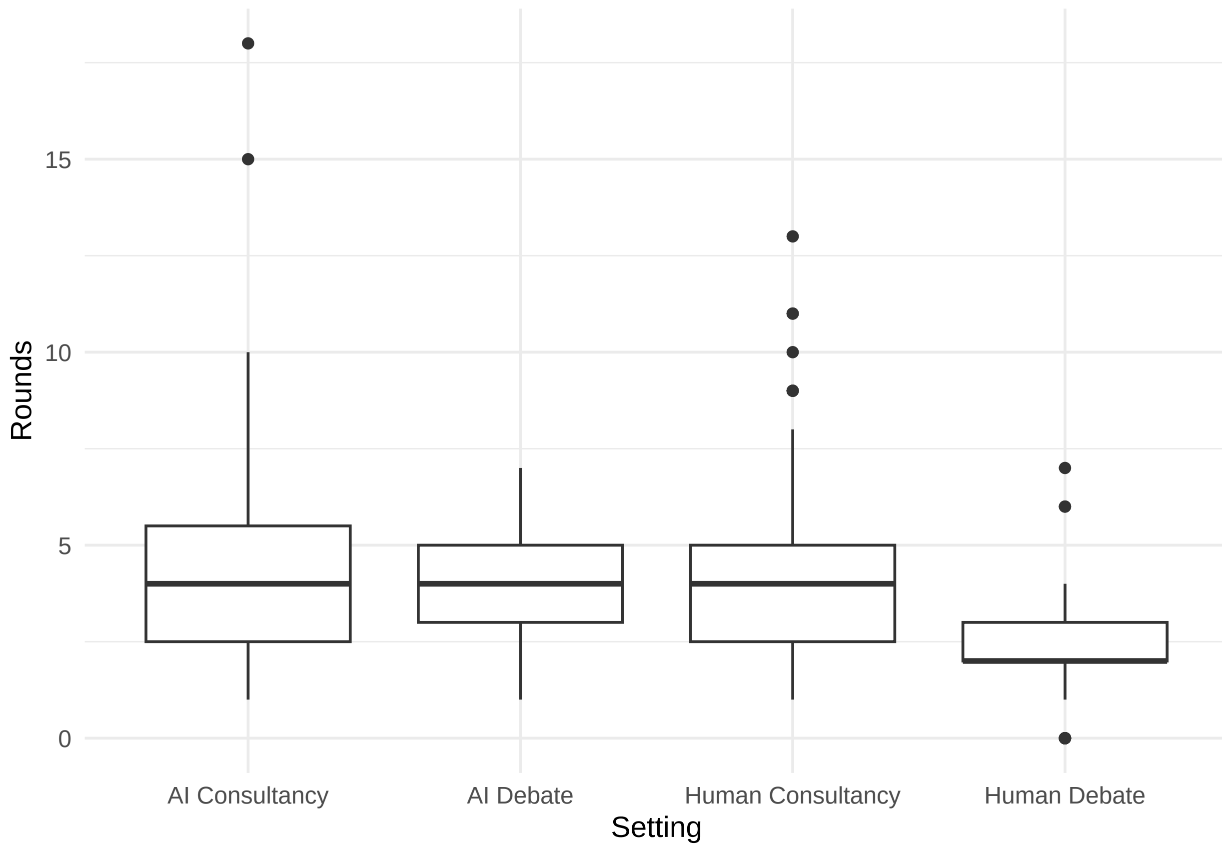
```
##
##  Pairwise comparisons using t tests with pooled SD
##
```

```
## data:  debater_turns$`Max judge rounds by room` and debater_turns$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 <- debater_turns %>%
  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
debater_turns %>%
  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
```

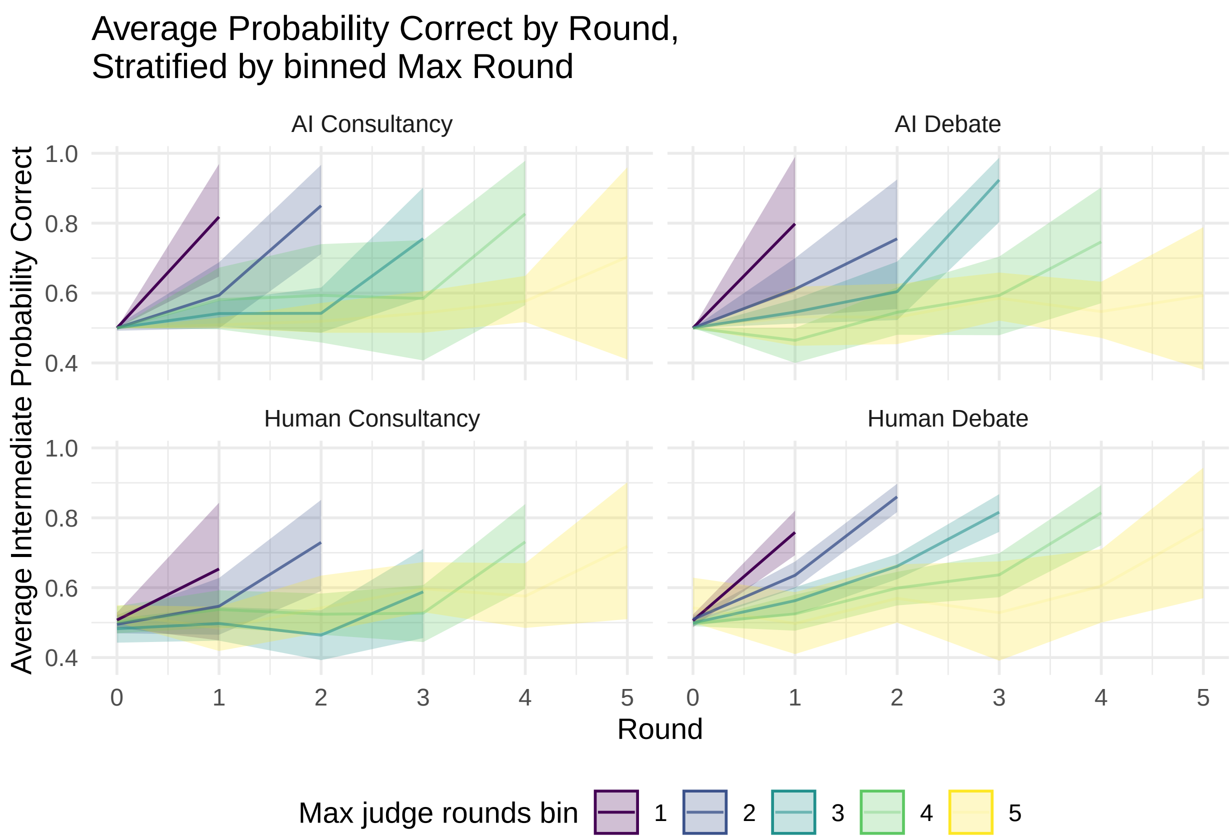
```
##   <chr>                 <dbl>
## 1 AI Consultancy         4.24
## 2 AI Debate              4.07
## 3 Human Consultancy      3.61
## 4 Human Debate           2.52
```

Length of debates, stratified

```
all_turns = 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",
    )
```

```
strat <- py$all_turns
strat <- strat %>%
  group_by(`Room name`, Participant) %>%
  mutate(`Max judge rounds by room` = max(`Num previous judging rounds`, na.rm = TRUE)) %>%
  ungroup()

generate_bins <- function(start, end, step) {
  breaks <- seq(start, end + 1, by = step)  # Extend the sequence to end + 1 to include the end point
  labels <- sapply(1:(length(breaks) - 1), function(i) {
    lower_bound = breaks[i]+1
    upper_bound = breaks[i+1]
    return(paste0(lower_bound, "-", upper_bound))  # Return the range string
  })
  breaks <- c(-Inf, breaks, Inf)  # Extend the breaks vector to include Inf
  labels <- c("0", labels, paste0(end+1,"+"))
  return(list(breaks = breaks, labels = labels))
}

# Now use this function to generate the breaks and labels:
bins <- generate_bins(0, 15, 3)

# Now use these dynamically generated values in your mutate function:
strat <- strat %>%
  mutate(`Max judge rounds bin` = cut(`Max judge rounds by room`,
                                      breaks = bins$breaks,
                                      labels = bins$labels,
                                      right = TRUE,
                                      include.lowest = TRUE))
strat <- strat %>%
  mutate(`Max judge rounds bin` = cut(`Max judge rounds by room`,
                                      breaks = c(-Inf, 0, 3, 6, 9, 12, 15, Inf),
                                      labels = c("0", "1-3", "4-6", "7-9", "10-12", "13-15", "16+"),
                                      right = TRUE,
                                      include.lowest = TRUE))
# Bootstrap mean function
bootstrap_mean <- function(data, indices) {
  return(mean(data[indices], na.rm = TRUE))
```

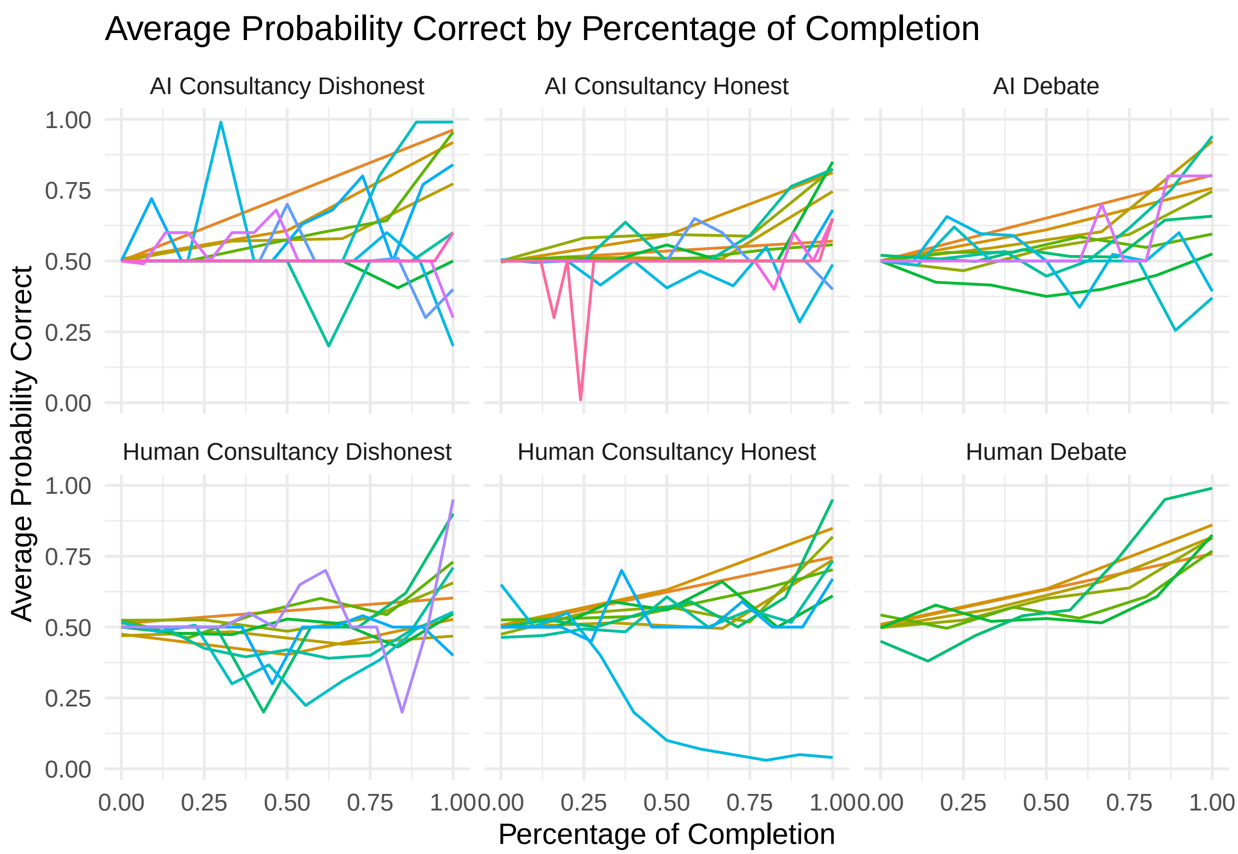
```
}

# deprecated, keep original max round except if above cutoff
strat <- strat %>%
  mutate(`Max judge rounds bin` = ifelse(`Max judge rounds by room` > 5, "6+", as.character(`Max judge r
  mutate(`Max judge rounds bin` = factor(`Max judge rounds bin`,
                                         levels = c("0", "1", "2", "3", "4", "5"),
                                          ordered = TRUE))

# Extract unique bin values
unique_bins <- levels(strat$`Max judge rounds bin`)[2:length(levels(strat$`Max judge rounds bin`))]

# Create a decreasing sequence of alpha values
alpha_values <- seq(1, 0.1, length.out = length(unique_bins))

# Create a named vector for mapping
alpha_map <- setNames(alpha_values, unique_bins)

strat %>%
  filter(`Max judge rounds bin` != "0") %>%  # Remove entries with "0" bin
  group_by(Final_Setting, `Num previous judging rounds`, `Max judge rounds bin`) %>%
  do({
    boot_result <- boot(data = .$`Probability correct`, statistic = bootstrap_mean, R = 1000)
    data.frame(
      mean_accuracy = mean(boot_result$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 = `Num previous judging rounds`, y = mean_accuracy, col = `Max judge rounds bin`)) +
  geom_ribbon(aes(ymin = lower_ci, ymax = upper_ci, fill = `Max judge rounds bin`, group = `Max judge ro
  labs(title = "Average Probability Correct by Round, \nStratified by binned Max Round",
       x = "Round",
       y = "Average Intermediate Probability Correct") +
  geom_line(aes(alpha = `Max judge rounds bin`)) +
  scale_alpha_manual(values = alpha_map) +
  facet_wrap(~Final_Setting) +
  theme_minimal() +
  theme(legend.position = "bottom")
```




```
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 roo
  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 the `.groups` 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...
```

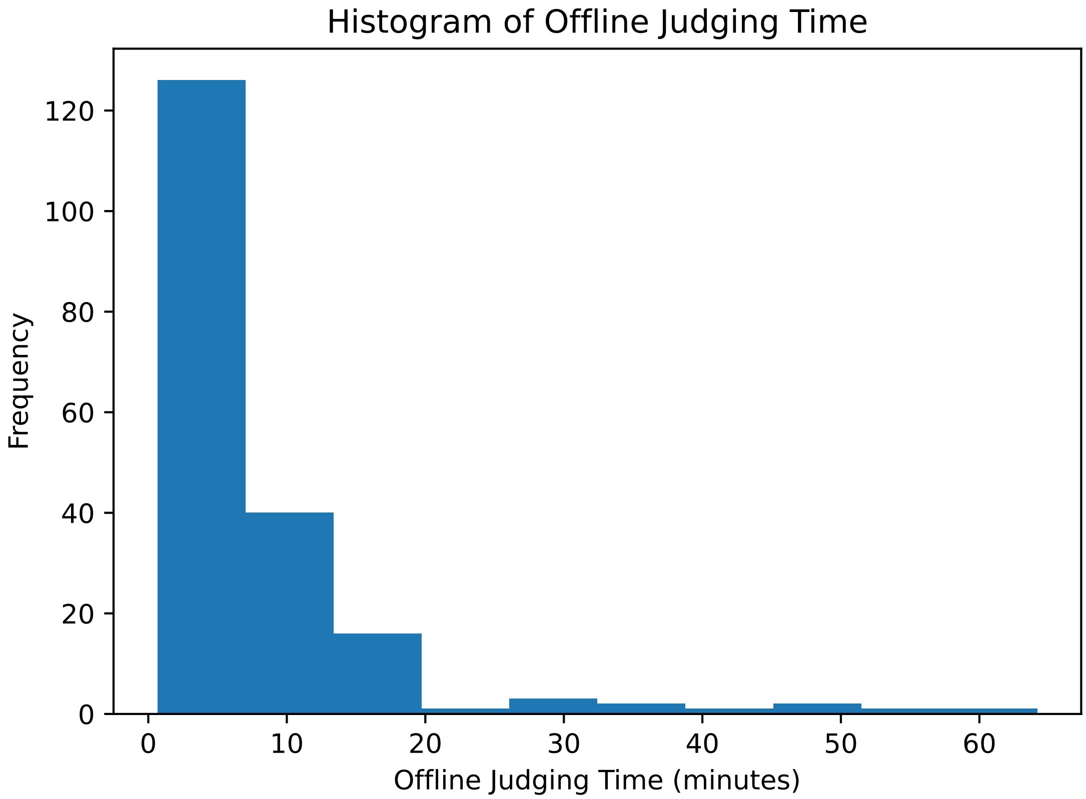
```python
# Filter out rows with NaT values
valid_judging_time = judgments["Offline judging time"].dropna()

# 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 in
```

```
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()
```

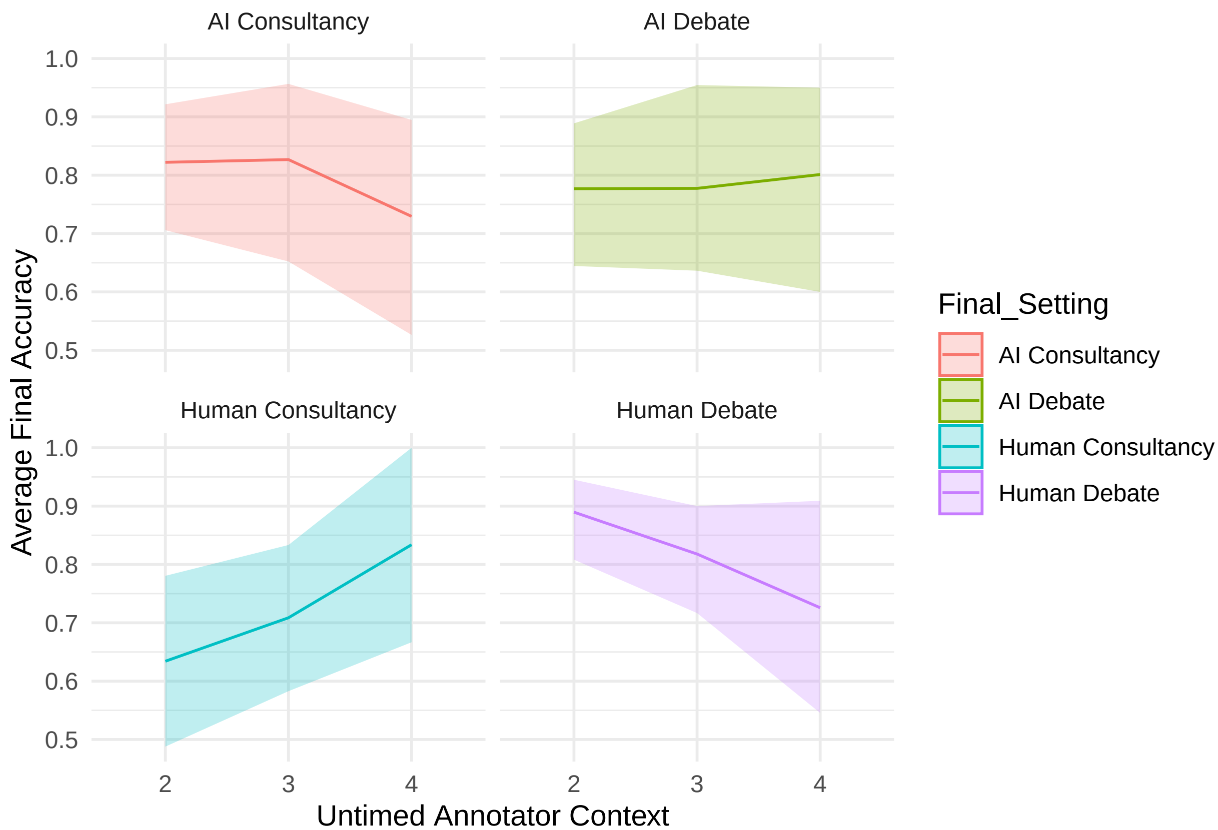
```
## <string>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True i
```

```
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  ... Proportion_Context
## 0   AI Consultancy  ...                NaN
## 1   AI Consultancy  ...           0.010417
## 2   AI Consultancy  ...                NaN
## 3   AI Consultancy  ...                NaN
## 4   AI Consultancy  ...           0.291667
## ..             ...  ...                ...
## 59    Human Debate  ...                NaN
## 60    Human Debate  ...           0.076923
## 61    Human Debate  ...           0.018568
## 62    Human Debate  ...                NaN
## 63    Human Debate  ...                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)
```

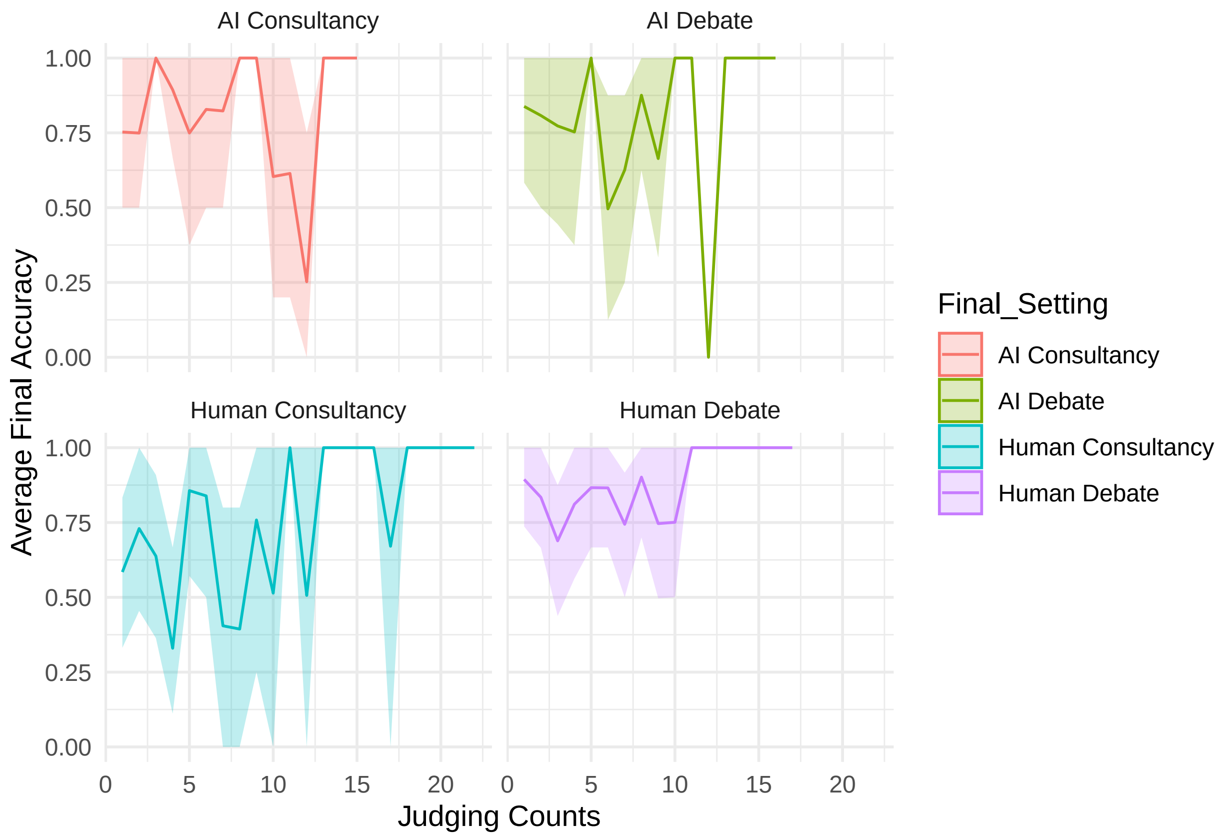


Judge Skill

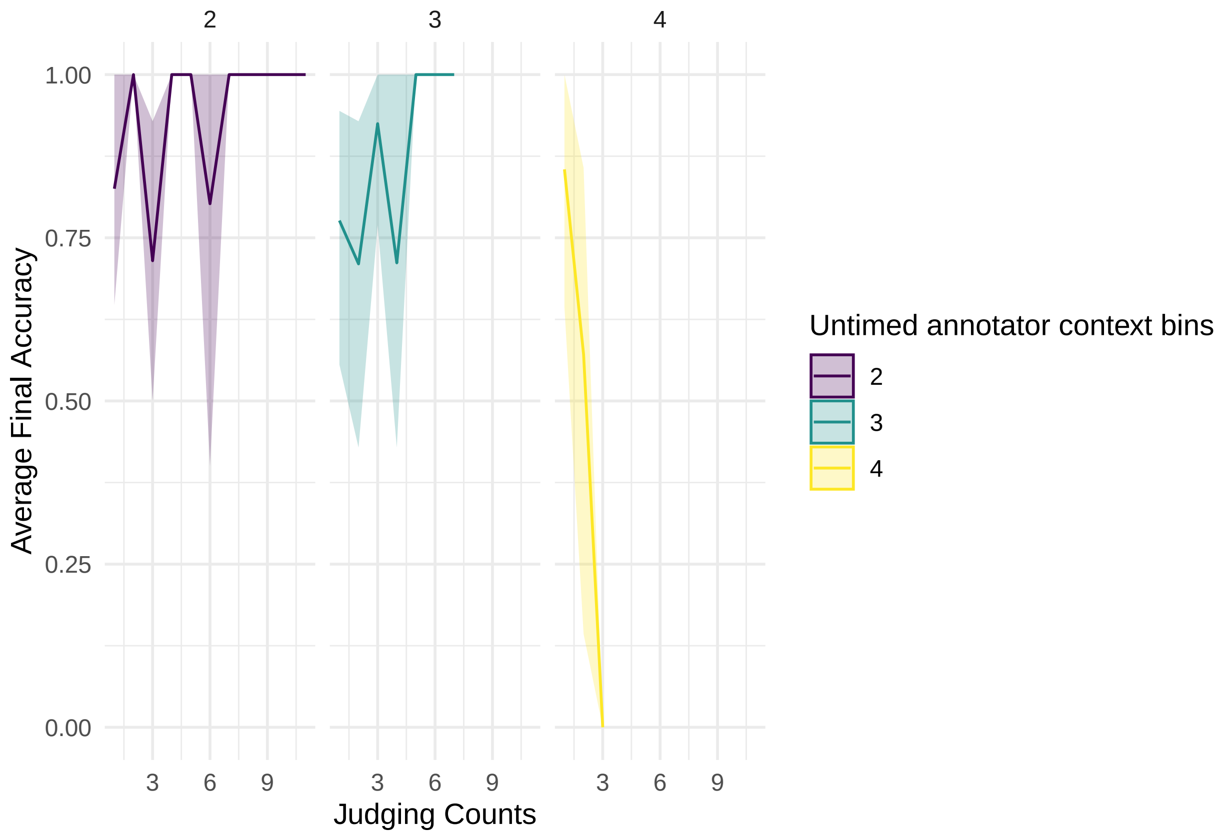
Judge "Experience"

```
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) +
```

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




```r
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`)
```



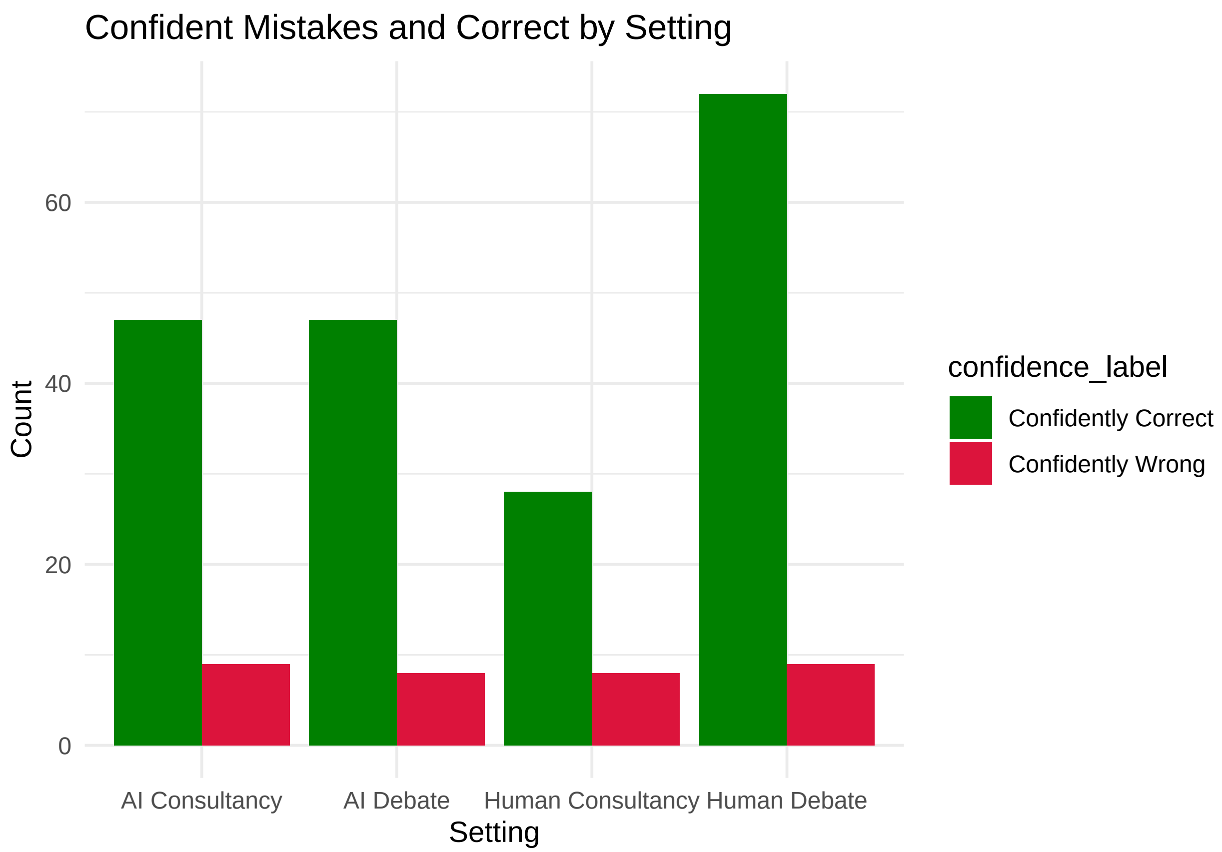
Calibration

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

```
library(ggplot2)
library(dplyr)

correctColor = "#008000"
incorrectColor = "#DC143C"

# Segregate confidently correct and confidently wrong
judgments_online$confidence_label <- case_when(
  judgments_online$`Final probability correct` > 0.95 ~ "Confidently Correct",
  judgments_online$`Final probability correct` < 0.05 ~ "Confidently Wrong",
  TRUE ~ "Neutral"
)

# Filter out only the rows with confidently correct and confidently wrong labels
filtered_data <- judgments_online %>%
  filter(confidence_label != "Neutral")

# Count the occurrences for each setting and confidence label
count_data <- filtered_data %>%
  group_by(`Final_Setting`, confidence_label) %>%
  summarise(count = n())
```

```
## ‘summarise()‘ has grouped output by ’Final_Setting’. You can override using the
## ‘.groups‘ argument.
```

```
# Plot
ggplot(count_data, aes(x = `Final_Setting`, y = count, fill = confidence_label)) +
  geom_bar(stat = "identity", position = "dodge") +
  scale_fill_manual(values = c("Confidently Correct" = correctColor, "Confidently Wrong" = incorrectCol
  labs(title = "Confident Mistakes and Correct by Setting", y = "Count", x = "Setting") +
  theme_minimal()
```

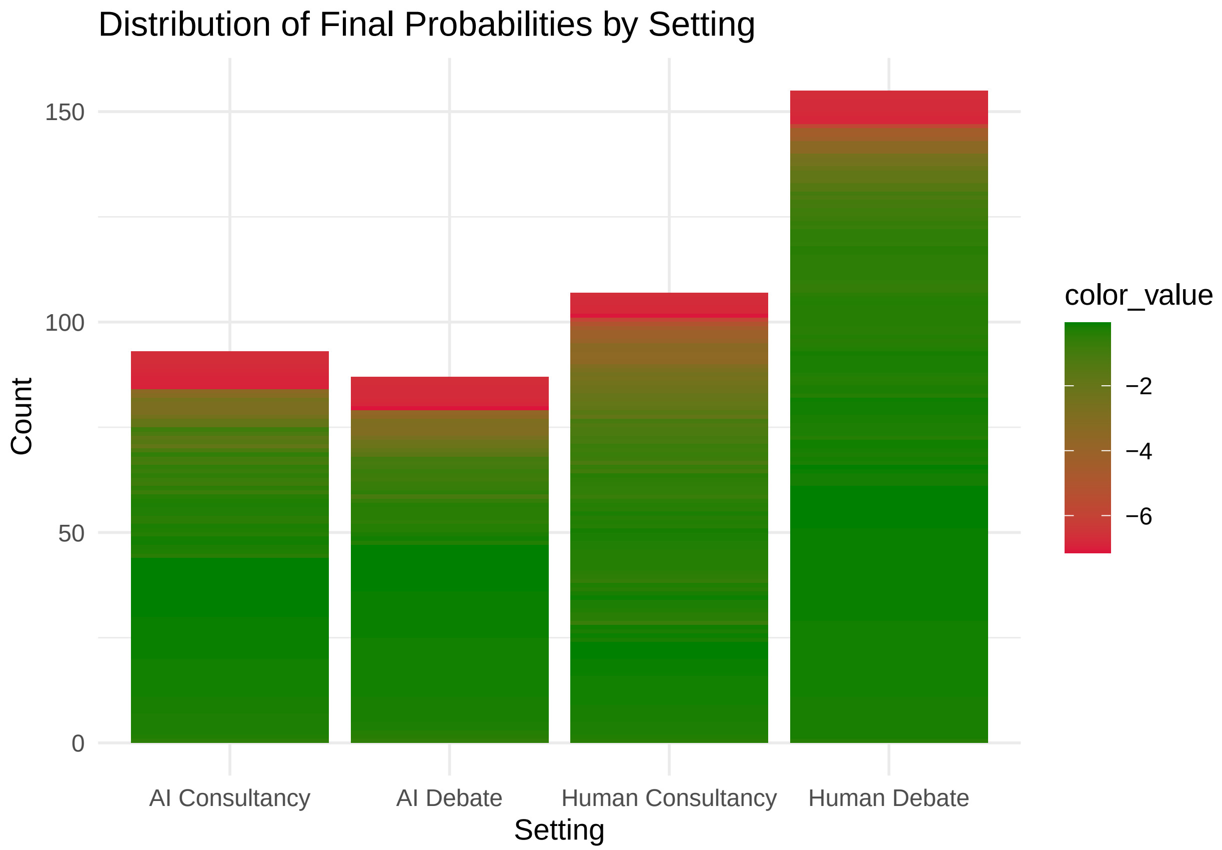



```
# Calculate the color value for each row
judgments_online$color_value <- log2(judgments_online$`Final probability correct`) - (0.05 * judgments_

# Count the occurrences for each setting and 'Final probability correct' value
count_data <- judgments_online %>%
  group_by(`Final_Setting`, `Final probability correct`, color_value) %>%
  summarise(count = n())
```

```
## ‘summarise()‘ has grouped output by ’Final_Setting’, ’Final probability
## correct’. You can override using the ‘.groups‘ argument.
```

```
# Plot
ggplot(count_data, aes(x = `Final_Setting`, y = count, fill = color_value, group = `Final probability c
  geom_bar(stat = "identity", position = "stack") +
  scale_fill_gradient(low = "#DC143C", high = "#008000") +  # Adjust as needed
```

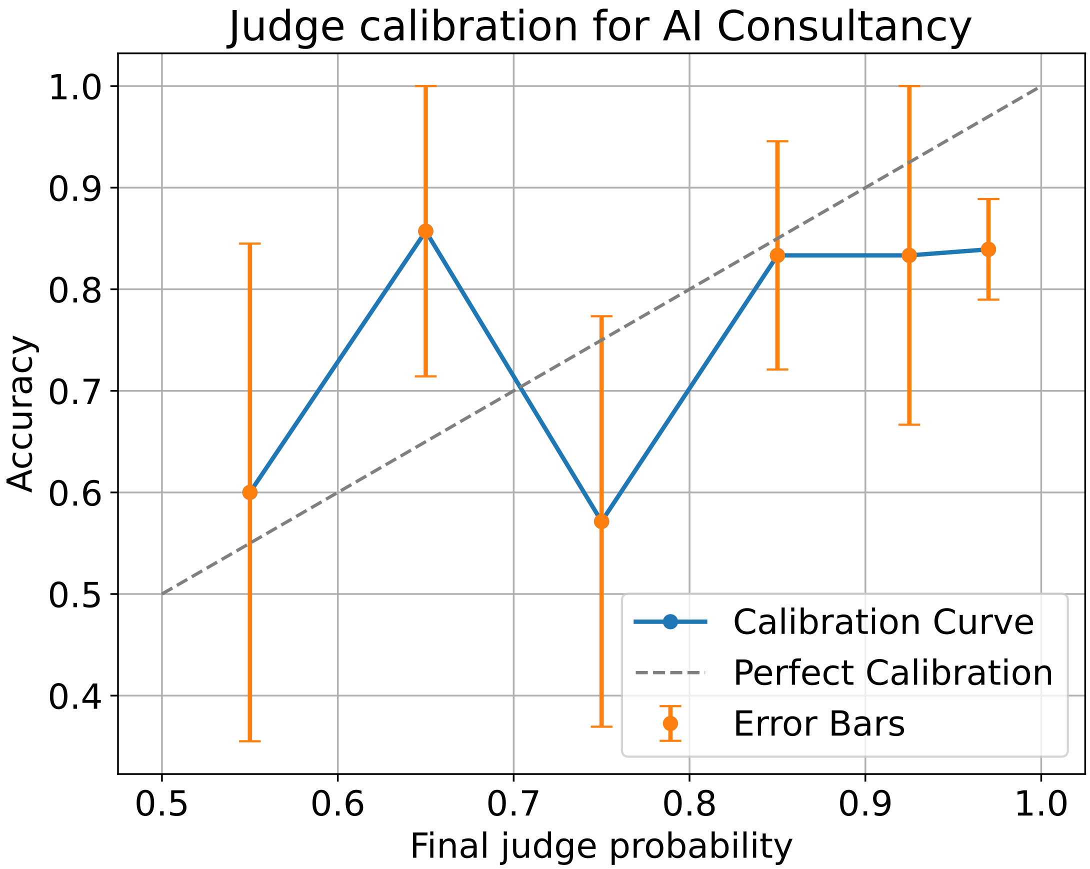
```
  labs(title = "Distribution of Final Probabilities by Setting", y = "Count", x = "Setting") +
  theme_minimal()
```



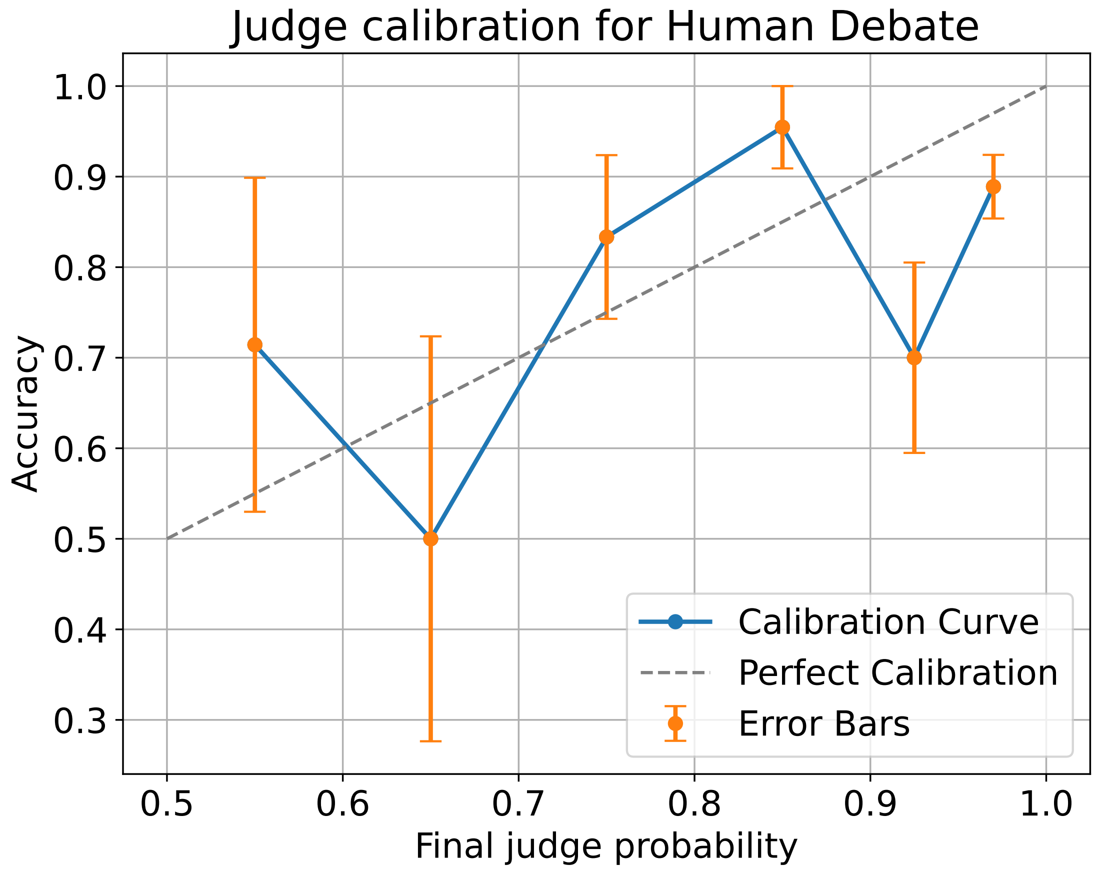

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.calibration import calibration_curve

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')
    ax.set_ylabel('Accuracy')
```

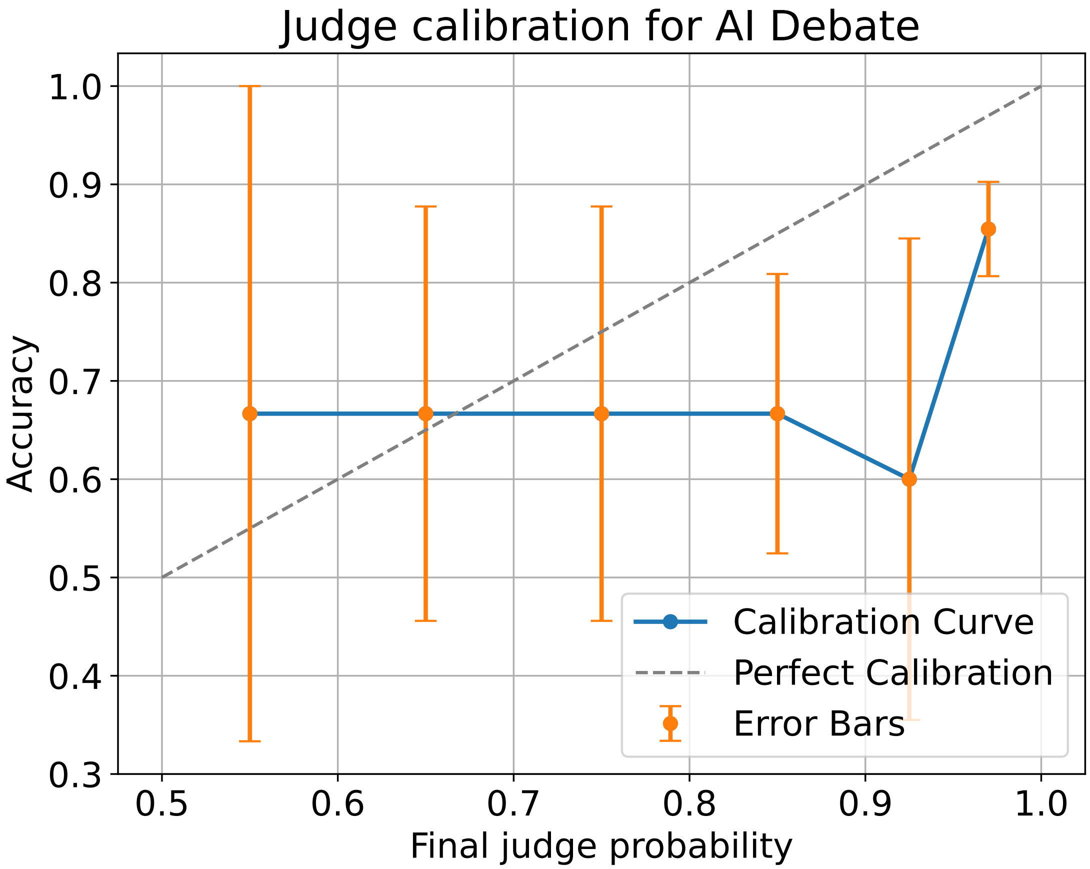
```python
    ax.set_title(f'Judge calibration for {setting_name}')
    ax.plot([0.5, 1], [0.5, 1], linestyle='--', color='gray', label='Perfect Calibration')
    ax.grid(True)
    ax.legend()
    # Calculate ECE
    actual_labels = df['outcome'].values
    predicted_probs = df['Final probability correct'].values
    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)
```

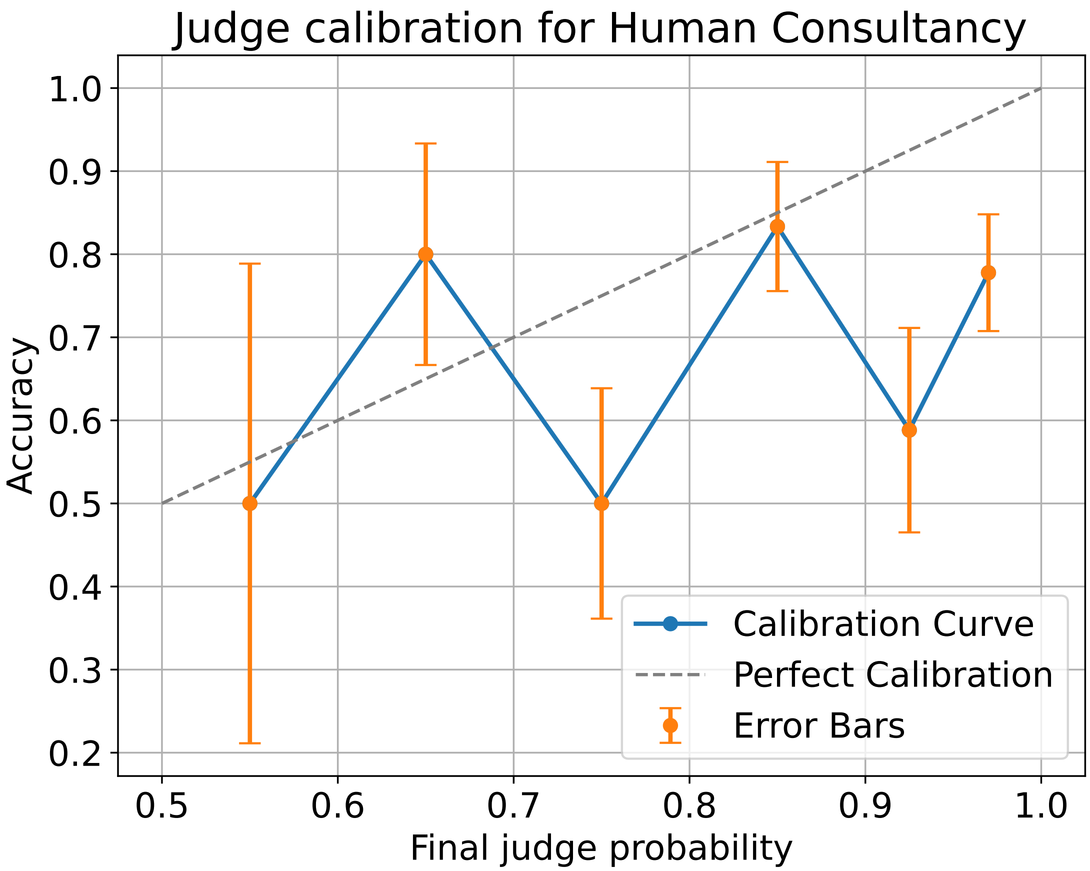
```
## Expected Calibration Error (ECE) for AI Consultancy: 0.0213
## Expected Calibration Error (ECE) for Human Debate: 0.0152
## Expected Calibration Error (ECE) for AI Debate: 0.0268
## Expected Calibration Error (ECE) for Human Consultancy: 0.0220
##
## <string>:4: UserWarning: Boolean Series key 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
Accuracy
Final judge probability
Calibration Curve
Perfect Calibration
Error Bars
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.5
0.6
0.7
0.8
0.9
1.0


Judge calibration for Human Debate
Accuracy
Final judge probability
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
Calibration Curve
Perfect Calibration
Error Bars


Judge calibration for AI 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 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"
```

```r
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              FALSE                0.2000000
## 289            FALSE   TRUE              FALSE                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_setting
## 146                                               0.5
## 214                                               0.5
## 289                                               0.5
##     sampled_consultancies_all_debates_weights_grouped_setting
## 146                                                       0.5
## 214                                                       0.5
## 289                                                       0.5
##     sampled_consultancies_debates_weights
## 146                             0.0000000
## 214                             0.3333333
## 289                             0.5000000
##     sampled_consultancies_debates_weights_setting
## 146                                             0
## 214                                             1
## 289                                             1
##     sampled_consultancies_debates_weights_grouped_setting  fpc
## 146                                                     0 0.33
## 214                                                     1 0.01
## 289                                                     1 0.01
##      confidence_label color_value
## 146           Neutral   -1.849462
## 214 Confidently Wrong   -6.743856
## 289 Confidently Wrong   -6.743856
```

```
# 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-
## 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 me
##     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
```

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## 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 i
## 43                                                                                     Whic
## 78                                                                             How did Eart
## 81                                                                         Why does Koroby
## 91                                                                Did the questions Tremain
## 94                                                                  Why did the physicist a
## 99                                                                        What was the bl
## 113                                                                             What is l
## 136                                                                                Why wa
## 140
## 149                                                       Why was the main character daydream
## 177                                                       Generally, which of the following b
## 179                                                                 Which of these sets of d
## 185                                                                           What was the
## 186
## 191
## 202                                                                  Why do Bob and Quezy h
## 211
## 215                                                                 Why was Dr. Crander so
## 216                                                                 What is not a type techn
## 219                                        What best describes how the overall tone changed f
## 236                                                            What would best describe Asa's
## 240                                                                         Why did the Earth
## 241                                                                Who are the four to blame
## 254                                                      What did Zen think of the plan the r
## 270                                                    Why is Grannie Annie so concerned abo
## 276                                                                      How many compan
```

```
## 290                                                                                                                   Who are the four to blame
## 306                                                                                                                   What was the population o
## 324                                                                                                                                       Which i
## 331                                                                                                                            Why does Koroby 
## 332                                                                                                  How did the planet of Niobe compare to
## 338                                                                                                               Which best describes the relat
## 342                                                                                                          What is the relationship between 
## 348                                                                                                                                What is the 
## 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              FALSE                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              FALSE                1.0000000
## 149            FALSE  FALSE              FALSE                0.2500000
## 177            FALSE  FALSE              FALSE                0.5000000
## 179            FALSE  FALSE              FALSE                0.5000000
## 185            FALSE   TRUE              FALSE                1.0000000
## 186            FALSE  FALSE              FALSE                0.5000000
## 191            FALSE  FALSE              FALSE                0.2000000
## 202            FALSE  FALSE              FALSE                0.5000000
## 211            FALSE   TRUE              FALSE                0.5000000
## 215            FALSE   TRUE              FALSE                1.0000000
## 216            FALSE  FALSE              FALSE                0.5000000
## 219            FALSE   TRUE              FALSE                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              FALSE                1.0000000
## 276            FALSE   TRUE              FALSE                0.5000000
## 290            FALSE   TRUE              FALSE                0.2500000
## 306            FALSE  FALSE              FALSE                0.5000000
## 324            FALSE   TRUE              FALSE                0.5000000
## 331            FALSE   TRUE              FALSE                0.2500000
## 332            FALSE   TRUE              FALSE                0.5000000
## 338            FALSE   TRUE              FALSE                0.5000000
## 342            FALSE  FALSE              FALSE                0.5000000
## 348            FALSE   TRUE              FALSE                1.0000000
## 356            FALSE   TRUE              FALSE                0.3333333
## 366            FALSE  FALSE              FALSE                0.2500000
## 378            FALSE   TRUE              FALSE                0.3333333
## 387            FALSE  FALSE              FALSE                0.5000000
## 401            FALSE  FALSE              FALSE                0.2500000
## 411            FALSE  FALSE              FALSE                0.5000000
## 414            FALSE   TRUE              FALSE                0.5000000
## 421            FALSE   TRUE              FALSE                1.0000000
## 424            FALSE   TRUE              FALSE                0.5000000
## 425            FALSE   TRUE              FALSE                0.3333333
## 429            FALSE  FALSE              FALSE                0.2000000
## 431            FALSE   TRUE              FALSE                1.0000000
## 433            FALSE   TRUE              FALSE                0.3333333
## 436            FALSE   TRUE              FALSE                1.0000000
## 439            FALSE   TRUE              FALSE                0.2500000
```

```
## 448           FALSE   TRUE             FALSE                0.2000000
## 510           FALSE   TRUE             FALSE                0.1666667
## 533           FALSE   TRUE             FALSE                0.5000000
## 538           FALSE   TRUE             FALSE                0.5000000
## 544           FALSE   TRUE             FALSE                1.0000000
## 550           FALSE   TRUE             FALSE                0.2500000
## 561           FALSE   TRUE             FALSE                0.2500000
## 598           FALSE   TRUE             FALSE                0.1428571
## 602           FALSE   TRUE             FALSE                0.5000000
## 606           FALSE   TRUE             FALSE                0.5000000
## 626           FALSE   TRUE             FALSE                0.2500000
## 637           FALSE   TRUE             FALSE                0.3333333
## 641           FALSE   TRUE             FALSE                0.3333333
## 647           FALSE   TRUE             FALSE                0.5000000
## 648           FALSE   TRUE             FALSE                0.2000000
## 658           FALSE   TRUE             FALSE                0.3333333
## 677           FALSE   TRUE             FALSE                0.3333333
## 679           FALSE   TRUE             FALSE                0.2500000
## 680           FALSE   TRUE             FALSE                1.0000000
## 683           FALSE   TRUE             FALSE                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_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_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_debates_weights
## 21                              0.0000000
## 43                              0.0000000
## 78                              0.0000000
## 81                              0.0000000
## 91                              0.2500000
## 94                              0.0000000
## 99                              0.0000000
## 113                             0.0000000
## 136                             0.0000000
## 140                             1.0000000
## 149                             0.0000000
## 177                             0.0000000
## 179                             0.0000000
## 185                             1.0000000
## 186                             0.0000000
## 191                             0.0000000
## 202                             0.0000000
## 211                             1.0000000
## 215                             1.0000000
```

```
## 216                           0.0000000
## 219                           0.2500000
## 236                           0.0000000
## 240                           0.0000000
## 241                           0.0000000
## 254                           0.0000000
## 270                           1.0000000
## 276                           1.0000000
## 290                           0.3333333
## 306                           0.0000000
## 324                           1.0000000
## 331                           0.5000000
## 332                           1.0000000
## 338                           1.0000000
## 342                           0.0000000
## 348                           1.0000000
## 356                           0.5000000
## 366                           0.0000000
## 378                           0.5000000
## 387                           0.0000000
## 401                           0.0000000
## 411                           0.0000000
## 414                           1.0000000
## 421                           1.0000000
## 424                           1.0000000
## 425                           0.5000000
## 429                           0.0000000
## 431                           1.0000000
## 433                           0.5000000
## 436                           1.0000000
## 439                           0.3333333
## 448                           0.3333333
## 510                           0.2500000
## 533                           0.5000000
## 538                           1.0000000
## 544                           1.0000000
## 550                           0.2500000
## 561                           0.5000000
## 598                           0.2500000
## 602                           0.5000000
## 606                           1.0000000
## 626                           0.3333333
## 637                           0.5000000
## 641                           0.5000000
## 647                           1.0000000
## 648                           0.3333333
## 658                           0.5000000
## 677                           0.5000000
## 679                           0.3333333
## 680                           1.0000000
## 683                           1.0000000
##     sampled_consultancies_debates_weights_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_grouped_setting  fpc
## 21                                                     0 0.70
## 43                                                     0 0.90
## 78                                                     0 0.99
## 81                                                     0 0.99
## 91                                                     1 0.98
## 94                                                     0 0.99
## 99                                                     0 0.85
## 113                                                    0 0.99
## 136                                                    0 0.99
## 140                                                    1 0.99
## 149                                                    0 0.85
## 177                                                    0 0.85
## 179                                                    0 0.90
## 185                                                    1 0.99
## 186                                                    0 0.95
## 191                                                    0 0.95
## 202                                                    0 0.90
## 211                                                    1 0.95
## 215                                                    1 0.80
## 216                                                    0 0.99
## 219                                                    1 0.80
## 236                                                    0 0.99
## 240                                                    0 0.90
## 241                                                    0 0.99
## 254                                                    0 0.95
## 270                                                    1 0.70
## 276                                                    1 0.99
## 290                                                    1 0.99
## 306                                                    0 0.99
## 324                                                    1 0.99
## 331                                                    1 0.99
## 332                                                    1 0.99
## 338                                                    1 0.99
## 342                                                    0 0.99
## 348                                                    1 0.85
## 356                                                    1 0.85
## 366                                                    0 0.95
## 378                                                    1 0.98
## 387                                                    0 0.88
```

```
## 401                                                                       0 0.96
## 411                                                                       0 0.99
## 414                                                                       1 0.99
## 421                                                                       1 0.99
## 424                                                                       1 0.99
## 425                                                                       1 0.99
## 429                                                                       0 0.99
## 431                                                                       1 0.99
## 433                                                                       1 0.99
## 436                                                                       1 0.99
## 439                                                                       1 0.95
## 448                                                                       1 0.99
## 510                                                                       1 0.99
## 533                                                                       1 0.98
## 538                                                                       1 0.90
## 544                                                                       1 0.98
## 550                                                                       1 0.99
## 561                                                                       1 0.95
## 598                                                                       1 0.94
## 602                                                                       1 0.91
## 606                                                                       1 0.86
## 626                                                                       1 0.97
## 637                                                                       1 0.95
## 641                                                                       1 0.99
## 647                                                                       1 0.99
## 648                                                                       1 0.99
## 658                                                                       1 0.99
## 677                                                                       1 0.80
## 679                                                                       1 0.75
## 680                                                                       1 0.75
## 683                                                                       1 0.80
##         confidence_label color_value
## 21               Neutral -0.71457317
## 43               Neutral -0.25200309
## 78  Confidently Correct -0.06449957
## 81  Confidently Correct -0.21449957
## 91  Confidently Correct -0.17914635
## 94  Confidently Correct -0.21449957
## 99               Neutral -0.43446525
## 113 Confidently Correct -0.21449957
## 136 Confidently Correct -0.21449957
## 140 Confidently Correct -0.11449957
## 149              Neutral -0.38446525
## 177              Neutral -0.38446525
## 179              Neutral -0.35200309
## 185 Confidently Correct -0.11449957
## 186              Neutral -0.27400058
## 191              Neutral -0.22400058
## 202              Neutral -0.25200309
## 211              Neutral -0.17400058
## 215              Neutral -0.42192809
## 216 Confidently Correct -0.11449957
## 219              Neutral -0.62192809
## 236 Confidently Correct -0.36449957
```

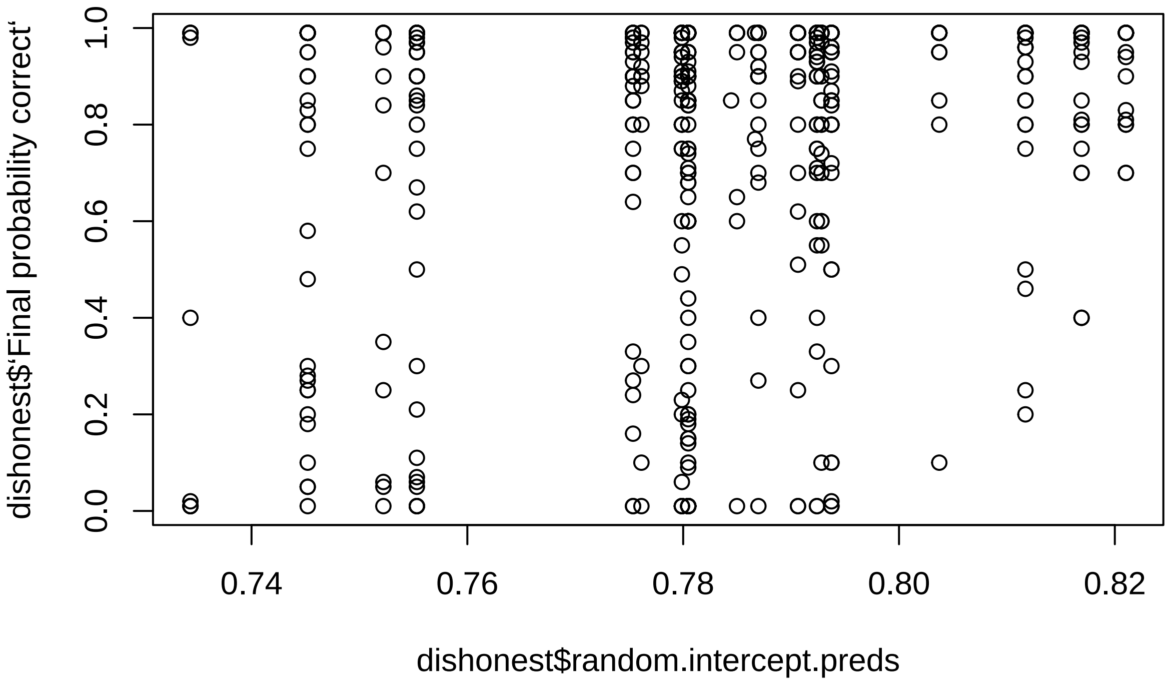
```
## 240             Neutral -0.30200309
## 241 Confidently Correct -0.16449957
## 254             Neutral -0.27400058
## 270             Neutral -0.61457317
## 276 Confidently Correct -0.11449957
## 290 Confidently Correct -0.06449957
## 306 Confidently Correct -0.11449957
## 324 Confidently Correct -0.16449957
## 331 Confidently Correct -0.11449957
## 332 Confidently Correct -0.11449957
## 338 Confidently Correct -0.16449957
## 342 Confidently Correct -0.21449957
## 348             Neutral -0.38446525
## 356             Neutral -0.43446525
## 366             Neutral -0.22400058
## 378 Confidently Correct -0.17914635
## 387             Neutral -0.38442457
## 401 Confidently Correct -0.15889369
## 411 Confidently Correct -0.11449957
## 414 Confidently Correct -0.11449957
## 421 Confidently Correct -0.16449957
## 424 Confidently Correct -0.16449957
## 425 Confidently Correct -0.16449957
## 429 Confidently Correct -0.21449957
## 431 Confidently Correct -0.11449957
## 433 Confidently Correct -0.16449957
## 436 Confidently Correct -0.21449957
## 439             Neutral -0.37400058
## 448 Confidently Correct -0.16449957
## 510 Confidently Correct -0.16449957
## 533 Confidently Correct -0.12914635
## 538             Neutral -0.25200309
## 544 Confidently Correct -0.07914635
## 550 Confidently Correct -0.16449957
## 561             Neutral -0.17400058
## 598             Neutral -0.13926734
## 602             Neutral -0.33606155
## 606             Neutral -0.41759144
## 626 Confidently Correct -0.19394335
## 637             Neutral -0.27400058
## 641 Confidently Correct -0.11449957
## 647 Confidently Correct -0.06449957
## 648 Confidently Correct -0.11449957
## 658 Confidently Correct -0.16449957
## 677             Neutral -0.47192809
## 679             Neutral -0.51503750
## 680             Neutral -0.56503750
## 683             Neutral -0.57192809
```

```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)
```

```r
# 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)
```

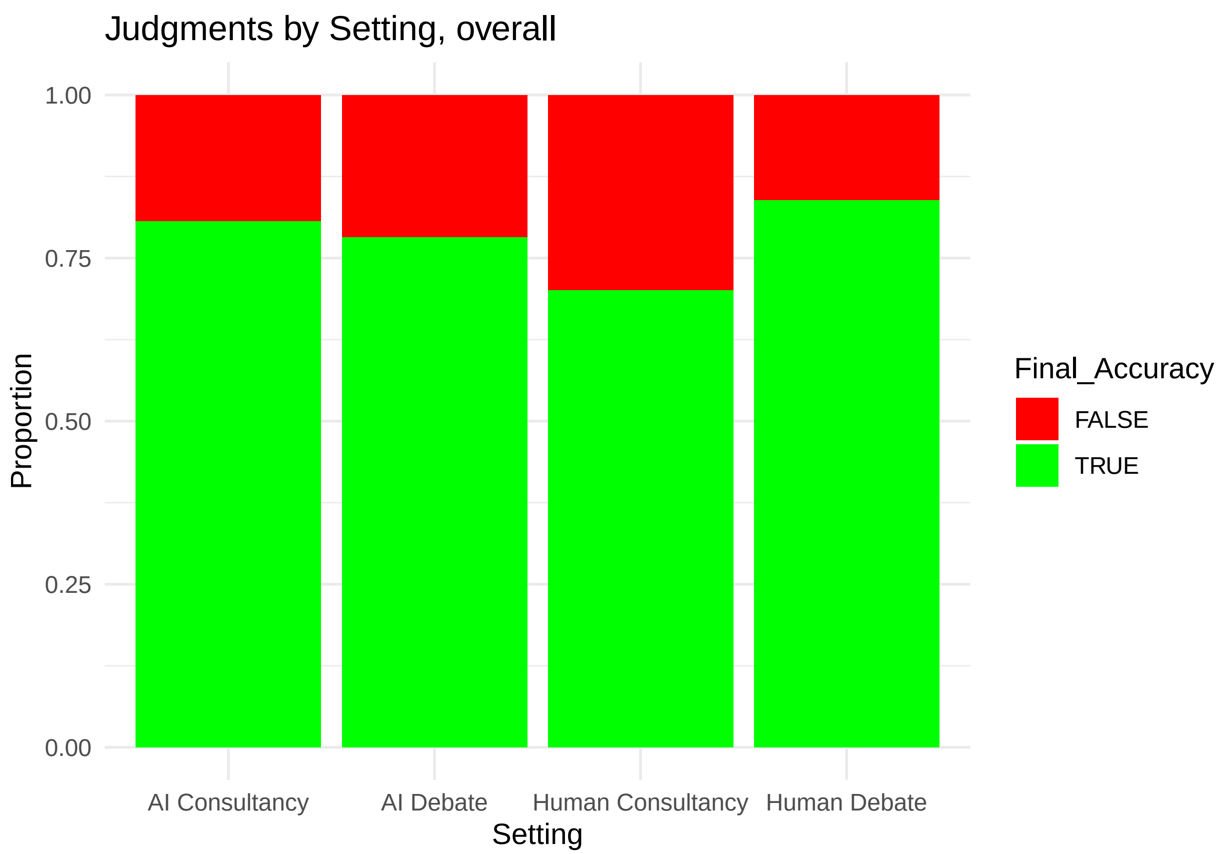
```
##
##         AI Consultancy AI Debate Human Consultancy Human Debate
##   FALSE             18        19                32           25
##   TRUE              75        68                75          130
```

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

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

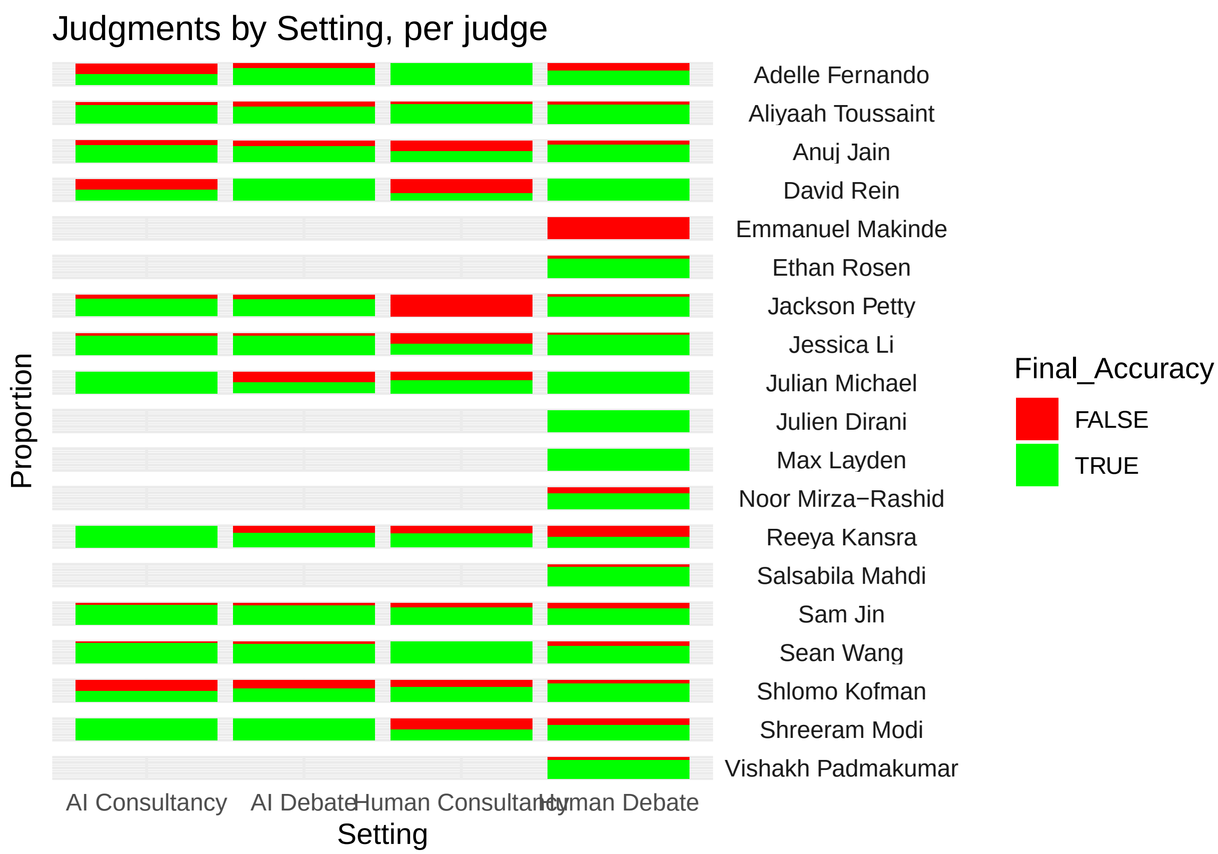
```
##
##           Human Consultancy Dishonest Human Consultancy Honest Human Debate
##    FALSE                           26                        6           25
##    TRUE                            33                       42          130
```

```r
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

```r
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
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
Proportion
AI Consultancy
AI Debate
Human Consultancy
Human Debate
Setting
Final_Accuracy
FALSE
TRUE