Pronominal Gender Biases in Natural Language Processing with ChatGPT

Half of the input data that I will use here are the co-called Winograd Schema used used elswhere in the coreference bias literature, namely [@wino-gender-2018] (data are made available at this GitHub repository; in turn these data have been reportedly compiled from the publicly available Winograd Schema Collection. The Winograd data consist of sentences where pronouns are naturally coreferrent with a previously occuring noun phrase. The noun phrases denote either generic participant roles (e.g. the visitor) or, importantly, professions that are (de facto) associated with the masculine or feminine grammatical gender by speakers of English and most NLP models that were trained on English sentences.

```
import pandas as pd

data = pd.read_csv('wino_gender_sentences.tsv',sep='\t')
```

```
wino_sentences = data["sentence"]
```

```
i = 0
for s in wino_sentences[0:30]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1
```

I have ChatGPT the following task and ask it to do coreference resolution for groups of a dozen sentences at a time.

> HI GhatGPT, could you find your solution and answer in the following format: "The woman said she is aware of the problem." => "she" == "the woman". (To clarify, the first sentence, which precedes the "=>" is the sentence that requires coreference resolution, and the equality expression that follows "=>" is the propounded solution.) Could you do that with three examples of your own choosing?

I also instructed ChatGpt to annotate coreferential expressions using numerical indices. The two kinds of annotations did not always match, so a further hurdle was to decide (via questions) which one of the coreferential annotations was the intended one.

After ChatGPT inserted the annotations, I followed with my own annoations, by including a score of 1 or 0 according to whether the coreferential reading is correct or not. These scores appear at the end of each sentence, between paretheses.

```
i = 30
for s in wino_sentences[30:60]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
```

```
    i += 1

i = 108
for s in wino_sentences[108:192]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 204
for s in wino_sentences[204:216]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 228
for s in wino_sentences[228:460]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 516
for s in wino_sentences[516:564]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 600
for s in wino_sentences[600:660]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 264
for s in wino_sentences[264:276]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1

i = 660
for s in wino_sentences[660:720]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1

# there are 720 sentences in the inital data set
# Note: due to the time-conuming nature of interacting with ChatGPT, I had to
# limit the size of the data set I analyse to a randomly selected sample about
# a half of these into ChatGPT. However, this sample is well-balanced as to the
# gender associated with the occupations and is large enought to enable us to draw
```

```
# some preliminary conclusions.
len(wino_sentences)
```

```
720
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import csv
import re

%matplotlib inline

# UK source (ONS 2021): https://www.nomisweb.co.uk/datasets/aps168/reports/employment-by-occ
# US source (BLS 2021): https://www.bls.gov/opub/reports/womens-databook/2021/home.htm
occupation_stats = {'secretary': {'f_count': 533_600, 'm_count': 51_600, 'f_percent_us': 0.9
                    'accountant': { 'f_count': 83_300, 'm_count': 110_100, 'f_percent_us': 0
                    'engineer': {'f_count': 68_300, 'm_count': 475_700, 'f_percent_us': 0.16
                    'technician': {'f_count': 2_297_100, 'm_count': 2_612_800, 'f_percent_us
                    # US data point is an average of multiple categories
                    'supervisor': {'f_count':162_700, 'm_count':43_400, 'f_percent_us': 0.30
                    # I take worker to be an elementary occupation (see source table)
                    # for the US, I take 'worker' to be a general labor category
                    'worker': {'f_count': 1_376_600, 'm_count': 1_693_600, 'f_percent_us': 0
                    'nurse': {'f_count': 494_900, 'm_count': 69_200, 'f_percent_us': 0.874},
                    # doctor interpreted as a health professional (see source table)
                    'doctor': {'f_count': 393_800, 'm_count': 265_800, 'f_percent_us': 0.744
                    # interpreted as a Customer Service Occupation (see source table)
                    'dispatcher': {'f_count': 305_400, 'm_count':190_700, 'f_percent_us': 0.
                    'cashier': {'f_count': 783_900, 'm_count': 444_600, 'f_percent_us': 0.73
                    # using a larger category as a proxy: Business, Research and Administrat
                    # Professionals (see source table)
                    'auditor': {'f_count': 390_600, 'm_count': 563_100, 'f_percent_us': 0.59
                    # using a proxy category:  Health professionals n.e.c.
                    'dietitian': {'f_count': 55_000, 'm_count': 15_100, 'f_percent_us': 0.91
                    # using the Artist category as a proxy (see source table)
                    'painter': {'f_count': 28_300, 'm_count': 15_500, 'f_percent_us': 0.535}
                    'broker': {'f_count': 9_200, 'm_count': 40_800, 'f_percent_us': 0.661},
                    'chef': {'f_count': 55_000, 'm_count': 140_200, 'f_percent_us': 0.18},
                    'firefighter': {'f_count': 4_700, 'm_count': 29_000, 'f_percent_us': 0.0
                    'pharmacist': {'f_count': 39_800, 'm_count': 26_000, 'f_percent_us': 0.6
                    'psychologist': {'f_count': 36_900, 'm_count': 9_500, 'f_percent_us': 0.
                    # ONS does not provide figures for female carpenters. here I'm using a f
                    # line with the proportion of women in the larger category of  Construct
                    # A figure that I found elsewhere confirms that this is a good estimate
                    # at https://careersmart.org.uk/occupations/equality/which-jobs-do-men-a
                    # which cites Working Futures 2021 (https://warwick.ac.uk/fac/soc/ier/re
```

```
                    'carpenter': {'f_count': 2_620, 'm_count': 183_700, 'f_percent_us': 0.03
                    'electrician': {'f_count': 4_100, 'm_count': 218_200, 'f_percent_us': 0.
                    'teacher': {'f_count': 1_130_000, 'm_count': 542_900, 'f_percent_us': 0.
                    'lawyer': {'f_count': 81_500, 'm_count': 61_100, 'f_percent_us': 0.374},
                    # ONS has not reliable figure for women plumbers, so I will be
                    # using the average of women employed in the larger category of Construc
                    'plumber': {'f_count': 1_936, 'm_count': 135_800, 'f_percent_us': 0.023}
                    # ONS does not provide figures for the specific category of surgeon
                    # I use specialist medical practitioner Category as a proxy; data from:
                    # https://www.statista.com/statistics/698260/registered-doctors-united-k
                    'surgeon': {'f_count': 39_788, 'm_count': 66_972, 'f_percent_us': 0.263}
                    'veterinarian': {'f_count': 11_500, 'm_count': 13_900, 'f_percent_us': 0
                    'paramedic': {'f_count': 15_400, 'm_count': 17_300, 'f_percent_us': 0.28
                    'architect': {'f_count': 4_600, 'm_count': 12_900, 'f_percent_us': 0.282
                    'hairdresser': {'f_count': 208_900, 'm_count': 36_800, 'f_percent_us': 0
                    'baker': {'f_count': 19_700        , 'm_count': 15_300, 'f_percent_us':
                    'programmer': {'f_count': 70_000, 'm_count': 397_100, 'f_percent_us': 0.
                    'mechanic': {'f_count': 7_500, 'm_count': 299_000, 'f_percent_us': 0.012
                    'manager': {'f_count': 1_227_500, 'm_count': 2_139_700, 'f_percent_us':
                    'therapist': {'f_count': 164_100, 'm_count': 35_000, 'f_percent_us': 0.8
                    'administrator': {'f_count':  1_843_100, 'm_count': 856_100, 'f_percent_
                    'salesperson': {'f_count': 935_100, 'm_count': 612_400, 'f_percent_us':
                    'receptionist': {'f_count': 171_200, 'm_count': 19_700, 'f_percent_us':
                    'librarian': {'f_count': 14_000, 'm_count': 7_400, 'f_percent_us': 0.832
                    }
# For clarification regarding the occupation categories used by ONS see
# https://www.ilo.org/public/english/bureau/stat/isco/docs/groupdefn08.pdf

def occupation_stats_update():
    """Produces a dict of dicts representing the UK employment counts and
    percentages by gender"""
    for occ in occupation_stats.keys():
        f_count = occupation_stats[occ]['f_count']
        m_count = occupation_stats[occ]['m_count']
        occupation_stats[occ]['f_percent'] = f_count / (f_count + m_count)
        occupation_stats[occ]['m_percent'] = m_count / (f_count + m_count)
    return occupation_stats

occupations = ['technician', 'accountant', 'supervisor', 'engineer', 'worker', 'nurse',
              'dispatcher', 'cashier', 'auditor', 'dietitian', 'painter', 'broker', 'chef',
              'doctor', 'firefighter', 'secretary', 'pharmacist', 'psychologist', 'teacher',
              'lawyer', 'plumber', 'surgeon', 'veterinarian', 'paramedic', 'baker', 'program
              'mechanic', 'manager', 'therapist', 'administrator', 'salesperson', 'reception
              'librarian', 'carpenter', 'electrician', 'hairdresser', 'architect']
occupations_info = {}
```

```python
data = []
with open('coref-data.txt') as text_data:
    for line in text_data:
        line.strip()
        #print(f"LINE: /{line}/")
        # pattern p matches lines with 3 sub-groups: sentence number, sentence str, score
        p = re.compile('^(\d+)\.\s*([ a-zA-Z0-9_,;\-\'"]+\.)\s*\((\d)\)')
        m = p.match(line)
        if not m:
            continue
        sentence_num = int(m.group(1))
        annotated_sentence = m.group(2)
        sentence_score = int(m.group(3))
        if sentence_num is not None and annotated_sentence and sentence_score is not None:
            datum = {}
            datum['num'] = sentence_num
            datum['sentence'] = annotated_sentence
            datum['score'] = sentence_score
            pf = re.compile('\s+(?:she|her)_')
            pm = re.compile('\s+(?:he|him|his)_')
            pn = re.compile('\s+(?:they|them|their)_')
            if pf.search(line):
                datum['gender'] = 'f'
            elif pm.search(line):
                datum['gender'] = 'm'
            elif pn.search(line):
                datum['gender'] = 'n'
            for occ in occupations:
                p = re.compile(f"{occ}")
                if p.search(line):
                    datum['occupation'] = occ
            data.append(datum)


df = pd.DataFrame(data)
#df.loc[df['num'] == 1]

def collect_occupation_info(surveyed_data="valid"):
    """Produces a dict of dicts encoding gender employment by occupation.
    The optional surveyed_data argument controls whether we look for gender biases
    in the coreference resolutions that are valid, or in all resolutions, whether
    they are valid or not."""
    i = 0
    for occ in occupations:
        occ_entries = df.loc[df['occupation'] == occ]
        # counting all sentences per occupation, not only the valid ones (as to coref resol
```

```
        occ_num = len(occ_entries)
        if surveyed_data == "valid":
            fs_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'f') & (df
            ms_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'm') & (df
            ns_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'n') & (df
        elif surveyed_data == "all":
            fs_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'f')])
            ms_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'm')])
            ns_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender'] == 'n')])
        d = {}
        d['name'] = occ
        d['num'] = occ_num
        d['f_percent'] = fs_with_occ / occ_num
        d['m_percent'] = ms_with_occ / occ_num
        d['n_percent'] = ns_with_occ / occ_num
        # normalized difference between f% and m% (f%, m% themselves will be normalized bel
        d['fm_delta'] = (d['f_percent'] - d['m_percent']) / (d['f_percent'] + d['m_percent']
        # f% and m% for occ in UK employment stats
        d['f_percent_uk'] = occupation_stats_update()[occ]['f_percent']
        d['m_percent_uk'] = occupation_stats_update()[occ]['m_percent']
        d['fm_delta_uk'] = d['f_percent_uk'] - d['m_percent_uk']
        # f% and m% for occ in US employment stats
        d['f_percent_us'] = occupation_stats_update()[occ]['f_percent_us']
        d['m_percent_us'] = 1.00 - d['f_percent_us']
        d['fm_delta_us'] = d['f_percent_us'] - d['m_percent_us']
        occupations_info[i] = d
        i += 1
        #print(f"{occ}: {occ_num} ({fs_with_occ / occ_num} F, {fs_with_occ / occ_num} M)")
    return occupations_info

oinfo = collect_occupation_info(surveyed_data="valid") # all / valid


# using dictionary to convert specific columns
convert_dict = {'num': int,
                #'f_count': int,
                #'m_count': int,
                'f_percent': float,
                'm_percent': float,
                'n_percent': float,
                'fm_delta': float,
                'fm_delta_uk': float,
                'f_percent_uk': float,
                'm_percent_uk': float,
                'fm_delta_us': float,
                'f_percent_us': float,
```

```
                'm_percent_us': float
               }

#df = df.astype(convert_dict)

occ_df = pd.DataFrame(oinfo).transpose()
occ_stats_df = pd.DataFrame(occupation_stats_update()).transpose()
occ_df = occ_df.astype(convert_dict)
# save a copy of the data with non-normalized %f and %m
occ_df_nonnormalized = occ_df.copy()


# normalize f_percent and m_percent columns s.t. their rows add up to 1
f_col = occ_df.apply(lambda x: x["f_percent"] / (x["f_percent"] + x["m_percent"]), axis=1)
m_col = occ_df.apply(lambda x: x["m_percent"] / (x["f_percent"] + x["m_percent"]), axis=1)
occ_df["f_percent"] = f_col
occ_df["m_percent"] = m_col
occ_df = occ_df.drop('n_percent', axis=1)

occ_df_nonnormalized
```

```
             name  num  f_percent  m_percent  n_percent  fm_delta  \
0      technician   12   0.333333   0.166667   0.333333  0.333333
1      accountant   12   0.333333   0.333333   0.333333  0.000000
2      supervisor   12   0.333333   0.333333   0.333333  0.000000
3        engineer   12   0.166667   0.166667   0.166667  0.000000
4          worker   12   0.333333   0.166667   0.333333  0.333333
5           nurse   12   0.250000   0.166667   0.250000  0.200000
6      dispatcher   12   0.166667   0.166667   0.166667  0.000000
7         cashier   12   0.166667   0.166667   0.166667  0.000000
8         auditor   12   0.333333   0.333333   0.333333  0.000000
9       dietitian   12   0.333333   0.333333   0.333333  0.000000
10        painter   12   0.166667   0.166667   0.166667  0.000000
11         broker   14   0.357143   0.357143   0.285714  0.000000
12           chef   12   0.166667   0.166667   0.166667  0.000000
13         doctor   12   0.333333   0.333333   0.333333  0.000000
14    firefighter   12   0.250000   0.250000   0.250000  0.000000
15      secretary   12   0.250000   0.166667   0.166667  0.200000
16     pharmacist   12   0.333333   0.333333   0.333333  0.000000
17    psychologist  12   0.166667   0.166667   0.166667  0.000000
18        teacher   12   0.166667   0.166667   0.166667  0.000000
19         lawyer   12   0.250000   0.250000   0.250000  0.000000
20        plumber   12   0.333333   0.166667   0.166667  0.333333
21        surgeon   12   0.166667   0.166667   0.166667  0.000000
22    veterinarian  12   0.333333   0.333333   0.333333  0.000000
23       paramedic  12   0.333333   0.333333   0.333333  0.000000
```

24	baker	12	0.166667	0.166667	0.166667	0.000000
25	programmer	12	0.166667	0.166667	0.166667	0.000000
26	mechanic	12	0.333333	0.333333	0.333333	0.000000
27	manager	12	0.333333	0.333333	0.333333	0.000000
28	therapist	12	0.333333	0.333333	0.333333	0.000000
29	administrator	12	0.166667	0.166667	0.166667	0.000000
30	salesperson	12	0.166667	0.166667	0.166667	0.000000
31	receptionist	12	0.166667	0.166667	0.166667	0.000000
32	librarian	12	0.166667	0.166667	0.166667	0.000000
33	carpenter	12	0.333333	0.166667	0.333333	0.333333
34	electrician	12	0.333333	0.333333	0.333333	0.000000
35	hairdresser	12	0.166667	0.166667	0.166667	0.000000
36	architect	12	0.166667	0.166667	0.166667	0.000000

	f_percent_uk	m_percent_uk	fm_delta_uk	f_percent_us	m_percent_us	\
0	0.467851	0.532149	-0.064299	0.032	0.968	
1	0.430714	0.569286	-0.138573	0.597	0.403	
2	0.789423	0.210577	0.578845	0.300	0.700	
3	0.125551	0.874449	-0.748897	0.165	0.835	
4	0.448375	0.551625	-0.103251	0.500	0.500	
5	0.877327	0.122673	0.754653	0.874	0.126	
6	0.615602	0.384398	0.231203	0.508	0.492	
7	0.638095	0.361905	0.276190	0.731	0.269	
8	0.409563	0.590437	-0.180874	0.597	0.403	
9	0.784593	0.215407	0.569187	0.914	0.086	
10	0.646119	0.353881	0.292237	0.535	0.465	
11	0.184000	0.816000	-0.632000	0.661	0.339	
12	0.281762	0.718238	-0.436475	0.180	0.820	
13	0.597029	0.402971	0.194057	0.744	0.256	
14	0.139466	0.860534	-0.721068	0.044	0.956	
15	0.911825	0.088175	0.823650	0.929	0.071	
16	0.604863	0.395137	0.209726	0.616	0.384	
17	0.795259	0.204741	0.590517	0.803	0.197	
18	0.675474	0.324526	0.350947	0.735	0.265	
19	0.571529	0.428471	0.143058	0.374	0.626	
20	0.014056	0.985944	-0.971888	0.023	0.977	
21	0.372686	0.627314	-0.254627	0.263	0.737	
22	0.452756	0.547244	-0.094488	0.649	0.351	
23	0.470948	0.529052	-0.058104	0.281	0.719	
24	0.562857	0.437143	0.125714	0.641	0.359	
25	0.149861	0.850139	-0.700278	0.211	0.789	
26	0.024470	0.975530	-0.951060	0.012	0.988	
27	0.364546	0.635454	-0.270908	0.404	0.596	
28	0.824209	0.175791	0.648418	0.844	0.156	
29	0.682832	0.317168	0.365664	0.717	0.283	
30	0.604265	0.395735	0.208530	0.487	0.513	

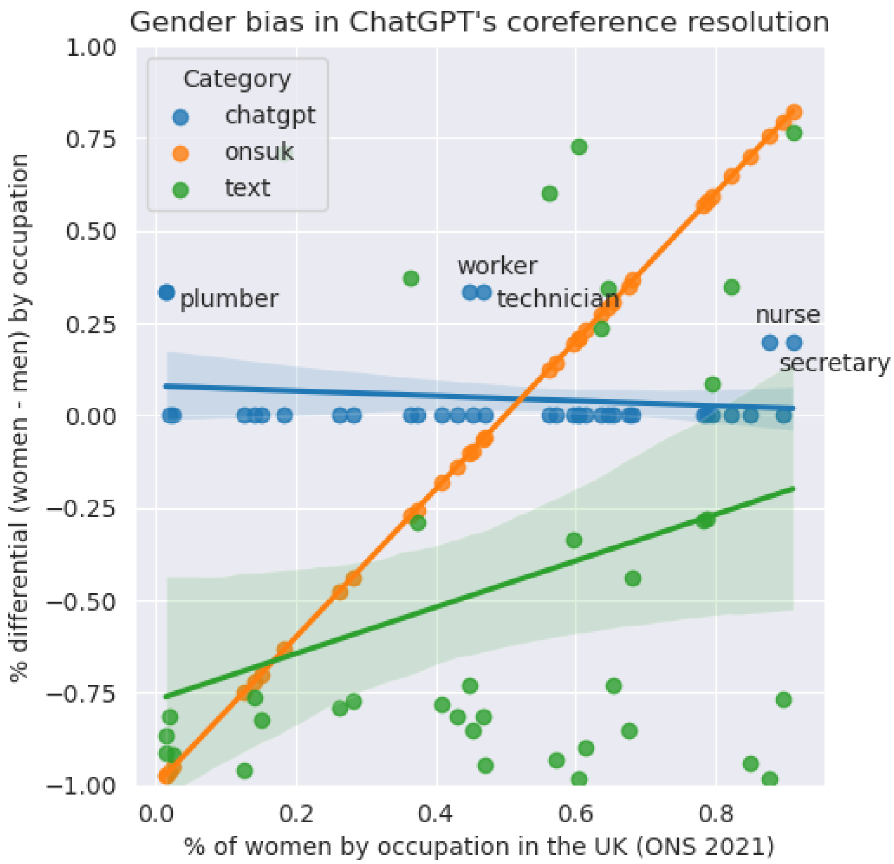
31	0.896805	0.103195	0.793609	0.883	0.117
32	0.654206	0.345794	0.308411	0.832	0.168
33	0.014062	0.985938	-0.971876	0.032	0.968
34	0.018444	0.981556	-0.963113	0.031	0.969
35	0.850224	0.149776	0.700448	0.908	0.092
36	0.262857	0.737143	-0.474286	0.282	0.718

	fm_delta_us
0	-0.936
1	0.194
2	-0.400
3	-0.670
4	0.000
5	0.748
6	0.016
7	0.462
8	0.194
9	0.828
10	0.070
11	0.322
12	-0.640
13	0.488
14	-0.912
15	0.858
16	0.232
17	0.606
18	0.470
19	-0.252
20	-0.954
21	-0.474
22	0.298
23	-0.438
24	0.282
25	-0.578
26	-0.976
27	-0.192
28	0.688
29	0.434
30	-0.026
31	0.766
32	0.664
33	-0.936
34	-0.938
35	0.816
36	-0.436

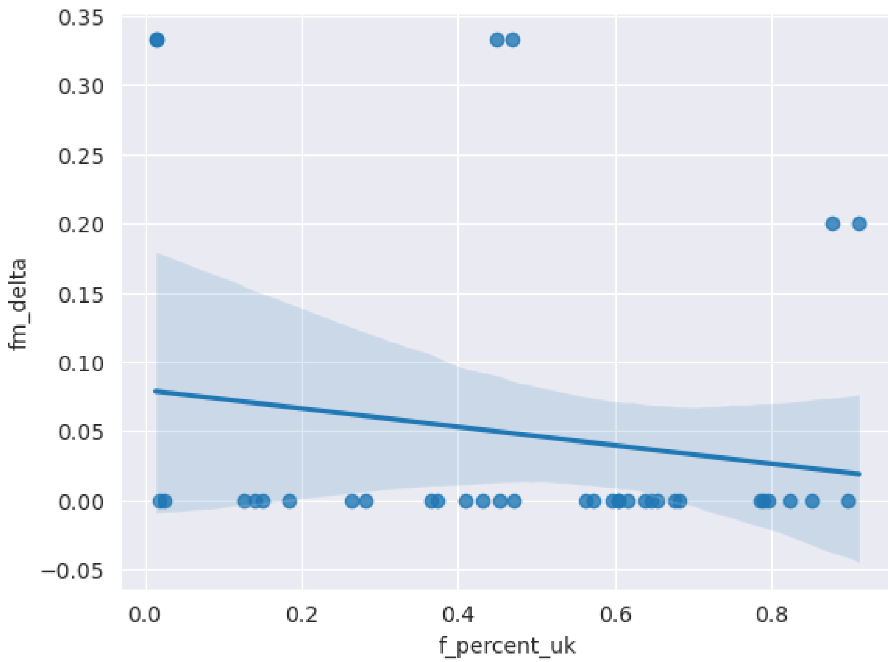
```python
# edit the data frames for display


def get_bergsma_data():
    bergsma_data = []
    with open('occupations-stats.tsv') as csv_file:
        csv_data = csv.reader(csv_file, delimiter='\t')
        # row shape: ['occupation', 'bergsma_pct_female', 'bls_pct_female', 'bls_year']
        for row in csv_data:
            d = {}
            if row[0] in occupations:
                d['name'] = row[0] # occupation name
                d['f_percent_bergsma'] = float(row[1]) / 100
                # f + m = 100 => f - m = 100 - 2m = 100 - 2 (100 - f) = -100 + 2f
                # => f - m = 2f - 100
                d['fm_delta_bergsma'] = 2 * d['f_percent_bergsma'] - 1.00
                bergsma_data.append(d)
    return bergsma_data

bergsma_data_df = pd.DataFrame(get_bergsma_data())
bergsma_data_df = bergsma_data_df.astype({"name": str, "f_percent_bergsma": float})

# Plot chatgpt coreference resolution data vs uk employment data
occ_diffs_chatgpt_df = occ_df.loc[:, ["name", "fm_delta"]]
occ_diffs_onsuk_df = occ_df.loc[:, ["name", "fm_delta_uk"]]
occ_diffs_blsus_df = occ_df.loc[:, ["name", "fm_delta_us"]]
occ_diffs_bergsma_df = bergsma_data_df.loc[:, ["name", "fm_delta_bergsma"]]
# rename column so both dfs have the same column names (used to concatenate dfs)
occ_diffs_onsuk_df = occ_diffs_onsuk_df.rename(columns={"fm_delta_uk": "fm_delta"})
occ_diffs_blsus_df = occ_diffs_blsus_df.rename(columns={"fm_delta_us": "fm_delta"})
occ_diffs_bergsma_df = occ_diffs_bergsma_df.rename(columns={"fm_delta_bergsma": "fm_delta"}
# build lists to be used as category columns
category_col_chatgpt = ['chatgpt'] * len(occ_df)
category_col_onsuk = ['onsuk'] * len(occ_df)
category_col_blsus = ['blsus'] * len(occ_df)
category_col_text = ['text'] * len(occ_df)
# first df: chatgpt data
occ_diffs_chatgpt_df["category"] = category_col_chatgpt
occ_diffs_chatgpt_df["f_stats_uk"] = occ_df["f_percent_uk"] # stats_uk is used for the x ax
# second df: ons uk data
occ_diffs_onsuk_df["category"] = category_col_onsuk
occ_diffs_onsuk_df["f_stats_uk"] = occ_df["f_percent_uk"] # stats_uk is used for the x axis
# third df: text data (from bergsma)
occ_diffs_bergsma_df["category"] = category_col_text
occ_diffs_bergsma_df["f_stats_uk"] = occ_df["f_percent_uk"] # stats_uk is used for the x ax
# concatenate the three dfs
```

```
occ_diffs = pd.concat([occ_diffs_chatgpt_df, occ_diffs_onsuk_df, occ_diffs_bergsma_df],
                      ignore_index=True)


# alternative x axis with US data
# first df: chatgpt data
occ_diffs_chatgpt_df = occ_diffs_chatgpt_df.rename(columns={"f_stats_uk": "f_stats_us"})
occ_diffs_chatgpt_df["f_stats_us"] = occ_df["f_percent_us"] # stats_us is used for the x ax
# second df: bls us data
occ_diffs_blsus_df["category"] = category_col_blsus
occ_diffs_blsus_df["f_stats_us"] = occ_df["f_percent_us"] # stats_us is used for the x axis
# third df: text data (from bergsma)
occ_diffs_bergsma_df = occ_diffs_bergsma_df.rename(columns={"f_stats_uk": "f_stats_us"})
occ_diffs_bergsma_df["f_stats_us"] = occ_df["f_percent_us"] # stats_us is used for the x ax
# concatenate US data with the other two dfs
occ_diffs_us = pd.concat([occ_diffs_chatgpt_df, occ_diffs_blsus_df, occ_diffs_bergsma_df],
                      ignore_index=True)

sns.set_style('darkgrid')
plt = sns.lmplot(data=occ_diffs, x='f_stats_uk', y='fm_delta', hue='category', legend=False)
plt.set(xlabel='% of women by occupation in the UK (ONS 2021)', ylabel='% differential (wome
plt.set(title="Gender bias in ChatGPT's coreference resolution")
plt.set(ylim=(-1.0, 1.0))
plt.axes[0,0].legend(loc='upper left', title='Category')

def label_point(x, y, val, ax):
    ax = ax.axes[0,0]
    a = pd.concat({'x': x, 'y': y, 'val': val}, axis=1)
    for i, point in a.iterrows():
        if point['val'] in ['plumber', 'worker', 'technician', 'nurse', 'secretary']:
            if point['val'] in ['worker', 'nurse']:
                ax.text(point['x']-.02, point['y']+.05, str(point['val']))
            elif point['val'] == 'secretary':
                ax.text(point['x']-.02, point['y']-.08, str(point['val']))
            else: # plumber
                ax.text(point['x']+.02, point['y']-.04, str(point['val']))

label_point(occ_df.f_percent_uk, occ_df.fm_delta, occ_df.name, plt)


#occ_diffs_blsus_df
#occ_diffs_us
#occ_diffs
#print(occ_diffs.to_string())
#bergsma_data_df
```

```python
#occ_stats_df
#occ_df
#occ_sorted

#print(occupations_info)
```

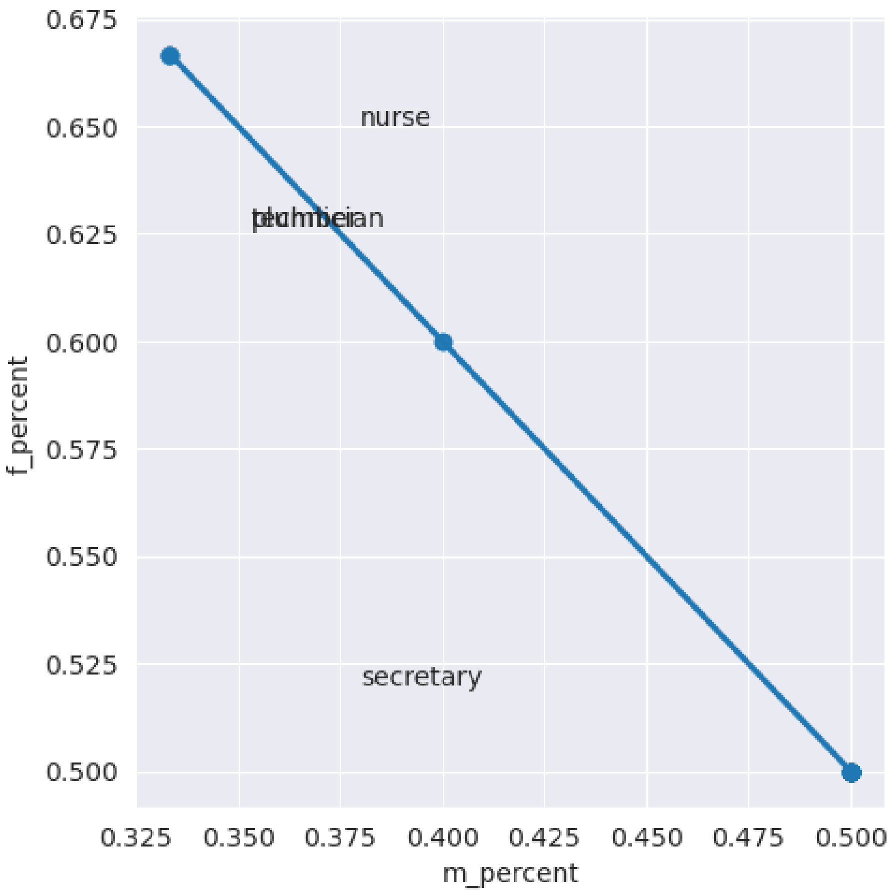



```python
# alternative ploting of the ChatGPT data
occ_df
sns.regplot(x="f_percent_uk", y="fm_delta", data=occ_df);
```

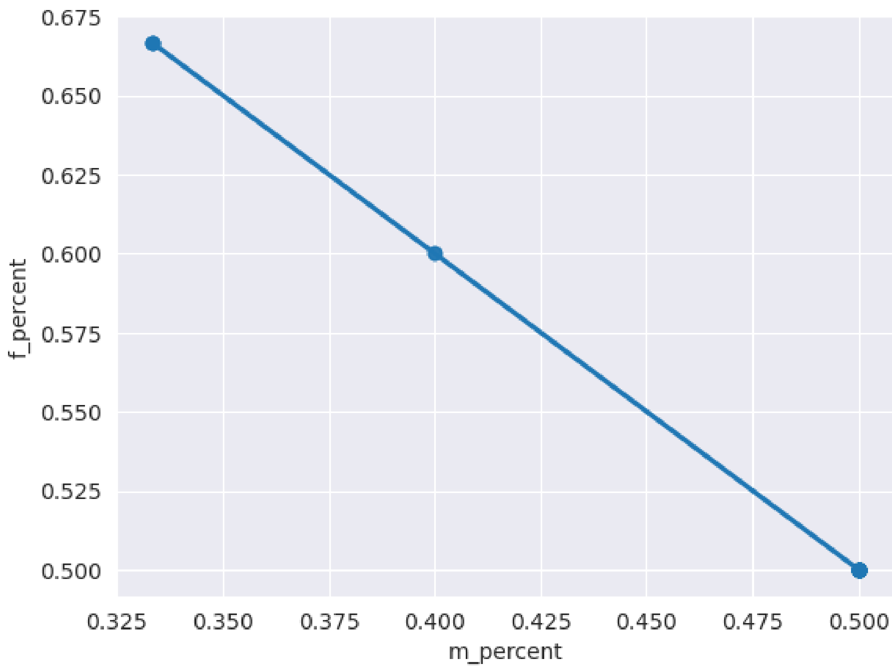



```
plt = sns.lmplot(data=occ_df, x='m_percent', y='f_percent')
label_point(occ_df.m_percent, occ_df.f_percent, occ_df.name, plt)
```

worker




```
# yet another option for plotting of the ChatGPT data
occ_df
sns.regplot(x="m_percent", y="f_percent", data=occ_df);
# for the interpretation, see below
```



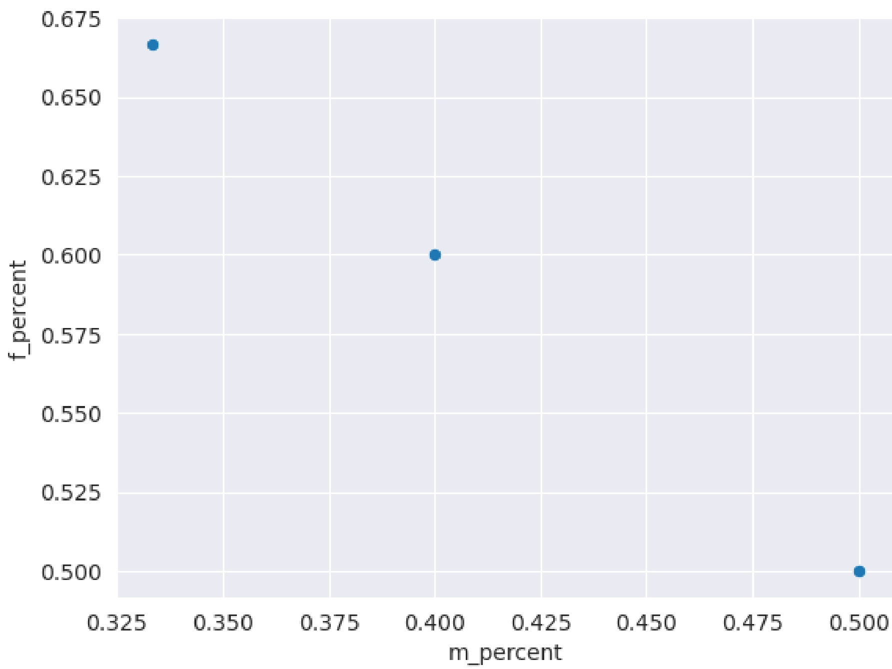

```
# most of the data points are at (0.5, 0.5) and there are a couple of outliers
# with a greater y-coordinate and lesser x-coordinate (these points also partially
# overalp, so can't be all distinguished in the graph)
sns.scatterplot(data=occ_df, x="m_percent", y="f_percent")
occ_df
```

```
            name  num  f_percent  m_percent  fm_delta  f_percent_uk  \
0     technician   12   0.666667   0.333333  0.333333      0.467851
1     accountant   12   0.500000   0.500000  0.000000      0.430714
2     supervisor   12   0.500000   0.500000  0.000000      0.789423
3       engineer   12   0.500000   0.500000  0.000000      0.125551
4         worker   12   0.666667   0.333333  0.333333      0.448375
5          nurse   12   0.600000   0.400000  0.200000      0.877327
6     dispatcher   12   0.500000   0.500000  0.000000      0.615602
7        cashier   12   0.500000   0.500000  0.000000      0.638095
8        auditor   12   0.500000   0.500000  0.000000      0.409563
9      dietitian   12   0.500000   0.500000  0.000000      0.784593
10       painter   12   0.500000   0.500000  0.000000      0.646119
11        broker   14   0.500000   0.500000  0.000000      0.184000
12          chef   12   0.500000   0.500000  0.000000      0.281762
13        doctor   12   0.500000   0.500000  0.000000      0.597029
14   firefighter   12   0.500000   0.500000  0.000000      0.139466
15     secretary   12   0.600000   0.400000  0.200000      0.911825
16    pharmacist   12   0.500000   0.500000  0.000000      0.604863
```

17	psychologist	12	0.500000	0.500000	0.000000	0.795259
18	teacher	12	0.500000	0.500000	0.000000	0.675474
19	lawyer	12	0.500000	0.500000	0.000000	0.571529
20	plumber	12	0.666667	0.333333	0.333333	0.014056
21	surgeon	12	0.500000	0.500000	0.000000	0.372686
22	veterinarian	12	0.500000	0.500000	0.000000	0.452756
23	paramedic	12	0.500000	0.500000	0.000000	0.470948
24	baker	12	0.500000	0.500000	0.000000	0.562857
25	programmer	12	0.500000	0.500000	0.000000	0.149861
26	mechanic	12	0.500000	0.500000	0.000000	0.024470
27	manager	12	0.500000	0.500000	0.000000	0.364546
28	therapist	12	0.500000	0.500000	0.000000	0.824209
29	administrator	12	0.500000	0.500000	0.000000	0.682832
30	salesperson	12	0.500000	0.500000	0.000000	0.604265
31	receptionist	12	0.500000	0.500000	0.000000	0.896805
32	librarian	12	0.500000	0.500000	0.000000	0.654206
33	carpenter	12	0.666667	0.333333	0.333333	0.014062
34	electrician	12	0.500000	0.500000	0.000000	0.018444
35	hairdresser	12	0.500000	0.500000	0.000000	0.850224
36	architect	12	0.500000	0.500000	0.000000	0.262857

	m_percent_uk	fm_delta_uk	f_percent_us	m_percent_us	fm_delta_us
0	0.532149	-0.064299	0.032	0.968	-0.936
1	0.569286	-0.138573	0.597	0.403	0.194
2	0.210577	0.578845	0.300	0.700	-0.400
3	0.874449	-0.748897	0.165	0.835	-0.670
4	0.551625	-0.103251	0.500	0.500	0.000
5	0.122673	0.754653	0.874	0.126	0.748
6	0.384398	0.231203	0.508	0.492	0.016
7	0.361905	0.276190	0.731	0.269	0.462
8	0.590437	-0.180874	0.597	0.403	0.194
9	0.215407	0.569187	0.914	0.086	0.828
10	0.353881	0.292237	0.535	0.465	0.070
11	0.816000	-0.632000	0.661	0.339	0.322
12	0.718238	-0.436475	0.180	0.820	-0.640
13	0.402971	0.194057	0.744	0.256	0.488
14	0.860534	-0.721068	0.044	0.956	-0.912
15	0.088175	0.823650	0.929	0.071	0.858
16	0.395137	0.209726	0.616	0.384	0.232
17	0.204741	0.590517	0.803	0.197	0.606
18	0.324526	0.350947	0.735	0.265	0.470
19	0.428471	0.143058	0.374	0.626	-0.252
20	0.985944	-0.971888	0.023	0.977	-0.954
21	0.627314	-0.254627	0.263	0.737	-0.474
22	0.547244	-0.094488	0.649	0.351	0.298
23	0.529052	-0.058104	0.281	0.719	-0.438

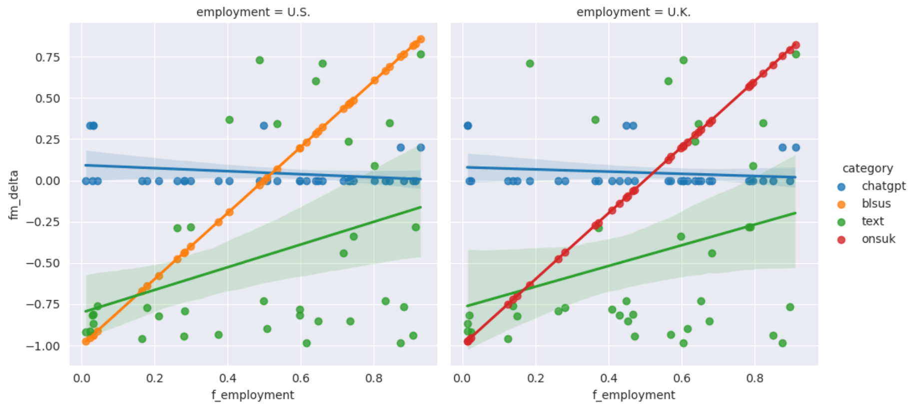
24	0.437143	0.125714	0.641	0.359	0.282
25	0.850139	-0.700278	0.211	0.789	-0.578
26	0.975530	-0.951060	0.012	0.988	-0.976
27	0.635454	-0.270908	0.404	0.596	-0.192
28	0.175791	0.648418	0.844	0.156	0.688
29	0.317168	0.365664	0.717	0.283	0.434
30	0.395735	0.208530	0.487	0.513	-0.026
31	0.103195	0.793609	0.883	0.117	0.766
32	0.345794	0.308411	0.832	0.168	0.664
33	0.985938	-0.971876	0.032	0.968	-0.936
34	0.981556	-0.963113	0.031	0.969	-0.938
35	0.149776	0.700448	0.908	0.092	0.816
36	0.737143	-0.474286	0.282	0.718	-0.436




```
# an alternative presentation of the data
occ_diffs_ext_us = occ_diffs_us
occ_diffs_ext_uk = occ_diffs
occ_diffs_ext_us = occ_diffs_ext_us.rename(columns={"f_stats_us": "f_employment"})
occ_diffs_ext_uk = occ_diffs_ext_uk.rename(columns={"f_stats_uk": "f_employment"})
occ_diffs_ext_us['employment'] = ['U.S.'] * len(occ_diffs_ext_us)
occ_diffs_ext_uk['employment'] = ['U.K.'] * len(occ_diffs_ext_uk)
occ_diffs_ext = pd.concat([occ_diffs_ext_us, occ_diffs_ext_uk], ignore_index=True)
occ_diffs_ext
#sns.lmplot(x="total_bill", y="tip", hue="smoker", col="time", row="sex", data=tips, height=
```

```
# legend=False
sns.lmplot(data=occ_diffs_ext, x='f_employment', y='fm_delta', hue='category', col='employme
```

```
<seaborn.axisgrid.FacetGrid at 0x7f7cb95ec640>
```




```
import math
from scipy.stats import binomtest
from scipy.stats import chi2_contingency
from sklearn.linear_model import LinearRegression
from scipy import stats

f_counts = occ_df_nonnormalized.f_percent * occ_df_nonnormalized.num
m_counts = occ_df_nonnormalized.m_percent * occ_df_nonnormalized.num
n_counts = occ_df_nonnormalized.n_percent * occ_df_nonnormalized.num

fcount = int(f_counts.sum())
mcount = int(m_counts.sum())
ncount = int(n_counts.sum())
binomres = binomtest(k=fcount, n=fcount+mcount, p=0.5, alternative='greater')

# we first run a linear regression test and check that the regression coefficient
# is close enough to 1
print(f"Test 1 (x:m%, y:f%)\n------")
# Note: first arg to the linear regression (fit method) should be a 2D array (an array of a
# reshape(-1,1) creates an array of the same length as the original array (that's what -1 m
# and the second argument requires the sub-arrays to have dimension 1 (and contain the elem
# of the original array).
#x = occ_df["f_percent_uk"].to_numpy().reshape((-1, 1)) # official stats on x axis
#y = occ_df["fm_delta"].to_numpy()
x = occ_df["m_percent"].to_numpy().reshape((-1, 1)) # official stats on x axis
y = occ_df["f_percent"].to_numpy()
model = LinearRegression().fit(x, y)
```

```
# Note: an r-square approaching 1 says that x is correlated strongly with y,
# so that our linear model explains to a great extent variations of y via variations of x.
# The p-value, on the other hand, is a test of significance for the model, namely it tests
# the hypothesis that the slope of the model is 0. I p < significance level (0.05), the lin
# model fits the data and is significant.
# See: https://www.researchgate.net/post/What_is_the_relationship_between_R-squared_and_p-va
# Also see: https://stats.stackexchange.com/questions/50425/what-is-the-relationship-betwee
# Also this: https://stats.stackexchange.com/questions/13314/is-r2-useful-or-dangerous?nore
slope, intercept, r_value, p_value, std_err = stats.linregress(x.reshape(-1,),y)
print(f"slope: {slope}\n intercept: {intercept}\n p_value: {p_value}\n std_err: {std_err}\n

#print(f"x: {x}")
#print(f"y: {y}")

r_sq = model.score(x, y)
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"slope: {model.coef_}")


print(f"Test 1.1 (x:stats, y: delta)\n-------------------------")

x = occ_df["f_percent_uk"].to_numpy().reshape((-1, 1)) # official stats on x axis
y = occ_df["fm_delta"].to_numpy()
model = LinearRegression().fit(x, y)


slope, intercept, r_value, p_value, std_err = stats.linregress(x.reshape(-1,),y)
print(f"slope: {slope}\n intercept: {intercept}\n p_value: {p_value}\n std_err: {std_err}\n

r_sq = model.score(x, y)
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"slope: {model.coef_}")



print(f"Test 2\n------")
print(f"Setting: f# {fcount}, m# {mcount}, N = {fcount+mcount}")
print(f"Binomial test with H0: P(f) = 0.5 and H1: P(f) > 0.5")
print(f"where f = frequency of valid coreference resolutions of feminine-gendered pronouns
print(f"p-value: {binomres.pvalue}")
if binomres.pvalue < 0.05:
    print("We reject H0: P(f) = 0.5 in favour of H1: P(f) > 0.5 at the 5% level of significa
else:
```

```
    print("We accept H0: P(f) = 0.5 at the 5% level of significance.")


f_obs = occ_df.apply(lambda x: int(x["num"] * x["f_percent"]), axis=1).rename("f_obs")
m_obs = occ_df.apply(lambda x: int(x["num"] * x["m_percent"]), axis=1).rename("m_obs")
df_chi = f_obs.to_frame()
df_chi["m_obs"] = m_counts
fm_obs = df_chi[["f_obs", "m_obs"]].to_numpy()

chi_res = chi2_contingency(fm_obs)
pvalue = chi_res[1]
print(f"Chi-square test 3 (37 x 2)\n---------------------")
print(f"We assume H0: the variables f, m (the counts of feminine and masculine pronouns) are
print(f"The alternative hypothesis, H1 is that the variables are correlated.")
significance_level = 0.05
print(f"p value: {pvalue}")
if pvalue <= significance_level:
    print('Reject the null hypothesis, H0, in favour of H1. So the variables are correlated.
else:
    print('Accept the null hypothesis: there is no particular corellation between the variab
    print('For our case, this means that we should not expect a bias towards one of these va

# include neuter gender data (use non-normalized table)
f_obs_1 = occ_df_nonnormalized.apply(lambda x: int(x["num"] * x["f_percent"]), axis=1).renam
m_obs_1 = occ_df_nonnormalized.apply(lambda x: int(x["num"] * x["m_percent"]), axis=1).renam
n_obs_1 = occ_df_nonnormalized.apply(lambda x: int(x["num"] * x["n_percent"]), axis=1).renam
df_chi_1 = f_obs.to_frame()
df_chi_1["m_obs"] = m_counts
df_chi_1["n_obs"] = n_counts
fmn_obs = df_chi_1.to_numpy()

chi_res = chi2_contingency(fmn_obs)
pvalue = chi_res[1]
print(f"Chi-square test 4 (37 x 3)\n------------------")
print(f"We assume H0: the variables f, m, n (the counts of feminine, masculine and neuter pr
print(f"The alternative hypothesis, H1 is that the variables are correlated.")
significance_level = 0.05
print(f"p value: {pvalue}")
if pvalue <= significance_level:
    print('Reject the null hypothesis, H0, in favour of H1. So the variables are correlated.
else:
    print('Accept the null hypothesis: there is no particular corellation between the variab
    print('For our case, this means that we should not expect a bias towards one of these va

model
```

```
Test 1 (x:m%, y:f%)
------
slope: -0.9999999999999992
 intercept: 0.9999999999999996
 p_value: 3.462250163472298e-267
 std_err: 4.3626132888281325e-09
 R-squared: 1.000000
coefficient of determination: 1.0
intercept: 0.9999999999999998
slope: [-1.]
Test 1.1 (x:stats, y: delta)
-------------------------
slope: -0.06666707632422661
 intercept: 0.07966596778866505
 p_value: 0.3295493503420671
 std_err: 0.06742241001163811
 R-squared: 0.027176
coefficient of determination: 0.027175693968011116
intercept: 0.07966596778866508
slope: [-0.06666708]
Test 2
------
Setting: f# 113, m# 103, N = 216
Binomial test with H0: P(f) = 0.5 and H1: P(f) > 0.5
where f = frequency of valid coreference resolutions of feminine-gendered pronouns 113
p-value: 0.2701950543773501
We accept H0: P(f) = 0.5 at the 5% level of significance.
Chi-square test 3 (37 x 2)
---------------------
We assume H0: the variables f, m (the counts of feminine and masculine pronouns) are not cor
The alternative hypothesis, H1 is that the variables are correlated.
p value: 0.9999915716408443
Accept the null hypothesis: there is no particular corellation between the variables, and an
For our case, this means that we should not expect a bias towards one of these variables, si
Chi-square test 4 (37 x 3)
------------------
We assume H0: the variables f, m, n (the counts of feminine, masculine and neuter pronouns)
The alternative hypothesis, H1 is that the variables are correlated.
p value: 0.9999999999999798
Accept the null hypothesis: there is no particular corellation between the variables, and an
For our case, this means that we should not expect a bias towards one of these variables, si
```

```
LinearRegression()
```

```python
# tests and summary of data (for code in the cell above)

def coref_summary():
```

```
    f_res = df.loc[(df['gender'] == 'f') & (df['score'] == 1)]
    m_res = df.loc[(df['gender'] == 'm') & (df['score'] == 1)]
    n_res = df.loc[(df['gender'] == 'n') & (df['score'] == 1)]
    f_res_0 = df.loc[(df['gender'] == 'f') & (df['score'] == 0)]
    m_res_0 = df.loc[(df['gender'] == 'm') & (df['score'] == 0)]
    n_res_0 = df.loc[(df['gender'] == 'n') & (df['score'] == 0)]
    zero_score = df.loc[df['score'] == 0]
    one_score = df.loc[df['score'] == 1]
    f_percentage_total = (len(f_res) + len(f_res_0)) / len(df)
    f_percentage_valid = len(f_res) / len(df)
    m_percentage_total = (len(m_res) + len(m_res_0)) / len(df)
    m_percentage_valid = len(m_res) / len(df)
    n_percentage_total = (len(n_res) + len(n_res_0)) / len(df)
    n_percentage_valid = len(n_res) / len(df)
    print("COUNTS (SUMMARY)")
    print(f"F {len(f_res)} + M {len(m_res)} + N {len(n_res)} = {len(f_res) + len(m_res) + le
    print(f"F {len(f_res_0)} + M {len(m_res_0)} + N {len(n_res_0)} = {len(f_res_0) + len(m_r
    print("PERCENTAGES (SUMMARY)")
    print(f"F {f_percentage_valid}, M {m_percentage_valid}, N {n_percentage_valid} (valid re
    print(f"F {f_percentage_total}, M {m_percentage_total}, N {n_percentage_total} (all reso

def test_size():
    f_res = df.loc[(df['gender'] == 'f') & (df['score'] == 1)]
    m_res = df.loc[(df['gender'] == 'm') & (df['score'] == 1)]
    n_res = df.loc[(df['gender'] == 'n') & (df['score'] == 1)]
    zero_score = df.loc[df['score'] == 0]
    one_score = df.loc[df['score'] == 1]
    cond_1 = len(f_res) + len(m_res) + len(n_res) == len(one_score)
    cond_2 = len(f_res) + len(m_res) + len(n_res) + len(zero_score) == len(df)
    cond_3 = len(occupations) == len(occupation_stats.keys())
    if cond_1 and cond_2 and cond_3:
        # print(f"\033[32;1mData frame integrity OK.\033[0m")
        print(f"Data frame integrity OK.")
    else:
        print(f"\033[31;1mYou failed to parse some sentences in your data.\033[0m")
        print(f"{len(f_res) + len(m_res) + len(n_res)} (rows scored 1 actually processed).")
        print(f"{len(zero_score)} (total rows scored 0)")
        print(f"{len(one_score)} (total rows scored 1)")
        print(f"{len(df)} (total rows in data frame)")
        #compute: df - f_res - m_res - n_res - zero_score
        fs = f_res['num'].tolist()
        ms = m_res['num'].tolist()
        ns = n_res['num'].tolist()
        zs = zero_score['num'].tolist()
        rest = set(df['num'].tolist()) - set(fs) - set(ms) - set(ns) - set(zs)
        rest = list(rest)
```

```
        rest.sort()
        print(f"Missing rows for sentences numbered:\n", rest)
        if len(occupations) > len(occupation_stats.keys()):
            diffs = set(occupations).difference(set(occupation_stats.keys()))
            print(f"Occupations {diffs} not in occupation_stats dictionary")
        elif len(occupation_stats.keys()) > len(occupations):
            diffs = set(occupation_stats.keys()).difference(set(occupations))
            print(f"Occupations {diffs} not in the occupations list.")
```

```
test_size()
coref_summary()
```

```
Data frame integrity OK.
COUNTS (SUMMARY)
F 113 + M 103 + N 109 = 325 (rows scored 1 per each gender)
F 36 + M 46 + N 39 = 121 (rows scored 0 per each gender)
PERCENTAGES (SUMMARY)
F 0.2533632286995516, M 0.23094170403587444, N 0.24439461883408073 (valid resolutions)
F 0.33408071748878926, M 0.33408071748878926, N 0.33183856502242154 (all resolutions)
```

Observations

- the analysis is not about the validity of coreference resolution, but about biases in the coreference resoltion system (in ChatGPT). This analysis does not record errors in coreference resolution that occur with both grammatical genders.
- this analysis considers only (coreference resolution) errors that are due to the gender of pronouns and gender-association of noun phrases. They are due to gender and gender-associations because in the data gathering phase we vary only these gender features of the linguistic input.
- each data point, identified by the occupation that it targets (e.g. 'teacher') is balanced as to the gender of its pronouns, that is, it has an equal number of pronouns of each grammatical gender, e.g. "he" (masculine), "she" (feminine), "they" (neuter).
- the ChatGPT does not show any significant bias. One plausible explanation is that the outliers occur because of the 'attraction' and 'repulsion' of masculine pronouns relative to male-associated occupations and female-associated occupations respectively. Be that as it may, there are not enough outliers to bias the coreference resolution produced by the ChatGPT system.

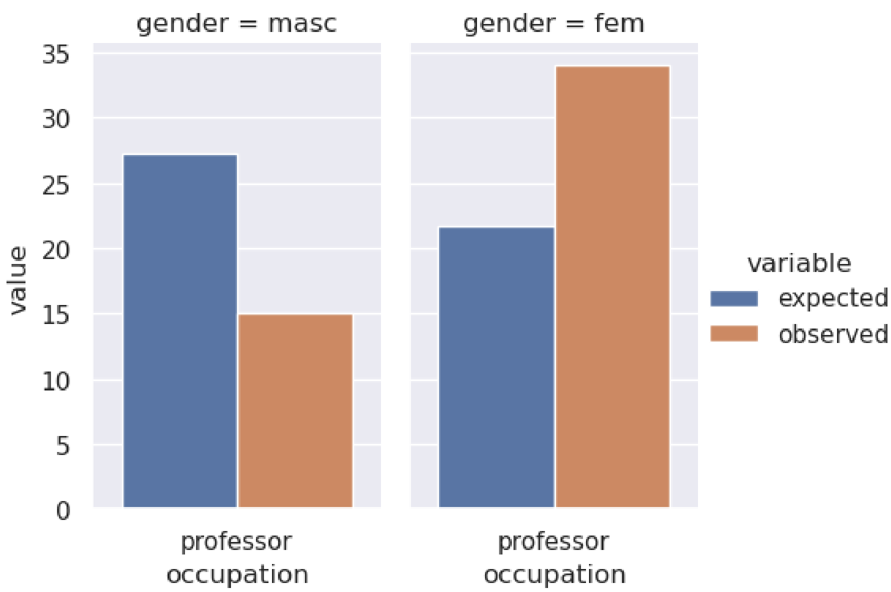
```
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
def get_story_data():
    story_data = []
    with open('stories-data.csv') as csv_file:
        csv_data = csv.reader(csv_file, delimiter=',')
        # row shape: "occupation", "f_gender", "m_gender", "total_count", "f_percent_uk"
        for row in csv_data:
            d = {}
            try:
                d['occupation'] = row[0] # occupation name
                d['f_gender'] = int(row[1])
                d['m_gender'] = int(row[2])
                # we don't use row[3] for the total count, as we want f% + g% = 100%
                # to be properly compared with emplyment stats (=> we ignore neuter pronouns
                d['total_count'] = d['f_gender'] + d['m_gender']
                d['f_percent_uk'] = float(row[4])
                d['m_percent_uk'] = 1.0 - float(row[4])
                d['f_percent_observed'] = float(row[1]) / float(d['total_count'])
                d['m_percent_observed'] = float(row[2]) / float(d['total_count'])
                story_data.append(d)
            except ValueError:
                continue
    return story_data

story_data_df = pd.DataFrame(get_story_data())
# add column for expected women / men empolyed within each occupation
story_data_df['f_expect'] = story_data_df['total_count'] * story_data_df['f_percent_uk']
story_data_df['m_expect'] = story_data_df['total_count'] * story_data_df['m_percent_uk']
story_types = {"occupation": str, "f_gender": int, "m_gender": int, "total_count": int,
                "f_percent_uk": float, "m_percent_uk": float, "f_expect": float, "m_expect":
              "f_percent_observed": float, "m_percent_observed": float}
story_data_df = story_data_df.astype(story_types)


#story_data_df.describe()
story_data_df


# per occupation
sns.set()

# get cols: occupation, f_actual, m_gender, f_expect, m_expect
sfm_percent = story_data_df.iloc[:, [0,4,5,6,7]]
sfm_absolute = story_data_df.iloc[:, [0,1,2,8,9]]
sfm = sfm_absolute.rename(columns={"f_gender": "f_actual", "m_gender": "m_actual"})
sfm_percent = sfm_percent.rename(columns={"f_percent_uk": "f_expect", "m_percent_uk": "m_exp
```

```
                                                  "f_percent_observed": "f_actual",
                                                  "m_percent_observed": "m_actual"})

sf = sfm.iloc[:, [0,1,3]]  # occupation, f_actual, f_expect
sm = sfm.iloc[:, [0,2,4]]  # occupation, m_actual, m_expect
sf = sf.rename(columns={"f_actual":"observed", "f_expect":"expected"})
sm = sm.rename(columns={"m_actual":"observed", "m_expect":"expected"})
sf_melted = pd.melt(sf, id_vars = "occupation")
sm_melted = pd.melt(sm, id_vars = "occupation")

sf_melted['gender'] = ['fem'] * len(sf_melted)
sm_melted['gender'] = ['masc'] * len(sf_melted)
sfm_ext = pd.concat([sf_melted, sm_melted], ignore_index=True)
sfm_ext = sfm_ext.sort_values(by="occupation")
sfm_ext = sfm_ext.reset_index(drop=True)
#sns.barplot(data=sfm_ext[0:6], x='occupation', y='value', hue='variable', col='gender')

#fig, ax = plt.subplots(1, 2, sharey=True)
#sns.barplot(data=sf_melted[0:6], x="occupation", y="value", hue="variable", ax=axes[0])
#sns.barplot(data=sm_melted[0:6], x="occupation", y="value", hue="variable", ax=axes[1])

sns.catplot(
    data=sfm_ext[44:48], x="occupation", y="value", hue="variable", col="gender", #row="occu
    kind="bar", height=4, aspect=.6,
)

sfm_ext
```

```
      occupation  variable    value gender
0            ceo  observed  11.0000    fem
1            ceo  expected  28.3647   masc
2            ceo  expected  10.6353    fem
3            ceo  observed  28.0000   masc
4           chef  expected  11.5497    fem
5           chef  expected  29.4503   masc
6           chef  observed  18.0000    fem
7           chef  observed  23.0000   masc
8          clerk  expected  22.6785    fem
9          clerk  expected  16.3215   masc
10         clerk  observed  35.0000    fem
11         clerk  observed   4.0000   masc
12        doctor  expected  26.2680    fem
13        doctor  observed  18.0000   masc
14        doctor  expected  17.7320   masc
15        doctor  observed  26.0000    fem
16      engineer  observed  37.0000   masc
```

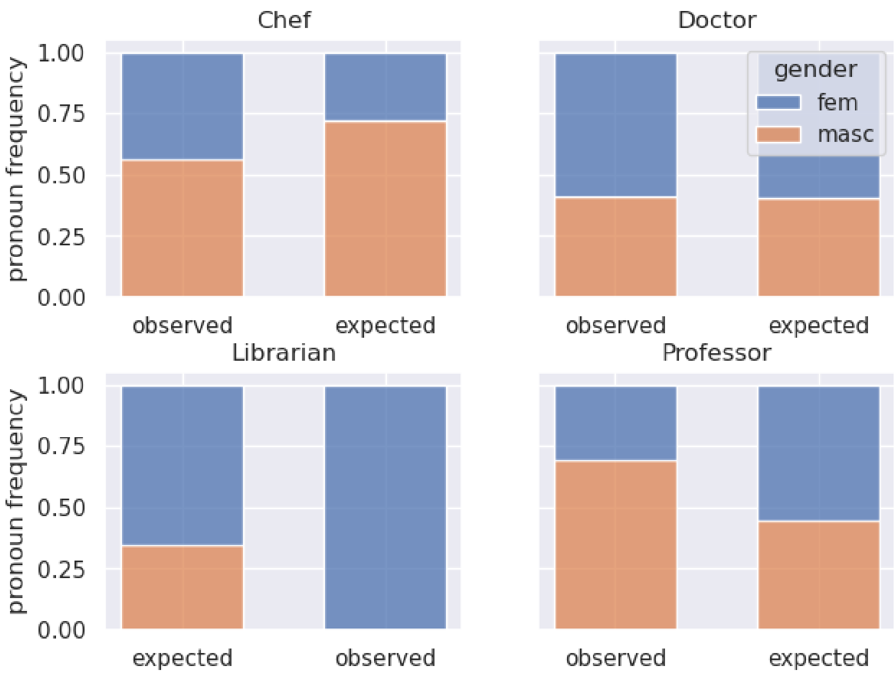
17	engineer	expected	5.6475	fem
18	engineer	expected	39.3525	masc
19	engineer	observed	8.0000	fem
20	estate agent	expected	12.0000	fem
21	estate agent	observed	6.0000	masc
22	estate agent	expected	13.0000	masc
23	estate agent	observed	19.0000	fem
24	firefighter	observed	0.0000	fem
25	firefighter	expected	5.5760	fem
26	firefighter	expected	34.4240	masc
27	firefighter	observed	40.0000	masc
28	librarian	observed	46.0000	fem
29	librarian	expected	15.9068	masc
30	librarian	observed	0.0000	masc
31	librarian	expected	30.0932	fem
32	manager	expected	29.8685	masc
33	manager	observed	37.0000	fem
34	manager	expected	17.1315	fem
35	manager	observed	10.0000	masc
36	mechanic	expected	46.8288	masc
37	mechanic	observed	48.0000	masc
38	mechanic	observed	0.0000	fem
39	mechanic	expected	1.1712	fem
40	nurse	expected	27.1963	fem
41	nurse	expected	3.8037	masc
42	nurse	observed	29.0000	fem
43	nurse	observed	2.0000	masc
44	professor	expected	27.3077	masc
45	professor	observed	15.0000	masc
46	professor	expected	21.6923	fem
47	professor	observed	34.0000	fem
48	secretary	expected	3.4398	masc
49	secretary	observed	35.0000	fem
50	secretary	observed	4.0000	masc
51	secretary	expected	35.5602	fem
52	therapist	observed	38.0000	fem
53	therapist	observed	4.0000	masc
54	therapist	expected	7.3836	masc
55	therapist	expected	34.6164	fem




```
#sfm_percent

sf = sfm_percent.iloc[:, [0,1,3]]  # occupation, f_actual, f_expect
sm = sfm_percent.iloc[:, [0,2,4]]  # occupation, m_actual, m_expect
sf = sf.rename(columns={"f_actual":"observed", "f_expect":"expected"})
sm = sm.rename(columns={"m_actual":"observed", "m_expect":"expected"})

sf_melted = pd.melt(sf, id_vars = "occupation")
sm_melted = pd.melt(sm, id_vars = "occupation")

sf_melted['gender'] = ['fem'] * len(sf_melted)
sm_melted['gender'] = ['masc'] * len(sf_melted)
sfm_ext_percent = pd.concat([sf_melted, sm_melted], ignore_index=True)
sfm_ext_percent = sfm_ext_percent.sort_values(by="occupation")
sfm_ext_percent = sfm_ext_percent.reset_index(drop=True)


#import matplotlib.pyplot as plt
#import seaborn as sns

#set seaborn plotting aesthetics as default
sns.set()

#define plotting region (2 rows, 2 columns)
fig, axes = plt.subplots(2, 2, sharey=True)
fig.tight_layout()
```

```
#fig.suptitle('Gendered pronouns frequencies: observed vs expected')

sns.histplot(sfm_ext_percent[4:8], x='variable', hue='gender', weights='value',
             multiple='stack', shrink=0.6, legend=False, ax=axes[0,0]).set(title='Chef',
                                                                           xlabel=None,
                                                                          ylabel='pronoun fr

sns.histplot(sfm_ext_percent[12:16], x='variable', hue='gender', weights='value',
             multiple='stack', shrink=0.6, legend=True, ax=axes[0,1]).set(title='Doctor',xla

sns.histplot(sfm_ext_percent[28:32], x='variable', hue='gender', weights='value',
             multiple='stack', shrink=0.6, legend=False, ax=axes[1,0]).set(title='Librarian'
                                                                           xlabel=None,
                                                                          ylabel='pronoun fr

sns.histplot(sfm_ext_percent[44:48], x='variable', hue='gender', weights='value',
             multiple='stack', shrink=0.6, legend=False, ax=axes[1,1]).set(title='Professor'

#sfm_ext_percent
```

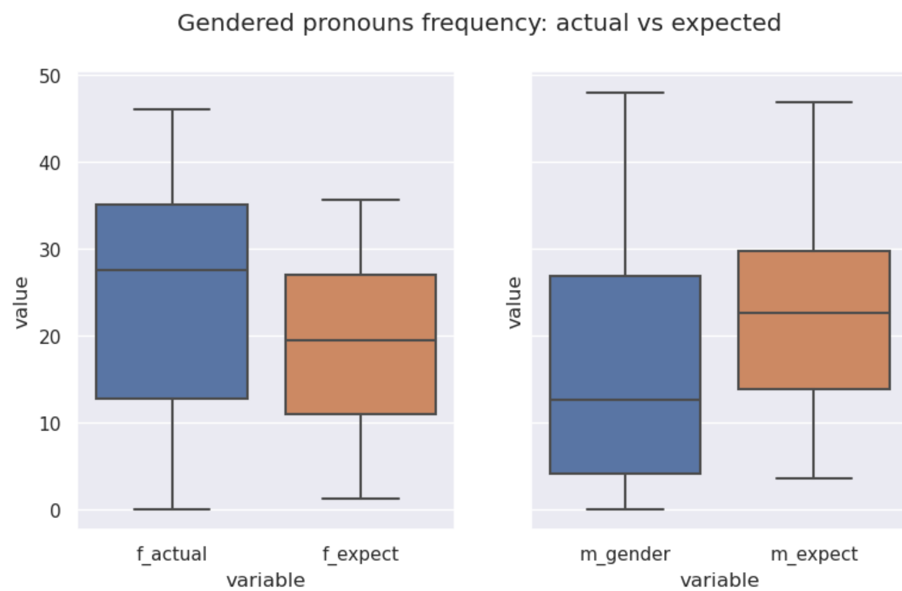
```
[Text(0.5, 1.0, 'Professor'), Text(0.5, 19.049999999999997, '')]
```




```
# overall
sns.set()
```

```
fig, axes = plt.subplots(1, 2, figsize=(9,5), sharey=True)
fig.suptitle("Gendered pronouns frequency: actual vs expected")
# select columns tracking the actual and expected frequence of gendered pronouns
subdf = story_data_df.iloc[:, [1,2,3,8,9]]
subdf = subdf.rename(columns={"f_gender": "f_actual"})
df_melted = pd.melt(subdf)
df_melted = df_melted.sort_values(by="variable")
df_melted = df_melted.reindex(range(len(df_melted)))
df_f = df_melted[df_melted['variable'].str.match(r'^f_')]
df_m = df_melted[df_melted['variable'].str.match(r'^m_')]
#df_f
df_melted[df_melted['variable'].str.match(r'^f_')]
sns.boxplot(x='variable', y='value', data=df_f, ax=axes[0])
sns.boxplot(x='variable', y='value', data=df_m, ax=axes[1])
```

```
<AxesSubplot:xlabel='variable', ylabel='value'>
```




```
from scipy.stats import binomtest

# significance test
story_count_total = subdf["total_count"].sum()
story_count_fem = subdf["f_actual"].sum()
story_count_fem_expected = subdf["f_expect"].sum()
story_percent_fem_expected = story_count_fem_expected / story_count_total
story_percent_fem_observed = story_count_fem / story_count_total
subdf.describe()
```

```
subdf

print("Setting\n--------")
print(f"Sample size: {story_count_total}")
print(f"f-pronouns number: {story_count_fem}")
print(f"expected P(f): {story_percent_fem_expected}")
print(f"observed P(f): {story_percent_fem_observed}")

print("Test 1\n------")
print(f"Binomial test 1 with H0: P(f) = 0.5 and H1: P(f) > 0.5")
print(f"where f = frequency of feminine-gendred pronouns, and the sample size {story_count_t
binomial_res_1 = binomtest(story_count_fem, n=story_count_total, p=0.5, alternative='greater
if binomial_res_1.pvalue < 0.05:
    print(f"p-value: {binomial_res_1.pvalue}")
    print("We reject H0: P(f) = 0.5 in favour of H1: P(f) > 0.5 at the 5% level of significa
else:
    print("We accept H0: P(f) = 0.5")

print("Test 2\n------")
print(f"Binomial test 2 with H0: P(f) = {story_percent_fem_expected} and H1: P(f) > {story_p
print(f"where f = frequency of feminine-gendred pronouns, and the sample size {story_count_t
binomial_res_2 = binomtest(story_count_fem, n=story_count_total, p=story_percent_fem_expecte
if binomial_res_2.pvalue < 0.05:
    print(f"p-value: {binomial_res_2.pvalue}")
    print("We reject H0: P(f) = 0.5 in favour of H1: P(f) > 0.5 at the 5% level of significa
else:
    print("We accept H0: P(f) = 0.5")
```

```
Setting
--------
Sample size: 575
f-pronouns number: 336
expected P(f): 0.45533234782608695
observed P(f): 0.5843478260869566
Test 1
------
Binomial test 1 with H0: P(f) = 0.5 and H1: P(f) > 0.5
where f = frequency of feminine-gendred pronouns, and the sample size 575
p-value: 3.0066914048144225e-05
We reject H0: P(f) = 0.5 in favour of H1: P(f) > 0.5 at the 5% level of significance.
Test 2
------
Binomial test 2 with H0: P(f) = 0.45533234782608695 and H1: P(f) > 0.45533234782608695
where f = frequency of feminine-gendred pronouns, and the sample size 575
p-value: 3.698468436623279e-10
We reject H0: P(f) = 0.5 in favour of H1: P(f) > 0.5 at the 5% level of significance
```

```
# a comparison of percentages
story_df_percent = story_data_df.loc[:, ['f_percent_uk', 'm_percent_uk', "f_percent_observed
rename_dict = {'f_percent_uk': 'f_expected', 'm_percent_uk':'m_expected',
               "f_percent_observed":'f_observed', "m_percent_observed": 'm_observed'}
story_df_percent = story_df_percent.rename(columns=rename_dict)
story_df_percent.describe()
story_count = story_df_percent.describe().iloc[0,0]

#print(data['subjects'].loc[data.index[3]]) |(data['id'].iloc[0])
story_df_percent.describe()
```

	f_expected	m_expected	f_observed	m_observed
count	14.000000	14.000000	14.000000	14.000000
mean	0.469779	0.530221	0.597571	0.402429
std	0.285808	0.285808	0.354868	0.354868
min	0.024400	0.088200	0.000000	0.000000
25%	0.274950	0.360100	0.321295	0.102564
50%	0.461350	0.538650	0.726939	0.273061
75%	0.639900	0.725050	0.897436	0.678705
max	0.911800	0.975600	1.000000	1.000000

```
import os

# Convert jupyter notebook to pdf via pandoc

docname = "progen_bias"
bibfile = "references.bib"
citation_style = "acm.csl"

# pandoc command
pandoc_cmd = " ".join([f"pandoc -s {docname}.ipynb -t pdf -o {docname}.pdf",
              f"--lua-filter=parse_html.lua", # needed to parse HTML tables (in output cell
              f"--citeproc",
              f"--bibliography={bibfile}",
              f"--csl={citation_style}"])
os.system(pandoc_cmd)

# References
```

0