progen_bias

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1 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.

2 Winograd Sentences

I used a collection of 432 Winograd sentences (36 occupations x 12 sentences for each occupation), about half of the entire initial database of 720 sentences (linked above). You can check these Winograd sentences below and see which of them have been left out of the study.

My reason for not looking at the entire database was that it extremely time-consuming to correlate the US and the UK labour market statistics, since employment terminology varies in the two countries. For this reason I looked at the more common professions. A more comprehensive study whould include all Winograd sentences and focus solely on the US employment statistics, which would – as far as I can see after having conducted the comparison with the UK emplyment statistics – still be representative, as the two labour markets haven't exhibited different patters of male/female employment in the subset of the data that I studied. Focusing on the US data would be methodologically sound insofar as the data on which ChatGPT is trained is likely on American English language texts.

[1]:
```
import pandas as pd

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

[2]:
```
wino_sentences = data["sentence"]
```

[3]:
```
i = 0
for s in wino_sentences[0:30]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
```

```
    i += 1
```

[4]:
```
i = 30
for s in wino_sentences[30:60]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[5]:
```
i = 108
for s in wino_sentences[108:192]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[6]:
```
i = 204
for s in wino_sentences[204:216]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[7]:
```
i = 228
for s in wino_sentences[228:460]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[8]:
```
i = 516
for s in wino_sentences[516:564]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[9]:
```
i = 600
for s in wino_sentences[600:660]:
    # uncomment to print sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[10]:
```
i = 264
for s in wino_sentences[264:276]:
    # uncomment to print the sentences
    #print(f"{i+1}. {s}")
    i += 1
```

[11]:
```
i = 660
for s in wino_sentences[660:720]:
    # uncomment to print sentences
```

```
    #print(f"{i+1}. {s}")
    i += 1
```

[12]:
```
# 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)
```

[12]: 720

3 ChatGPT: gendered pronouns coreference annotation task

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.

4 ChatGPT's Annotations and Labour Market Statistics

In this section, we process annotation data as well as labour market stats for the US and the UK markets.

[13]:
```
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-occupation
```

```
# 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': 0.929},
                    'accountant': { 'f_count': 83_300, 'm_count': 110_100,␣
 ↪'f_percent_us': 0.597},
                    'engineer': {'f_count': 68_300, 'm_count': 475_700,␣
 ↪'f_percent_us': 0.165},
                    'technician': {'f_count': 2_297_100, 'm_count': 2_612_800,␣
 ↪'f_percent_us': 0.032},
                    # 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': 0.50},
                    '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': 0.508},
                    'cashier': {'f_count': 783_900, 'm_count': 444_600,␣
 ↪'f_percent_us': 0.731},
                    # using a larger category as a proxy: Business, Research␣
 ↪and Administrative
                    # Professionals (see source table)
                    'auditor': {'f_count': 390_600, 'm_count': 563_100,␣
 ↪'f_percent_us': 0.597},
                    # using a proxy category:  Health professionals n.e.c.
                    'dietitian': {'f_count': 55_000, 'm_count': 15_100,␣
 ↪'f_percent_us': 0.914},
                    # 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': 0.044},
                    'pharmacist': {'f_count': 39_800, 'm_count': 26_000,␣
↪'f_percent_us': 0.616},
                    'psychologist': {'f_count': 36_900, 'm_count': 9_500,␣
↪'f_percent_us': 0.803},
                    # ONS does not provide figures for female carpenters. here␣
↪I'm using a figure in
                    # line with the proportion of women in the larger category␣
↪of  Construction and Building Trades
                    # A figure that I found elsewhere confirms that this is a␣
↪good estimate. The 2,399 figure is mentioned
                    # at https://careersmart.org.uk/occupations/equality/
↪which-jobs-do-men-and-women-do-occupational-breakdown-gender
                    # which cites Working Futures 2021 (https://warwick.ac.uk/
↪fac/soc/ier/researchthemesoverview/researchprojects/wf)
                    'carpenter': {'f_count': 2_620, 'm_count': 183_700,␣
↪'f_percent_us': 0.032},
                    'electrician': {'f_count': 4_100, 'm_count': 218_200,␣
↪'f_percent_us': 0.031},
                    'teacher': {'f_count': 1_130_000, 'm_count': 542_900,␣
↪'f_percent_us': 0.735},
                    '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 Construction and Building Trades
                    '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-kingdom-uk-by-gender-and-specialty/
                    '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': 0.649},
                    'paramedic': {'f_count': 15_400, 'm_count': 17_300,␣
↪'f_percent_us': 0.281},
                    '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': 0.908},
                    'baker': {'f_count': 19_700        , 'm_count': 15_300,␣
 ↪'f_percent_us': 0.641},
                    'programmer': {'f_count': 70_000, 'm_count': 397_100,␣
 ↪'f_percent_us': 0.211},
                    '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': 0.404},
                    'therapist': {'f_count': 164_100, 'm_count': 35_000,␣
 ↪'f_percent_us': 0.844},
                    'administrator': {'f_count':  1_843_100, 'm_count':␣
 ↪856_100, 'f_percent_us': 0.717},
                    'salesperson': {'f_count': 935_100, 'm_count': 612_400,␣
 ↪'f_percent_us': 0.487},
                    'receptionist': {'f_count': 171_200, 'm_count': 19_700,␣
 ↪'f_percent_us': 0.883},
                    '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', 'programmer',
               'mechanic', 'manager', 'therapist', 'administrator',␣
 ↪'salesperson', 'receptionist',
               'librarian', 'carpenter', 'electrician', 'hairdresser',␣
 ↪'architect']
```

```
occupations_info = {}

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 resolution)
        occ_num = len(occ_entries)
        if surveyed_data == "valid":
            fs_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender']␣
↪== 'f') & (df['score'] == 1)])
            ms_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender']␣
↪== 'm') & (df['score'] == 1)])
            ns_with_occ = len(df.loc[(df['occupation'] == occ) & (df['gender']␣
↪== 'n') & (df['score'] == 1)])
        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 below)
        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
```

[13]:

	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
```

5 Comparing frequency distributions (chat vs occupational stats)

[14]:
```python
import numpy as np
from scipy.stats import chi2_contingency, ks_2samp


yf1 = np.rint(occ_df['num'] * occ_df['f_percent'])
yf2 = np.rint(occ_df['num'] * occ_df['f_percent_us'])
ym1 = np.rint(occ_df['num'] * occ_df['m_percent'])
ym2 = np.rint(occ_df['num'] * occ_df['m_percent_us'])


# Chi-square test (fem)
chi2, p_value, _, _ = chi2_contingency([yf1, yf2])
print("Chi-square test p-value (femninine):", p_value)
# Chi-square test (masc)
chi2, p_value, _, _ = chi2_contingency([ym1, ym2])
print("Chi-square test p-value (masculine):", p_value)

# Kolmogorov-Smirnov test (fem)
ks_statistic, p_value = ks_2samp(yf1, yf2)
print("Kolmogorov-Smirnov test p-value (feminine):", p_value)
# Kolmogorov-Smirnov test (masc)
ks_statistic, p_value = ks_2samp(ym1, ym2)
print("Kolmogorov-Smirnov test p-value (masculine):", p_value)
```

```
Chi-square test p-value (femninine): 0.006156734399817722
Chi-square test p-value (masculine): 0.07757007196237156
Kolmogorov-Smirnov test p-value (feminine): 0.004179157677663992
Kolmogorov-Smirnov test p-value (masculine): 0.009448530279742039
```

6 Plotting the Coreference and Employment Data

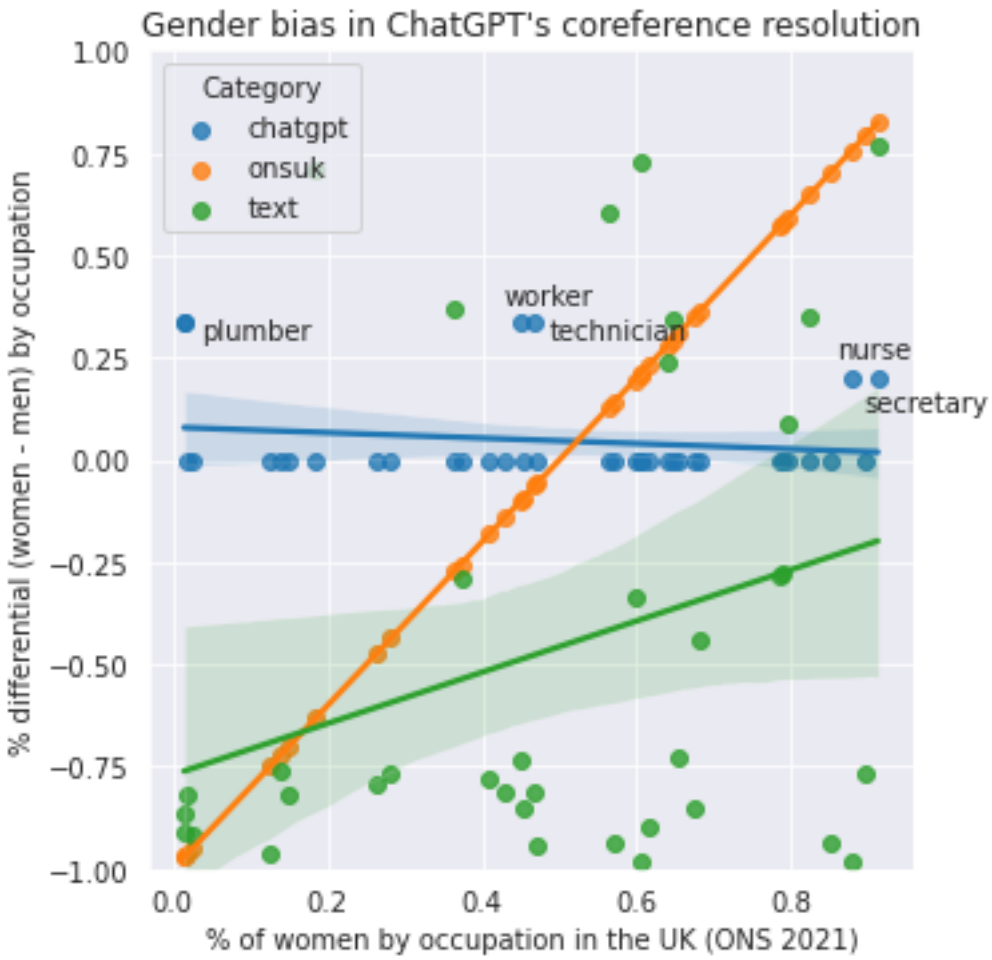
I take the data collected above and summarise them using a host of plots.

Note: in addition to coreference annotation and employment data, I will also add data about the frequency of various occupations on the web (see the 'Bergsma' data), focusing, as before, on English language texts.

[15]:
```
# 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 axis
# 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 axis
# 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 axis
# 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 axis
# 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 (women - men) by occupation')
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

#occ_stats_df
#occ_df
#occ_sorted

#print(occupations_info)
```



7 Comparison of distributions (text vs chat)

[16]:
```
bergsma_data_df
```

[16]:

	name	f_percent_bergsma	fm_delta_bergsma
0	technician	0.0942	-0.8116
1	accountant	0.0926	-0.8148
2	supervisor	0.3602	-0.2796
3	engineer	0.0199	-0.9602
4	worker	0.1343	-0.7314
5	mechanic	0.0089	-0.9822
6	manager	0.0518	-0.8964
7	therapist	0.6186	0.2372
8	administrator	0.1090	-0.7820
9	salesperson	0.3579	-0.2842
10	receptionist	0.6722	0.3444

11	librarian	0.8558	0.7116
12	pharmacist	0.1153	-0.7694
13	psychologist	0.3315	-0.3370
14	carpenter	0.1199	-0.7602
15	nurse	0.8831	0.7662
16	electrician	0.0080	-0.9840
17	teacher	0.5435	0.0870
18	lawyer	0.0735	-0.8530
19	plumber	0.0334	-0.9332
20	surgeon	0.0434	-0.9132
21	veterinarian	0.3555	-0.2890
22	paramedic	0.0752	-0.8496
23	architect	0.0283	-0.9434
24	hairdresser	0.8011	0.6022
25	baker	0.0893	-0.8214
26	programmer	0.0404	-0.9192
27	dispatcher	0.6857	0.3714
28	cashier	0.6746	0.3492
29	auditor	0.2804	-0.4392
30	dietitian	0.8649	0.7298
31	painter	0.1165	-0.7670
32	broker	0.1362	-0.7276
33	chef	0.0666	-0.8668
34	doctor	0.0920	-0.8160
35	firefighter	0.0309	-0.9382
36	secretary	0.1043	-0.7914

[17]:
```
import numpy as np
from scipy.stats import chi2_contingency, ks_2samp

ones = np.empty(len(occ_df['num'])); ones.fill(1)
f_percent_text = bergsma_data_df['f_percent_bergsma']
m_percent_text = ones - bergsma_data_df['f_percent_bergsma']

yf1 = np.rint(occ_df['num'] * f_percent_text)
yf2 = np.rint(occ_df['num'] * occ_df['f_percent'])
ym1 = np.rint(occ_df['num'] * m_percent_text)
ym2 = np.rint(occ_df['num'] * occ_df['m_percent'])


# Chi-square test (fem)
chi2, p_value, _, _ = chi2_contingency([yf1, yf2])
print("Chi-square test p-value (femninine):", p_value)
# Chi-square test (masc)
chi2, p_value, _, _ = chi2_contingency([ym1, ym2])
print("Chi-square test p-value (masculine):", p_value)
```

```
# Kolmogorov-Smirnov test (fem)
ks_statistic, p_value = ks_2samp(yf1, yf2)
print("Kolmogorov-Smirnov test p-value (feminine):", p_value)
# Kolmogorov-Smirnov test (masc)
ks_statistic, p_value = ks_2samp(ym1, ym2)
print("Kolmogorov-Smirnov test p-value (masculine):", p_value)
```

```
Chi-square test p-value (femninine): 1.2923159565570473e-05
Chi-square test p-value (masculine): 0.5594743262015124
Kolmogorov-Smirnov test p-value (feminine): 1.2659322249026965e-10
Kolmogorov-Smirnov test p-value (masculine): 1.2659322249026965e-10
```

[18]:
```
deltas = occ_df.loc[:,["name", "f_percent_us", "fm_delta", "fm_delta_us"]]
deltas["fm_delta_text"] = occ_diffs_bergsma_df["fm_delta"]
deltas
```

[18]:

	name	f_percent_us	fm_delta	fm_delta_us	fm_delta_text
0	technician	0.032	0.333333	-0.936	-0.8116
1	accountant	0.597	0.000000	0.194	-0.8148
2	supervisor	0.300	0.000000	-0.400	-0.2796
3	engineer	0.165	0.000000	-0.670	-0.9602
4	worker	0.500	0.333333	0.000	-0.7314
5	nurse	0.874	0.200000	0.748	-0.9822
6	dispatcher	0.508	0.000000	0.016	-0.8964
7	cashier	0.731	0.000000	0.462	0.2372
8	auditor	0.597	0.000000	0.194	-0.7820
9	dietitian	0.914	0.000000	0.828	-0.2842
10	painter	0.535	0.000000	0.070	0.3444
11	broker	0.661	0.000000	0.322	0.7116
12	chef	0.180	0.000000	-0.640	-0.7694
13	doctor	0.744	0.000000	0.488	-0.3370
14	firefighter	0.044	0.000000	-0.912	-0.7602
15	secretary	0.929	0.200000	0.858	0.7662
16	pharmacist	0.616	0.000000	0.232	-0.9840
17	psychologist	0.803	0.000000	0.606	0.0870
18	teacher	0.735	0.000000	0.470	-0.8530
19	lawyer	0.374	0.000000	-0.252	-0.9332
20	plumber	0.023	0.333333	-0.954	-0.9132
21	surgeon	0.263	0.000000	-0.474	-0.2890
22	veterinarian	0.649	0.000000	0.298	-0.8496
23	paramedic	0.281	0.000000	-0.438	-0.9434
24	baker	0.641	0.000000	0.282	0.6022
25	programmer	0.211	0.000000	-0.578	-0.8214
26	mechanic	0.012	0.000000	-0.976	-0.9192
27	manager	0.404	0.000000	-0.192	0.3714
28	therapist	0.844	0.000000	0.688	0.3492
29	administrator	0.717	0.000000	0.434	-0.4392

30	salesperson	0.487	0.000000	-0.026	0.7298
31	receptionist	0.883	0.000000	0.766	-0.7670
32	librarian	0.832	0.000000	0.664	-0.7276
33	carpenter	0.032	0.333333	-0.936	-0.8668
34	electrician	0.031	0.000000	-0.938	-0.8160
35	hairdresser	0.908	0.000000	0.816	-0.9382
36	architect	0.282	0.000000	-0.436	-0.7914

[19]:
```
import statsmodels.api as sm

# testing whether the two regression lines (text vs observed) are different
y = deltas.fm_delta_text.to_numpy() - deltas.fm_delta.to_numpy()
# create a linear regression for the difference between deltas (on the y-axis)
mod = sm.OLS(y, sm.add_constant(deltas.fm_delta_us.to_numpy()))
res = mod.fit()
print(res.summary())
# Given a p-value = 0.017, we should reject the null hypothesis that the two
# regression lines are the same
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.152
Model:                            OLS   Adj. R-squared:                  0.128
Method:                 Least Squares   F-statistic:                     6.276
Date:                Sun, 11 Jun 2023   Prob (F-statistic):             0.0170
Time:                        20:11:20   Log-Likelihood:                -30.327
No. Observations:                  37   AIC:                             64.65
Df Residuals:                      35   BIC:                             67.88
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.5046      0.093     -5.435      0.000      -0.693      -0.316
x1             0.3899      0.156      2.505      0.017       0.074       0.706
==============================================================================
Omnibus:                        3.240   Durbin-Watson:                   1.916
Prob(Omnibus):                  0.198   Jarque-Bera (JB):                2.996
Skew:                           0.653   Prob(JB):                        0.224
Kurtosis:                       2.511   Cond. No.                         1.68
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

8 Outlier detection

As we will shortly see, two separate methods detect the occupations of `broker` and `administrator` as outliers (indices 11 and 30 in the above data frame)

[20]:
```
import numpy as np
from scipy.stats import zscore

# gender-based percentage differences (observed in chatgpt)
y = deltas.fm_delta.to_numpy()
# baseline gender-based percentage differences (in online text in general)
x = deltas.fm_delta_us.to_numpy()

# Calculate the Z-scores for the target variable
z_scores = np.abs(zscore(y))

# Set a threshold for outlier detection (e.g., 3 standard deviations)
threshold = 2

# Identify the indices of outliers
outlier_indices = np.where(z_scores > threshold)[0]

# the outliers
deltas.iloc[outlier_indices]
```

[20]:

	name	f_percent_us	fm_delta	fm_delta_us	fm_delta_text
0	technician	0.032	0.333333	-0.936	-0.8116
4	worker	0.500	0.333333	0.000	-0.7314
20	plumber	0.023	0.333333	-0.954	-0.9132
33	carpenter	0.032	0.333333	-0.936	-0.8668

[21]:
```
import pandas as pd

# gender-based percentage differences (observed in chatgpt)
y = deltas.fm_delta
# baseline gender-based percentage differences (in online text in general)
x = deltas.fm_delta_us

# Calculate the first quartile (25th percentile)
q1 = y.quantile(0.25)

# Calculate the third quartile (75th percentile)
q3 = y.quantile(0.75)

# Calculate the interquartile range (IQR)
iqr = q3 - q1

# Set a threshold for outlier detection (e.g., 1.5 times the IQR)
```

```
threshold = 1.5

# Determine the lower and upper bounds for outlier detection
lower_bound = q1 - threshold * iqr
upper_bound = q3 + threshold * iqr

# Identify the outliers
outliers = (y < lower_bound) | (y > upper_bound)
outliers = outliers[outliers == True].index.values

# he outliers
deltas.iloc[outliers]
```

[21]:

	name	f_percent_us	fm_delta	fm_delta_us	fm_delta_text
0	technician	0.032	0.333333	-0.936	-0.8116
4	worker	0.500	0.333333	0.000	-0.7314
5	nurse	0.874	0.200000	0.748	-0.9822
15	secretary	0.929	0.200000	0.858	0.7662
20	plumber	0.023	0.333333	-0.954	-0.9132
33	carpenter	0.032	0.333333	-0.936	-0.8668

9 Dealing with outliers

We will adjust the values of outliers or simply remove them.

Note: the detection of outliers is done for our own information, but is not really necessary since we are not really using linear regression models. In other words, we don't claim that gender differential in online text mentions of various occupations is correlated to chatgpt's coreference resolutions with gendered pronouns. We are simply testing the differences between chatgpt's coreferential behaviour with gendered pronouns with other types of behaviour with gendered pronouns and want to find out if these behaviours are significantly different.

[22]:
```
# Create a copy of the original DataFrame
deltas_copy = deltas[['name', 'fm_delta', 'fm_delta_text', 'fm_delta_us']].
 ↪copy()
```

[23]:
```
import pandas as pd
import numpy as np

deltas_rep = deltas_copy
outlier_indices = list(outliers)

# Replace outliers with the median value of the 'col1' column
median_value = deltas_rep['fm_delta'].median()
print(median_value)
deltas_rep.loc[outlier_indices, 'fm_delta'] = median_value
```

```
# check that substitution of median values succeeded
deltas_copy.compare(deltas_rep)
deltas_rep
```

```
0.0
```

[23]:

	name	fm_delta	fm_delta_text	fm_delta_us
0	technician	0.0	-0.8116	-0.936
1	accountant	0.0	-0.8148	0.194
2	supervisor	0.0	-0.2796	-0.400
3	engineer	0.0	-0.9602	-0.670
4	worker	0.0	-0.7314	0.000
5	nurse	0.0	-0.9822	0.748
6	dispatcher	0.0	-0.8964	0.016
7	cashier	0.0	0.2372	0.462
8	auditor	0.0	-0.7820	0.194
9	dietitian	0.0	-0.2842	0.828
10	painter	0.0	0.3444	0.070
11	broker	0.0	0.7116	0.322
12	chef	0.0	-0.7694	-0.640
13	doctor	0.0	-0.3370	0.488
14	firefighter	0.0	-0.7602	-0.912
15	secretary	0.0	0.7662	0.858
16	pharmacist	0.0	-0.9840	0.232
17	psychologist	0.0	0.0870	0.606
18	teacher	0.0	-0.8530	0.470
19	lawyer	0.0	-0.9332	-0.252
20	plumber	0.0	-0.9132	-0.954
21	surgeon	0.0	-0.2890	-0.474
22	veterinarian	0.0	-0.8496	0.298
23	paramedic	0.0	-0.9434	-0.438
24	baker	0.0	0.6022	0.282
25	programmer	0.0	-0.8214	-0.578
26	mechanic	0.0	-0.9192	-0.976
27	manager	0.0	0.3714	-0.192
28	therapist	0.0	0.3492	0.688
29	administrator	0.0	-0.4392	0.434
30	salesperson	0.0	0.7298	-0.026
31	receptionist	0.0	-0.7670	0.766
32	librarian	0.0	-0.7276	0.664
33	carpenter	0.0	-0.8668	-0.936
34	electrician	0.0	-0.8160	-0.938
35	hairdresser	0.0	-0.9382	0.816
36	architect	0.0	-0.7914	-0.436

[24]:
```
# Create a copy of the original DataFrame
deltas_remove = deltas_copy
```

```
# Remove outliers from the 'fm_delta' column
deltas_remove = deltas_remove.drop(outlier_indices)

deltas_remove
```

[24]:

	name	fm_delta	fm_delta_text	fm_delta_us
1	accountant	0.0	-0.8148	0.194
2	supervisor	0.0	-0.2796	-0.400
3	engineer	0.0	-0.9602	-0.670
6	dispatcher	0.0	-0.8964	0.016
7	cashier	0.0	0.2372	0.462
8	auditor	0.0	-0.7820	0.194
9	dietitian	0.0	-0.2842	0.828
10	painter	0.0	0.3444	0.070
11	broker	0.0	0.7116	0.322
12	chef	0.0	-0.7694	-0.640
13	doctor	0.0	-0.3370	0.488
14	firefighter	0.0	-0.7602	-0.912
16	pharmacist	0.0	-0.9840	0.232
17	psychologist	0.0	0.0870	0.606
18	teacher	0.0	-0.8530	0.470
19	lawyer	0.0	-0.9332	-0.252
21	surgeon	0.0	-0.2890	-0.474
22	veterinarian	0.0	-0.8496	0.298
23	paramedic	0.0	-0.9434	-0.438
24	baker	0.0	0.6022	0.282
25	programmer	0.0	-0.8214	-0.578
26	mechanic	0.0	-0.9192	-0.976
27	manager	0.0	0.3714	-0.192
28	therapist	0.0	0.3492	0.688
29	administrator	0.0	-0.4392	0.434
30	salesperson	0.0	0.7298	-0.026
31	receptionist	0.0	-0.7670	0.766
32	librarian	0.0	-0.7276	0.664
34	electrician	0.0	-0.8160	-0.938
35	hairdresser	0.0	-0.9382	0.816
36	architect	0.0	-0.7914	-0.436

[25]:
```
# Create a copy of the original DataFrame
deltas_winsorized = deltas_copy

# Assuming you have defined the lower and upper bounds for winsorization as␣
↪'lower_bound' and 'upper_bound'
lower_bound = 10  # Example lower bound
upper_bound = 90  # Example upper bound
```

```
# Winsorize the outlier values in the 'fm_deltas' column
deltas_winsorized['fm_delta'] = np.where(deltas_winsorized['fm_delta'] <␣
 ↪lower_bound, lower_bound, deltas_winsorized['fm_delta'])
deltas_winsorized['fm_delta'] = np.where(deltas_winsorized['fm_delta'] >␣
 ↪upper_bound, upper_bound, deltas_winsorized['fm_delta'])


deltas_copy.compare(deltas_rep)
```

[25]:
```
Empty DataFrame
Columns: []
Index: []
```

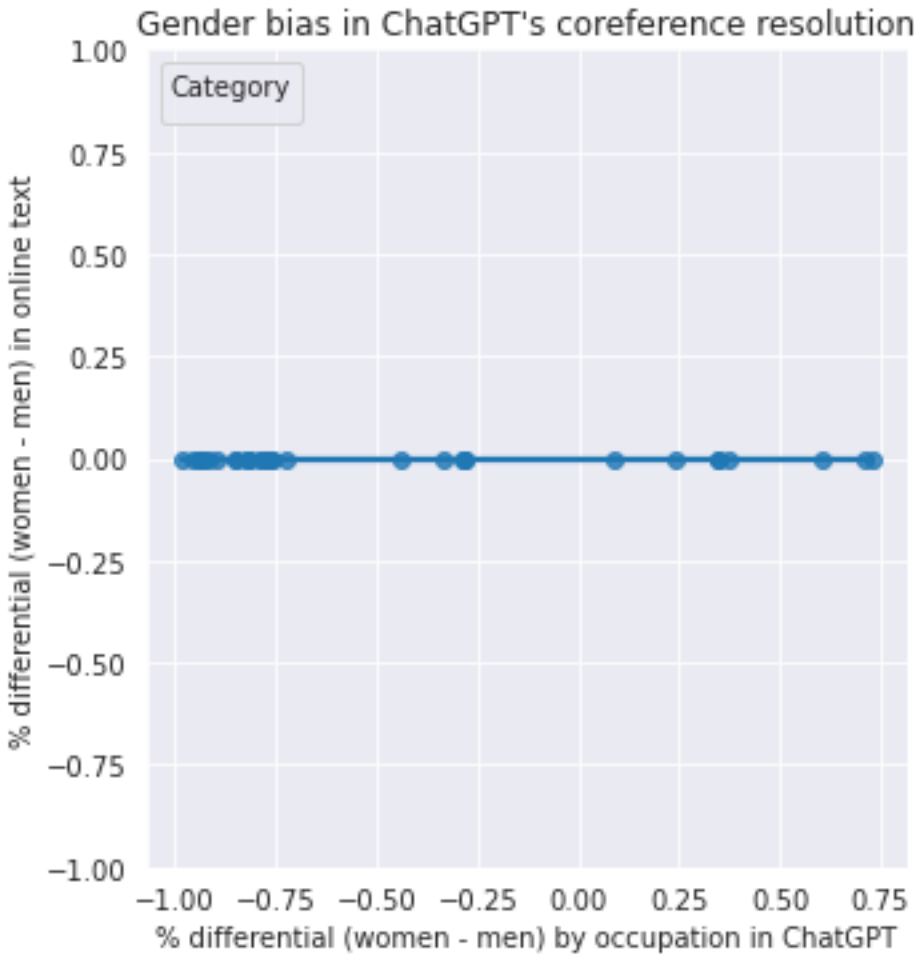
[26]:
```
from sklearn.linear_model import LinearRegression

# Assuming you have the DataFrame with outliers removed, saved as␣
 ↪'df_outliers_removed'

# Separate the target variable and explanatory variable
X = deltas_remove[['fm_delta_text']]  # Explanatory variable
y = deltas_remove['fm_delta']    # Target variable

# Create a linear regression model
model = LinearRegression()

# Fit the model to the data
model.fit(X, y)

# Print the intercept and coefficients
print("Intercept:", model.intercept_)
print("Coefficient:", model.coef_)
```

```
Intercept: 0.0
Coefficient: [0.]
```

[27]:
```
sns.set_style('darkgrid')
plt = sns.lmplot(data=deltas_remove, x='fm_delta_text',y='fm_delta',␣
 ↪legend=False)
plt.set(xlabel='% differential (women - men) by occupation in ChatGPT',␣
 ↪ylabel='% differential (women - men) in online text')
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')
```

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```

[27]: <matplotlib.legend.Legend at 0x7f4e48e5b2b0>



[28]:
```
from sklearn.metrics import r2_score, mean_squared_error

# Separate the target variable and explanatory variable
X = deltas_remove[['fm_delta_text']]  # Explanatory variable
y_true = deltas_remove['fm_delta']  # True target variable

# Make predictions using the trained model
y_pred = model.predict(X)

# Calculate R-squared
r2 = r2_score(y_true, y_pred)

# Calculate mean squared error
mse = mean_squared_error(y_true, y_pred)
```

```
# Print the performance metrics
print("R-squared:", r2)
print("Mean Squared Error:", mse)
```

```
R-squared: 1.0
Mean Squared Error: 0.0
```

10 T-test for chatgpt vs online text

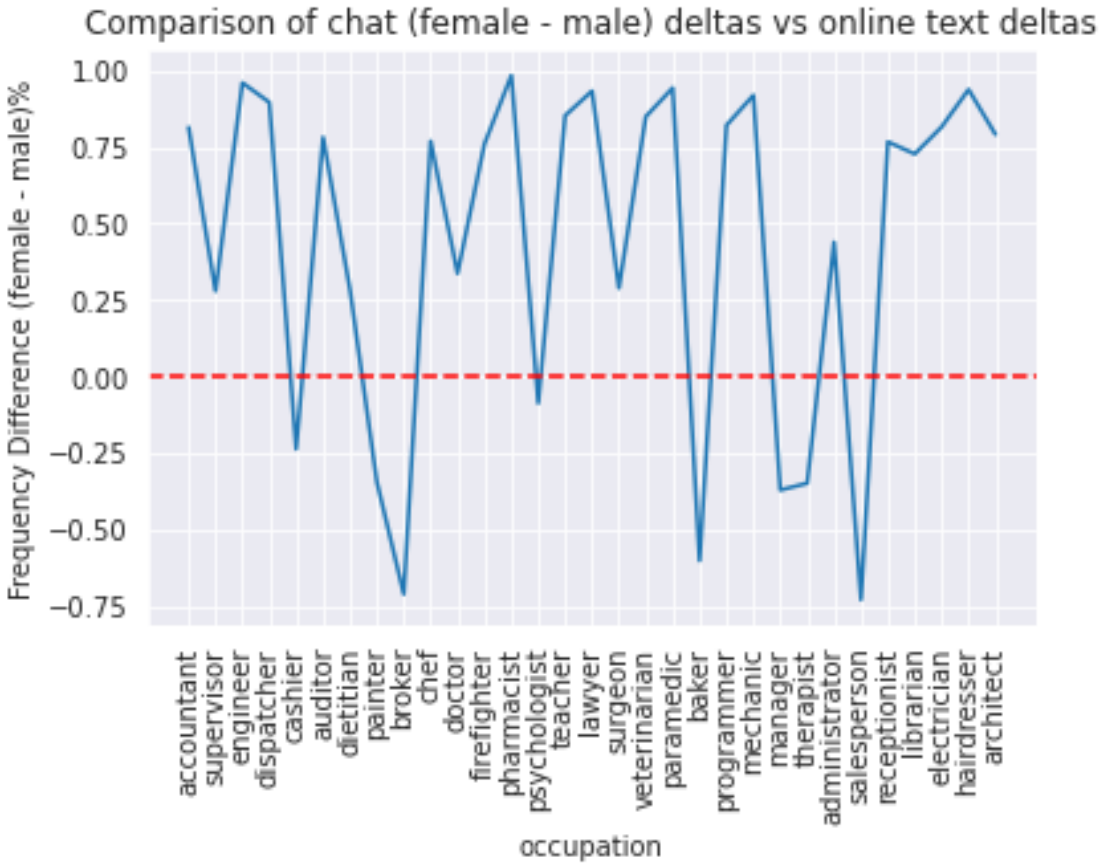
We want to test if there is a difference in frequencies per occupation between online text and ChatGPT generated data. (Recall that our data represent coreferential resolution per gender.)

[29]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
from scipy.stats import ttest_rel
import seaborn as sns
import matplotlib.pyplot as plt

y1 = deltas_remove['fm_delta_text'].to_numpy()
y2 = deltas_remove['fm_delta'].to_numpy()

# Calculate the frequency differences
delta = y2 - y1

# Calculate the frequency differences for each category of X
deltas_remove['delta_chat_text'] = delta

statistic, p_value = ttest_rel(y1, y2)

# Print the p-value
print("p-value:", p_value)
if p_value < 0.05:
  print(f"Null hypothesis rejected: ChatGPT's gendered responses are␣
 ↪significantly different than those in online texts.")
else:
  print(f"We can't reject the null hypothesis: ChatGPT's gendered responses are␣
 ↪not significantly different than those in online texts.")
```

```
p-value: 0.0001750618459869657
Null hypothesis rejected: ChatGPT's gendered responses are significantly
different than those in online texts.
```

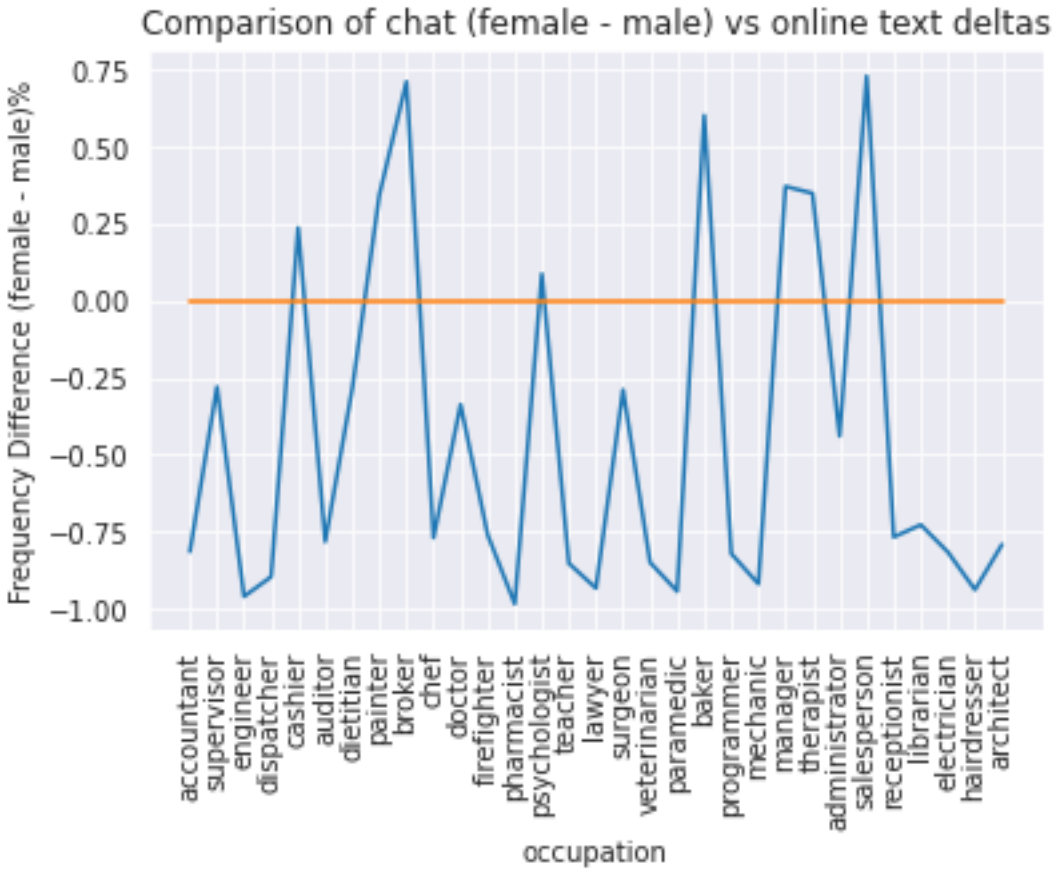
[30]:
```
import matplotlib.pyplot as plt

# Plot line graph
sns.lineplot(data=deltas_remove, x='name', y='delta_chat_text')
```

```
# Add a reference line at y=0
plt.axhline(y=0, color='red', linestyle='--')

# Set labels and title
plt.xlabel('occupation')
plt.ylabel('Frequency Difference (female - male)%')
plt.title('Comparison of chat (female - male) deltas vs online text deltas')
# Rotate x-axis labels vertically
plt.xticks(rotation=90)
# Show the plot
plt.show()
```



[31]:
```
# or compare the two gender differential to each other
# (rather than their difference to zero)
import matplotlib.pyplot as plt

# Plot line graph
sns.lineplot(data=deltas_remove, x='name', y='fm_delta_text')
```

```
sns.lineplot(data=deltas_remove, x='name', y='fm_delta')

# Add a reference line at y=0
#plt.axhline(y=0, color='red', linestyle='--')

# Set labels and title
plt.xlabel('occupation')
plt.ylabel('Frequency Difference (female - male)%')
plt.title('Comparison of chat (female - male) vs online text deltas')
# Rotate x-axis labels vertically
plt.xticks(rotation=90)
# Show the plot
plt.show()
```



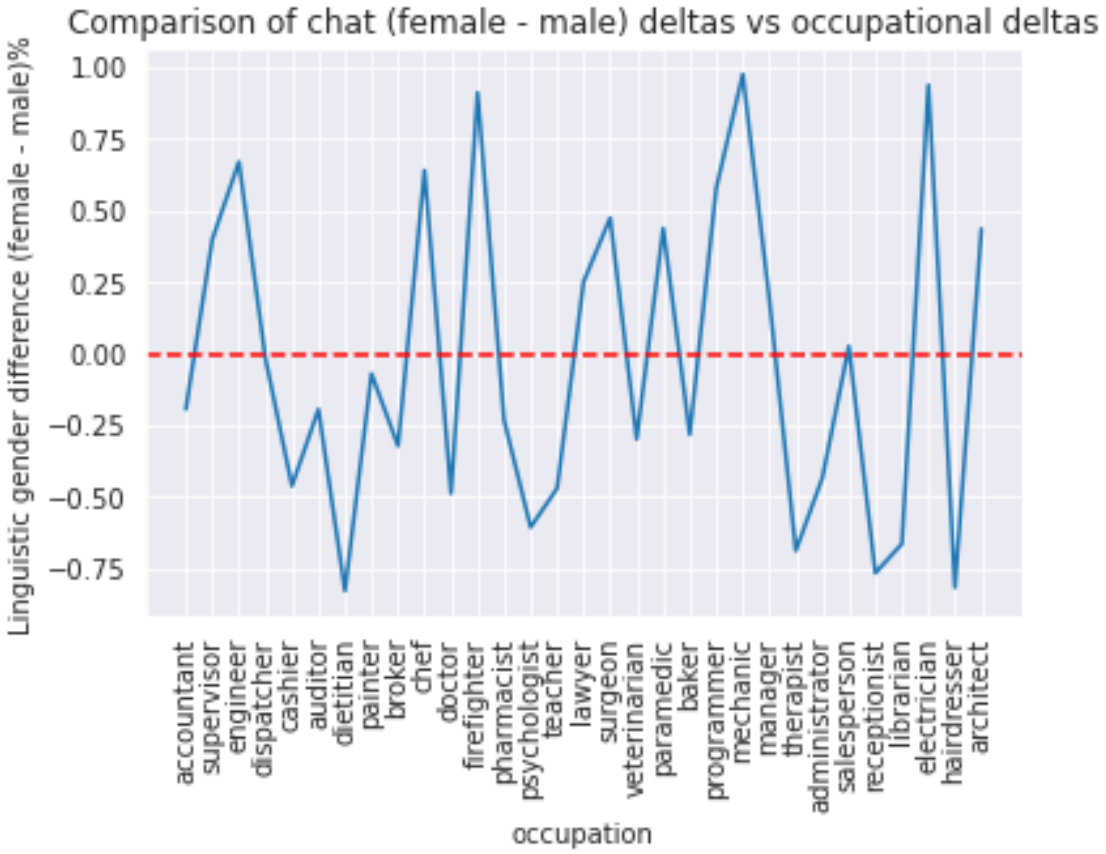
11 T-test for ChatGPT data vs ONS occupation data

[32]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
from scipy.stats import ttest_rel
import seaborn as sns
import matplotlib.pyplot as plt

y1 = deltas_remove['fm_delta_us'].to_numpy()
y2 = deltas_remove['fm_delta'].to_numpy()

# Calculate the frequency differences
delta = y2 - y1

# Calculate the frequency differences for each category of X
deltas_remove['delta_chat_onsus'] = delta

statistic, p_value = ttest_rel(y1, y2)

# Print the p-value
print("p-value:", p_value)

if p_value < 0.05:
  print(f"Null hypothesis rejected: ChatGPT's gendered responses are␣
 ↪significantly different than those in occupation statistics.")
else:
  print(f"We can't reject the null hypothesis: ChatGPT's gendered responses are␣
 ↪not significantly different than those in occupation statistics.")
```

```
p-value: 0.7726883706061562
We can't reject the null hypothesis: ChatGPT's gendered responses are not
significantly different than those in occupation statistics.
```

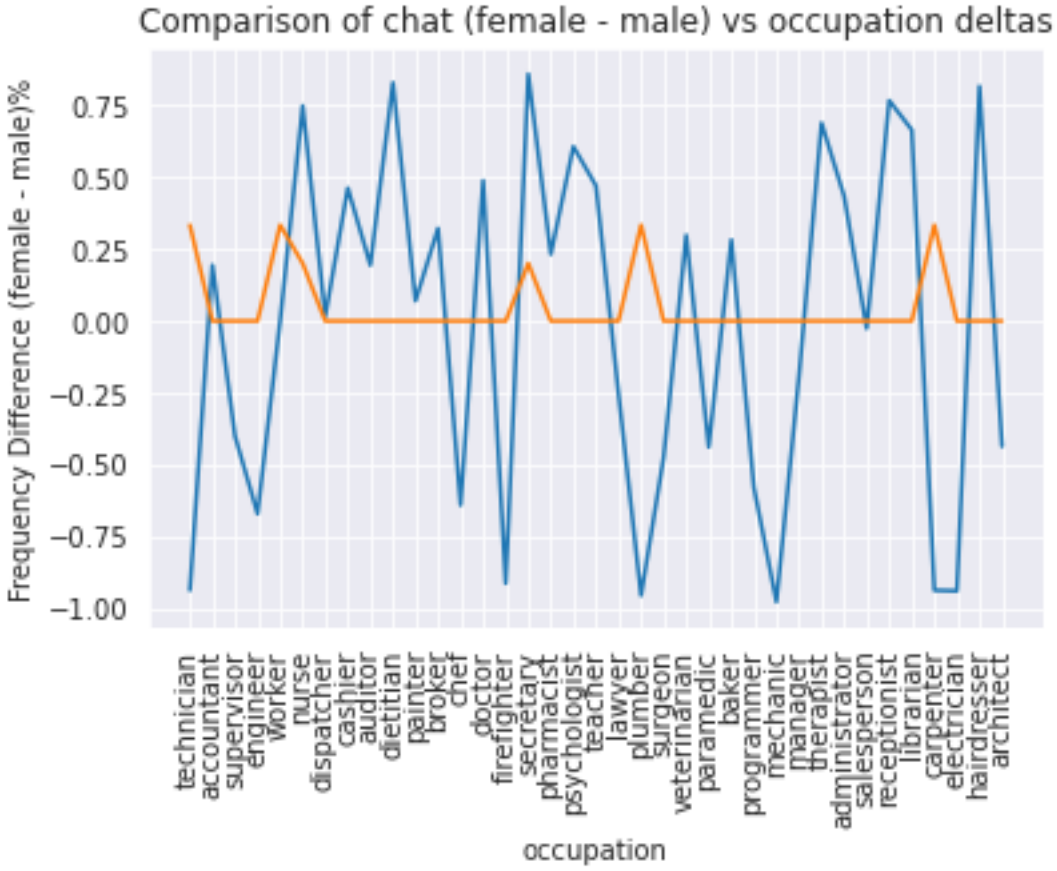
[33]:
```
import matplotlib.pyplot as plt

# Plot line graph
sns.lineplot(data=deltas_remove, x='name', y='delta_chat_onsus')

# Add a reference line at y=0
plt.axhline(y=0, color='red', linestyle='--')

# Set labels and title
plt.xlabel('occupation')
plt.ylabel('Linguistic gender difference (female - male)%')
plt.title('Comparison of chat (female - male) deltas vs occupational deltas')
# Rotate x-axis labels vertically
```

```
plt.xticks(rotation=90)
# Show the plot
plt.show()
```

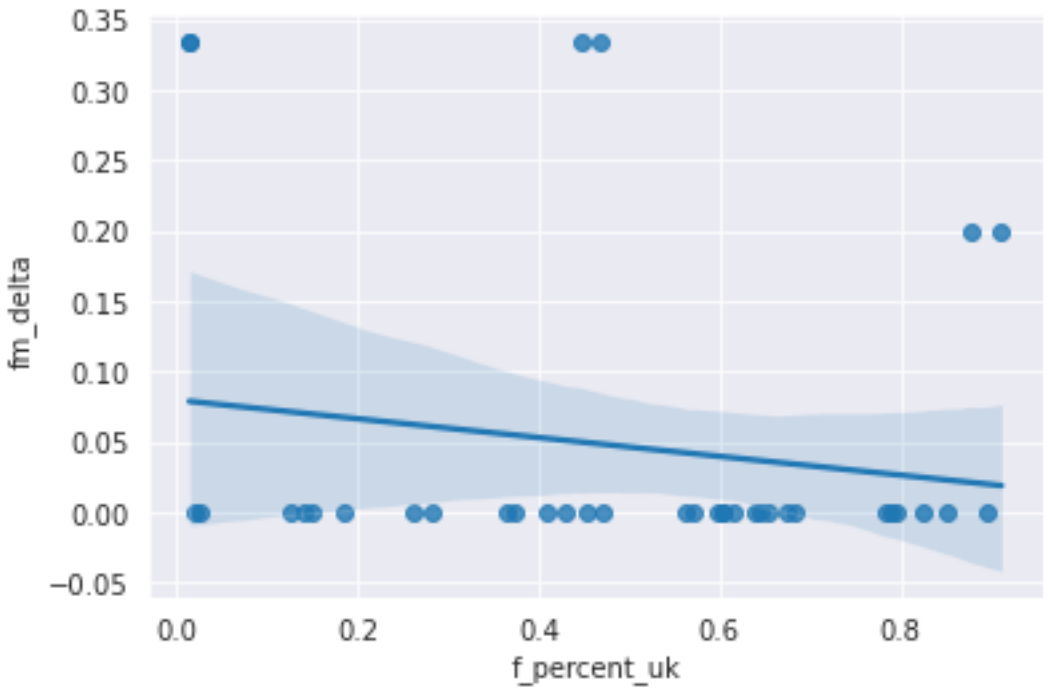


[34]:
```
# or compare the two gender differential to each other
# (rather than their difference to zero)
import matplotlib.pyplot as plt

# Plot line graph
sns.lineplot(data=deltas, x='name', y='fm_delta_us')
sns.lineplot(data=deltas, x='name', y='fm_delta')

# Add a reference line at y=0
#plt.axhline(y=0, color='red', linestyle='--')

# Set labels and title
plt.xlabel('occupation')
plt.ylabel('Frequency Difference (female - male)%')
plt.title('Comparison of chat (female - male) vs occupation deltas')
# Rotate x-axis labels vertically
```

```
plt.xticks(rotation=90)
# Show the plot
plt.show()
```

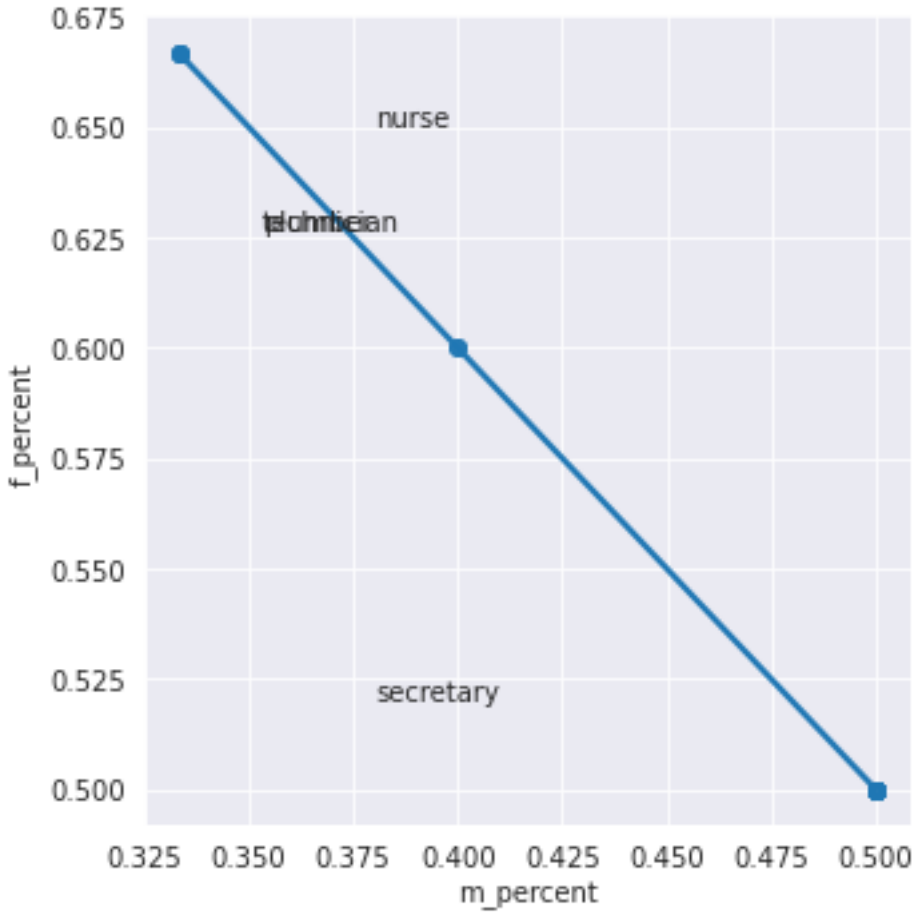


[35]:
```
# alternative ploting of the ChatGPT data
occ_df
sns.regplot(x="f_percent_uk", y="fm_delta", data=occ_df);
```

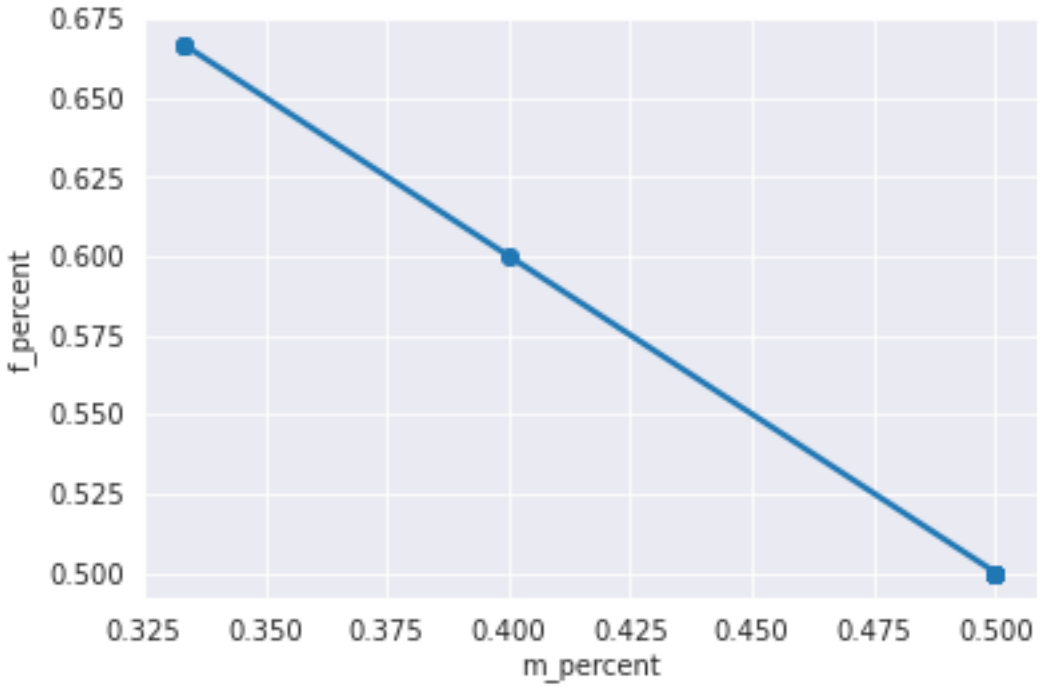


[36]:
```
plt = sns.lmplot(data=occ_df, x='m_percent', y='f_percent')
label_point(occ_df.m_percent, occ_df.f_percent, occ_df.name, plt)
```

worker



[37]:
```
# 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
```



[38]:
```
# 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
```

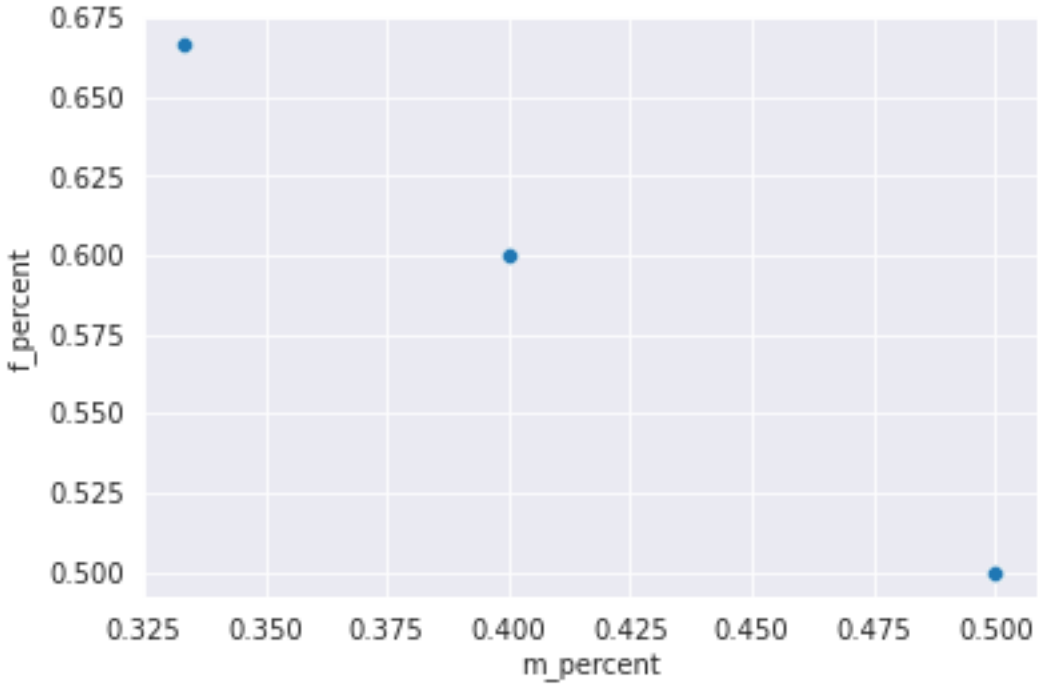
[38]:

	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

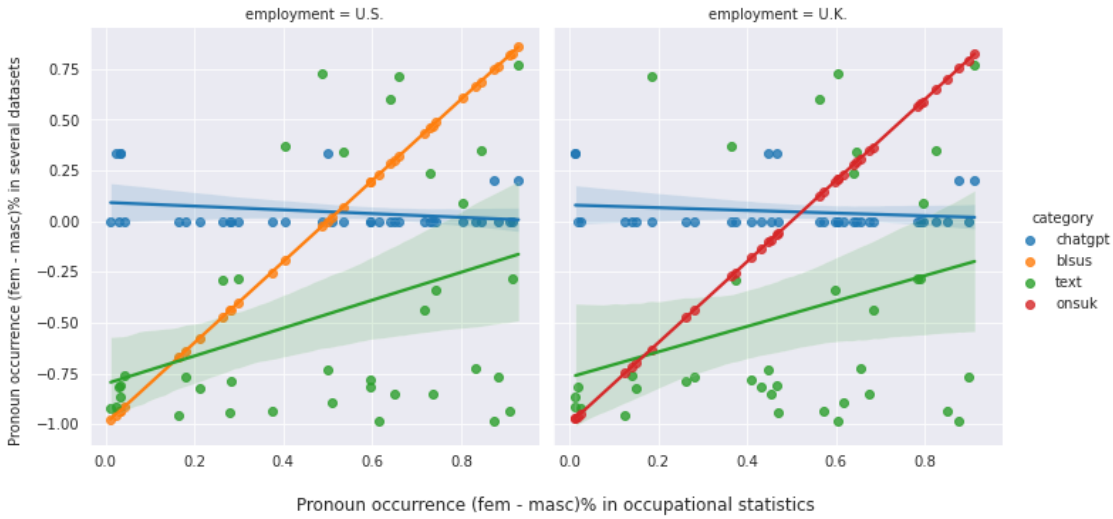
24	0.437143	0.125714	0.641	0.359	0.282
25	0.850139	-0.700278	0.211	0.789	-0.578
26	0.975530	-0.951060	0.012	0.988	-0.976
27	0.635454	-0.270908	0.404	0.596	-0.192
28	0.175791	0.648418	0.844	0.156	0.688
29	0.317168	0.365664	0.717	0.283	0.434
30	0.395735	0.208530	0.487	0.513	-0.026
31	0.103195	0.793609	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



[39]:
```
# 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 = df = pd.concat([occ_diffs_ext_us, occ_diffs_ext_uk])
```

```
# create lmplot with two side-by-side panels
g = sns.lmplot(data=occ_diffs_ext, x='f_employment', y='fm_delta',␣
 ↪hue='category', col='employment')
g.set_ylabels('Pronoun occurrence (fem - masc)% in several datasets      ')

# Access the underlying axes
axes = g.axes

# Adjust the y_labelpad parameter
for ax in axes.flatten():
    ax.yaxis.labelpad = 10  # Adjust the value as per your preference

# Access the underlying figure
fig = g.fig

# remove x-axis labels
g.set_xlabels('')
# add text centered under both x-axes
fig.text(0.5, 0, 'Pronoun occurrence (fem - masc)% in occupational statistics',
         ha='center', va='center', fontsize=12)
```

[39]: Text(0.5, 0, 'Pronoun occurrence (fem - masc)% in occupational statistics')



12 Statistical Significance for Coreference Data

I'll now look if there is any significant difference in how ChatGPT identified the entities that gendered (feminine and masculine) pronouns refer to – the coreference resolution task.

We make two comparisons between our regression lines. First comes the employment vs valid feminine pronouns. In particular, we compare the difference between female-to-male differentials in employment (using US labour market data) and the observed feminine-to-masculine differentials in valid coreferential resolutions in our interaction with ChatGPT.

Second, we look at differences between texts in general and the ChatGPT performance with feminine pronouns. More precisely, we compare the difference between female-to-male differentials in text (using data from Bergsma and Lin (2006), cited and made available by Rudinger et al 2018) and our coreference data obtained in interaction with ChatGPT, namely the observed feminine-to-masculine differentials in valid coreferential resolutions.

In either case, the null hypothesis is that there is no difference between the ChatGPT performance with gendered pronouns and the independently collected data about gender. As shown below, the null hypothesis is rejected in each of the two cases in favour of the alternative hypothesis that ChatGPT's performance is meaningfully different from what we should expect given the other data sources about empolyment and textual patterns.

[40]:
```
# testing whether the two regression lines (us employment vs observed) are␣
 ↪different
y = deltas.fm_delta_us.to_numpy() - deltas.fm_delta.to_numpy()
# create a linear regression for the difference between deltas (on the y-axis)
mod = sm.OLS(y, sm.add_constant(deltas.f_percent_us.to_numpy()))
res = mod.fit()
print(res.summary())
# Given a p-value = 9.23**29, we should reject the null hypothesis that the two
# regression lines are the same
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.972
Model:                            OLS   Adj. R-squared:                  0.971
Method:                 Least Squares   F-statistic:                     1214.
Date:                Sun, 11 Jun 2023   Prob (F-statistic):           9.23e-29
Time:                        20:11:25   Log-Likelihood:                 30.555
No. Observations:                  37   AIC:                            -57.11
Df Residuals:                      35   BIC:                            -53.89
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.0925      0.035    -31.451      0.000      -1.163      -1.022
x1             2.0920      0.060     34.840      0.000       1.970       2.214
==============================================================================
Omnibus:                       17.839   Durbin-Watson:                   1.945
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20.881
Skew:                          -1.708   Prob(JB):                     2.92e-05
Kurtosis:                       4.371   Cond. No.                         4.24
==============================================================================
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[41]:
```
# testing whether the two regression lines (text vs observed) are different
y = deltas.fm_delta_text.to_numpy() - deltas.fm_delta.to_numpy()
# create a linear regression for the difference between deltas (on the y-axis)
mod = sm.OLS(y, sm.add_constant(deltas.f_percent_us.to_numpy()))
res = mod.fit()
print(res.summary())
# Given a p-value = 0.017, we should reject the null hypothesis that the two
# regression lines are the same
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.152
Model:                            OLS   Adj. R-squared:                  0.128
Method:                 Least Squares   F-statistic:                     6.276
Date:                Sun, 11 Jun 2023   Prob (F-statistic):             0.0170
Time:                        20:11:25   Log-Likelihood:                -30.327
No. Observations:                  37   AIC:                             64.65
Df Residuals:                      35   BIC:                             67.88
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.8944      0.180     -4.968      0.000      -1.260      -0.529
x1             0.7797      0.311      2.505      0.017       0.148       1.412
==============================================================================
Omnibus:                        3.240   Durbin-Watson:                   1.916
Prob(Omnibus):                  0.198   Jarque-Bera (JB):                2.996
Skew:                           0.653   Prob(JB):                        0.224
Kurtosis:                       2.511   Cond. No.                         4.24
==============================================================================
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[42]:
```
# tests and summary of data (for code in the cell above)

def coref_summary(df):
    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) + len(n_res)} (rows scored 1 per each gender)")
    print(f"F {len(f_res_0)} + M {len(m_res_0)} + N {len(n_res_0)} =␣
↪{len(f_res_0) + len(m_res_0) + len(n_res_0)} (rows scored 0 per each␣
↪gender)")
    print("PERCENTAGES (SUMMARY)")
    print(f"F {f_percentage_valid}, M {m_percentage_valid}, N␣
↪{n_percentage_valid} (valid resolutions)")
    print(f"F {f_percentage_total}, M {m_percentage_total}, N␣
↪{n_percentage_total} (all resolutions)")

def test_size(df):
    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()
```

13 Remarks about the Coreference Resolution Results

- 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.

14 ChatGPT: Gendered Pronoun Generation Tasks

I asked ChatGPT to produce senteces with occupation noun phrases and pronouns coreferent with them, as well as suitable annotations marking coreference. Here are a couple of representative prompts I used for this task.

Author:

> Hi ChatGPT, could you build sentences that contain a noun phrases and pronouns that are coreferential, that is, refer to the same entity. For instance, I constructed two such sentences and annotated them using the same index number for coreferential expressions: 1. The man_1 looked around him_1 but he_1 could not see anything

because of the thick fog. 2. The woman_1 walked around the hospital for 10 minutes but she_1 could not find the ward. Could you build 5 sentences like these?

ChatGPT:

Sure! Here are five sentences that contain noun phrases and pronouns that are coreferential:

1. The boy_1 kept talking to himself_1, but no one else could hear him_1 because of the noise in the room.
2. The cat_1 curled up on the windowsill, lazily grooming itself_1 as it watched the birds outside.
3. The teacher_1 explained the concept to the class, but no one seemed to understand it_1.
4. The politician_1 gave a long speech, but the audience soon became bored with him_1.
5. The artist_1 painted a beautiful landscape, but she_1 was never able to sell it_1.

Author:

Could you build five similar sentences using the noun phrase "the secretary" and a coreferential pronoun?

ChatGPT:

Sure! Here are five sentences that contain the noun phrase "the secretary" and a coreferential pronoun:

1. The secretary_1 typed up the report, but she_1 made several mistakes while doing so.
2. The secretary_1 answered the phone, but she_1 couldn't understand what the caller was saying due to a bad connection.
3. The secretary_1 organized the files, but she_1 couldn't find the one she_1 was looking for.
4. The secretary_1 made copies of the documents, but she_1 ran out of ink halfway through the job.
5. The secretary_1 scheduled the meetings, but she_1 double-booked the conference room for two different groups.

Author:

Thanks. Now can you build ten sentences containing the noun phrase "the manager" and a coreferential pronoun? (Annotate the coreferential expressions as before.)

ChatGPT:

Sure! Here are ten sentences that contain the noun phrase "the manager" and a coreferential pronoun:

1. The manager_1 held a meeting with the team, but she_1 didn't have all of the necessary information.
2. The manager_1 reviewed the employee's performance, but he_1 didn't take into account their recent accomplishments.
3. The manager_1 made a decision on the project, but it_1 was met with criticism from the team.

4. The manager_1 gave a presentation to the clients, but she_1 stumbled over her words and lost their attention.
5. The manager_1 communicated the company's new policies, but he_1 didn't clearly explain them to the employees.
6. The manager_1 delegated tasks to the team, but she_1 didn't provide enough direction or support.
7. The manager_1 attempted to resolve a conflict between two employees, but he_1 only made the situation worse.
8. The manager_1 tried to improve the team's productivity, but her_1 efforts were met with resistance.
9. The manager_1 set unrealistic goals for the team, causing them_1 to become demotivated.
10. The manager_1 held a team-building event, but it_1 was a complete failure and made the team more resentful.

These are just a couple of examples showing how coreferential pronouns have been generated. ChatGPT did not always get the coreference right, as can be seen in the examples above (e.g. in sentence 10 just above, ChatGPT seems to consider the "it" to refer to the manager, rather than to the team-building event). Some other times, ChatGPT's annotations are mistaken for not identifying any coreferents at all, giving different indices to different noun phrases. In such cases, I prompted ChatGPT again for a coreferential interpretation, and in most cases it returned a valid coreferential annotation.

15 ChatGPT: Gendered Pronoun Generation Data

I collected the data generated by ChatGPT, given a score of 1 to each sentence where a gendered pronoun has been correctly resolved and bound to an antecedent occupation term which thus provides the pronoun's referent.

Our analysis consists of comparing how many times ChatGPT generated correct coreferential gendered pronouns for each grammatical gender (masculine and feminine) and checking whether there are any significant differences in these data.

[43]:
```
import seaborn as sns
import matplotlib.pyplot as plt

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": float,
              "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_expect",
                                          "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="occupation",
    kind="bar", height=4, aspect=.6,
)

sfm_ext
```

[43]:

	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

16 Main Plots for the Gender Pronoun Generation Data

Here are the main plots that represent the respective frequencies of gendered (feminine and masculine) pronoun generated by ChatGPT.

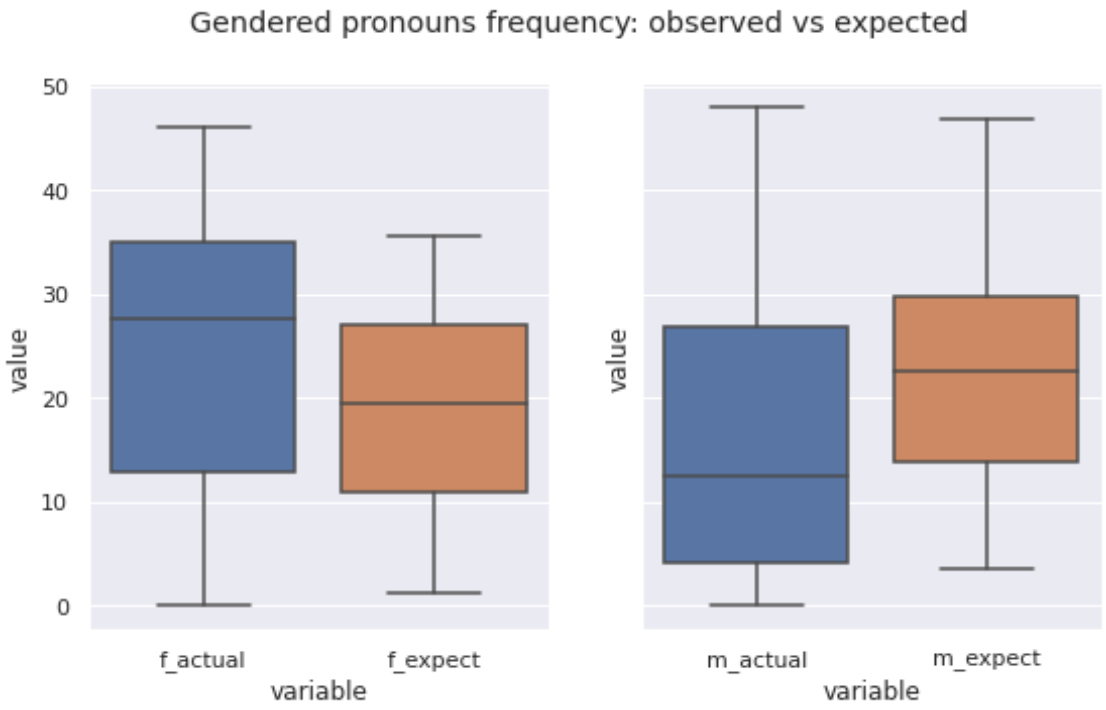
[44]:
```
#sfm_percent

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 frequency')

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',xlabel=None)

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 frequency')

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',xlabel=None)

#sfm_ext_percent
```

[44]: [Text(0.5, 1.0, 'Professor'), Text(0.5, 12.500000000000028, '')]

[45]:
```
# overall
sns.set()
fig, axes = plt.subplots(1, 2, figsize=(9,5), sharey=True)
fig.suptitle("Gendered pronouns frequency: observed 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"})
subdf = subdf.rename(columns={"m_gender": "m_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])
```

[45]: <AxesSubplot:xlabel='variable', ylabel='value'>



17 Statistical Significance for Generated Pronouns

We should now test if there are any biases in how ChatGPT generates pronouns with coreferential readings. As before, we use US empolyment statistics for male vs female proportions for the relevant occupations as a comparison class to detect any deviation that may entail (algorithmic) bias.

[46]:
```
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_total}")
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 significance.")
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_percent_fem_expected}")
print(f"where f = frequency of feminine-gendred pronouns, and the sample size␣
 ↪{story_count_total}")
binomial_res_2 = binomtest(story_count_fem, n=story_count_total,␣
 ↪p=story_percent_fem_expected, alternative='greater')
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 significance")
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

[47]:
```
from scipy.stats import variation, bartlett, levene, ttest_ind, shapiro
from statsmodels.stats.weightstats import ztest as ztest

var_f_obs, f_actual = variation(subdf["f_actual"], ddof=1), subdf["f_actual"].
 ↪to_numpy()
var_f_exp, f_expect = variation(subdf["f_expect"], ddof=1), subdf["f_expect"].
 ↪to_numpy()
var_m_obs, m_actual = variation(subdf["m_actual"], ddof=1), subdf["m_actual"].
 ↪to_numpy()
var_m_exp, m_expect = variation(subdf["m_expect"], ddof=1), subdf["m_expect"].
 ↪to_numpy()

print("Let's have a look at the variances for the two pairs of samples (f, m␣
 ↪pronouns):")
print(f"Variances {var_f_exp} (expected female) and {var_f_obs} (observed␣
 ↪female) are about the same.")
print(f"Variances {var_m_exp} (expected male) and {var_m_obs} (observed male)␣
 ↪are not far apart.\n")

def equal_variance_results(test_name):
    if p < 0.05:
        print(f"{test_name}: Null hypothesis rejected: samples do not have␣
 ↪equal variance.")
    else:
        print(f"{test_name}: Null hypothesis accepted: samples have equal␣
 ↪variance.\n")

print("Assume the null hypothesis that the two groups' variances are the same.")

stat, p = levene(m_expect, m_actual)
equal_variance_results("Levene test")
stat, p = bartlett(m_expect, m_actual)
equal_variance_results("Bartlett test")

stat, p = levene(f_expect, f_actual)
equal_variance_results("Levene test")
stat, p = levene(f_expect, f_actual)
equal_variance_results("Bartlett test")

stat, p_m_exp = stats.shapiro(m_expect)
stat, p_m_obs = stats.shapiro(m_actual)
stat, p_f_exp = stats.shapiro(f_expect)
stat, p_f_obs = stats.shapiro(f_actual)
```

```
print("Are our samples normally distributed? Assume they are (the null␣
 ↪hythesis).")
print(f"The p-values for the four samples of interest are: {p_m_exp},␣
 ↪{p_m_obs},  {p_f_exp}, {p_f_obs}")
print("So we can't reject our assumption of normality for each of the four␣
 ↪samples.")
```

```
Let's have a look at the variances for the two pairs of samples (f, m pronouns):
Variances 0.5996844780776515 (expected female) and 0.6178004131006635 (observed
female) are about the same.
Variances 0.5963923144579972 (expected male) and 0.9251819475622279 (observed
male) are not far apart.

Assume the null hypothesis that the two groups' variances are the same.
Levene test: Null hypothesis accepted: samples have equal variance.

Bartlett test: Null hypothesis accepted: samples have equal variance.

Levene test: Null hypothesis accepted: samples have equal variance.

Bartlett test: Null hypothesis accepted: samples have equal variance.

Are our samples normally distributed? Assume they are (the null hythesis).
The p-values for the four samples of interest are: 0.6710313558578491,
0.07080470025539398,  0.5529723167419434, 0.28363752365112305
So we can't reject our assumption of normality for each of the four samples.
```

18 Remarks about the results of gendered pronoun generation

- there is no significant bias against feminine pronouns (as to their coreference properties) by ChatGPT's, as it generates coreferential pron
- assuming a binominal distribution (which is reasonable given that each sentence has a either success or failure outcome), it follows that ChatGPT is biased against masculine pronouns (in the sense that it resolves them less often than explected taking as a baseline comparison class the proportion of men for each occupation in the US employment data)
- since the relevant data are not normally distributed, we cannot rely on t- and z-tests for an alternative test of the null hypothesis that there is no significant deviation from the expected mean for each group (successful resolutions of masculine vs feminine pronouns)

[48]:
```
# a comparison of percentages
story_df_percent = story_data_df.loc[:, ['f_percent_uk', 'm_percent_uk',␣
 ↪"f_percent_observed", "m_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()
```

[48]:

	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

[49]:
```
import os

"""uncomment & run this cell to convert to pdf from within the notebook

# 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 cells)
              f"--citeproc",
              f"--bibliography={bibfile}",
              f"--csl={citation_style}"])
os.system(pandoc_cmd)

# References

"""
```

[49]:
```
'uncomment & run this cell to convert to pdf from within the notebook\n\n#
Convert jupyter notebook to pdf via pandoc\n\ndocname = "progen_bias"\nbibfile =
"references.bib"\ncitation_style = "acm.csl"\n\n# pandoc command\npandoc_cmd = "
".join([f"pandoc -s {docname}.ipynb -t pdf -o {docname}.pdf",\n              f"
--lua-filter=parse_html.lua", # needed to parse HTML tables (in output cells)\n
f"--citeproc", \n              f"--bibliography={bibfile}",\n              f"--
csl={citation_style}"])\nos.system(pandoc_cmd)\n\n# References\n\n'
```

[ ]: