Final Project

Gender Bias

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In [4]:
```
import os
import string
import re

from gensim.models import Word2Vec
import matplotlib.pyplot as plt
from nltk.tokenize import sent_tokenize
import numpy as np
import pandas as pd
from sklearn.decomposition import PCA
from sklearn.metrics.pairwise import cosine_similarity
```

In [219…
```
max_line_length = 800000
```

In [220…
```
def read_files(dir_name):
    english_corpus = []
    spanish_corpus = []
    french_corpus = []
    german_corpus = []
    for filename in os.listdir(dir_name):
        if '.en' in filename[-3:] or '.en.' in filename:
            with open(f'{dir_name}/{filename}') as f:
                english_corpus.extend(f.readlines())
        if '.es' in filename[-3:] or '.es.' in filename:
            with open(f'{dir_name}/{filename}') as f:
                spanish_corpus.extend(f.readlines())
        if '.fr' in filename[-3:] or '.fr.' in filename:
            with open(f'{dir_name}/{filename}') as f:
                french_corpus.extend(f.readlines())
        if '.de' in filename[-3:] or '.de.' in filename:
            with open(f'{dir_name}/{filename}') as f:
                german_corpus.extend(f.readlines())
    return english_corpus[:max_line_length], spanish_corpus[:max_line_length],
        french_corpus[:max_line_length], german_corpus[:max_line_length]
```

In [221…
```
train_english, train_spanish, train_french, train_german = read_files('train'
dev_english, dev_spanish, dev_french, dev_german = read_files('dev')
```

In [222…

```
def preprocess(corpus, train: bool):
    if not train:
        useful = []
        for item in corpus:
            if len(item)> 4 and '<seg' in item:
                start = item.find('">')
                end = item.find('</')
                useful.append(item[start+3:end].lower())
    else:
        useful = [sentence.lower() for sentence in corpus]


    # Remove punctuation
    exclude = set(string.punctuation)
    nopun = []
    for st in useful:
        st = ''.join(ch for ch in st if ch not in exclude)
        nopun.append(st)

    # Add start and ending tokens, and make all words lowercase
    data = [sentence.split() for sentence in nopun]
    data = list(filter(lambda a: len(a)>2, data))  # Remove blank sentences
    return data
```

In [223…

```
train_english = preprocess(train_english,True)
dev_english = preprocess(dev_english,False)

print(len(train_english))
print(len(dev_english))
```

```
794854
15006
```

In [224…

```
train_spanish = preprocess(train_spanish,True)
dev_spanish = preprocess(dev_spanish,False)

print(len(train_spanish))
print(len(dev_spanish))
```

```
790263
15006
```

In [225…

```
train_french = preprocess(train_french,True)
dev_french = preprocess(dev_french,False)

print(len(train_french))
print(len(dev_french))
```

```
793714
15026
```

In [226…
```
train_german = preprocess(train_german,True)
dev_german = preprocess(dev_german,False)

print(len(train_german))
print(len(dev_german))
```

```
790857
14986
```

In [227…
```
english_data = train_english + dev_english
spanish_data = train_spanish + dev_spanish
french_data = train_french + dev_french
german_data = train_german + dev_german
```

In [229…
```
# Train embeddings on the full corpuses

english_model = Word2Vec(sentences=english_data, size=300, window=7, min_count
spanish_model = Word2Vec(sentences=spanish_data, size=300, window=7, min_count
french_model = Word2Vec(sentences=french_data, size=300, window=7, min_count=
german_model = Word2Vec(sentences=german_data, size=300, window=7, min_count=

print(f'English vocab size: {len(english_model.wv.vocab)}')
print(f'Spanish vocab size: {len(spanish_model.wv.vocab)}')
print(f'French vocab size: {len(french_model.wv.vocab)}')
print(f'German vocab size: {len(german_model.wv.vocab)}')
```

```
English vocab size: 54635
Spanish vocab size: 88502
French vocab size: 79132
German vocab size: 137550
```

In [230…
```
english_model.save("english.model")
spanish_model.save("spanish.model")
french_model.save("french.model")
german_model.save("german.model")
```

In [5]:
```
english_model = Word2Vec.load("english.model")
spanish_model = Word2Vec.load("spanish.model")
french_model = Word2Vec.load("french.model")
german_model = Word2Vec.load("german.model")
```

In [263…
```
english_words = ['President', 'Governor', 'Militant', 'Slow', 'Dress', 'Actres
spanish_words = ['Presidenta', 'Presidente', 'Gobernador', 'Militante', 'Lenta
french_words = ['Président', 'Présidente', 'Gouverneur', 'Militant', 'lente',
german_words = ['Präsident', 'Präsidentin', 'Gouverneur', 'Millitante', 'langs
```

Removed words: Spanish - Gobernadora, jugadora, policia

```
            French - Gouverneure, lent, joueureuse, utilisatrice,
    cousin

            German - Gouverneurin, spielerin, Rosen, ehrgeiz,
```

```
verletzlich, beschäftig, cousin, cousine
```

In [264…

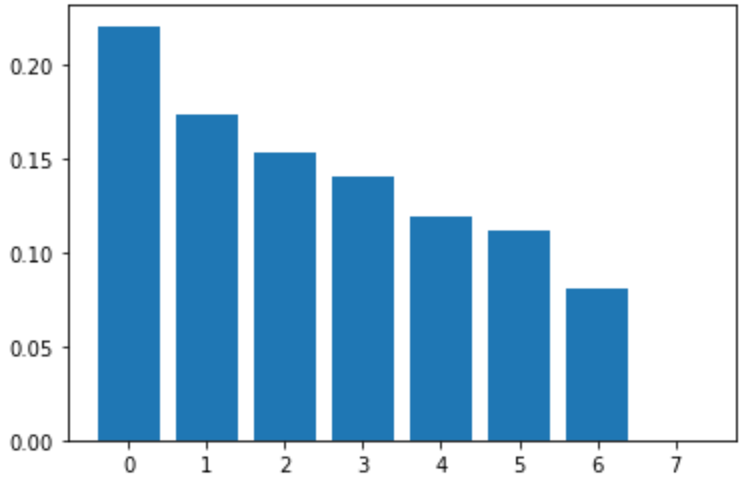
```
english_gender_pairs = [['man', 'woman'], ['he', 'she'], ['actor', 'actress'],
                        ['brother', 'sister'], ['husband', 'wife'],\
                        ['father', 'mother'],['son', 'daughter'], ['king', 'qu
spanish_gender_pairs = [['hombre', 'mujer'], ['el', 'ella'], ['actor', 'actri
                        ['hermano', 'hermana'], ['esposo', 'esposa'],\
                        ['padre', 'madre'], ['hijo', 'hija'], ['rey', 'reina'
french_gender_pairs = [['homme', 'femme'], ['il', 'elle'], ['acteur', 'actrice
                       ['frère', 'sœur'], ['époux', 'épouse'], \
                       ['père', 'mère'], ['fils', 'fille'], ['roi', 'reine']]
german_gender_pairs = [['mann', 'frau'], ['er', 'sie'], ['schauspieler', 'scha
                       ['bruder', 'schwester'], ['mann', 'ehefrau'],\
                       ['vater', 'mutter'], ['sohn', 'tochter'], ['könig', 'kö


def get_normalized_differences(model, pairs):
    differences = []
    for pair in pairs:
        norm_0 = model.wv[pair[0]]/np.linalg.norm(model.wv[pair[0]])
        norm_1 = model.wv[pair[1]]/np.linalg.norm(model.wv[pair[1]])
        differences.append(norm_0-norm_1)
    return differences

english_differences = get_normalized_differences(english_model, english_gende
spanish_differences = get_normalized_differences(spanish_model, spanish_gende
french_differences = get_normalized_differences(french_model, french_gender_pa
german_differences = get_normalized_differences(german_model, german_gender_pa
```

In [265…

```
def get_gender_dimension(differences, visualize=True):
    pca = PCA()
    pca.fit(differences)

    if visualize:
        plt.bar(np.arange(8), pca.explained_variance_ratio_)
        plt.show()

    return pca.components_[0]
```

In [266…

```
english_gd = get_gender_dimension(english_differences)
```



In [267…

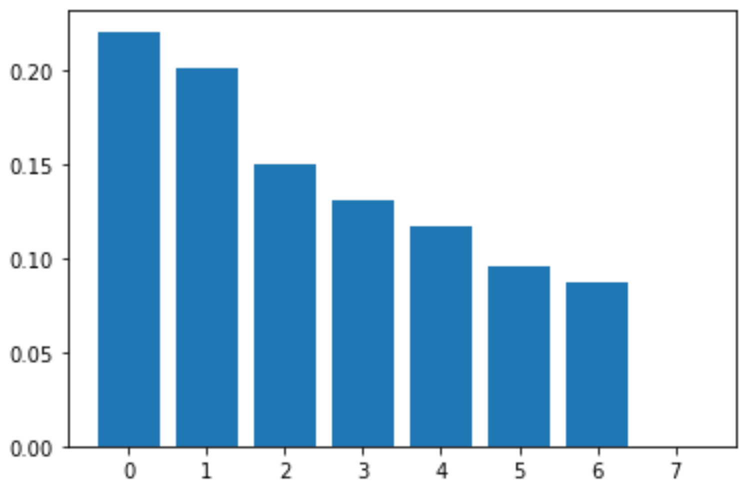
```
english_model.wv.similar_by_vector(english_gd)
```

Out[267…

```
[('actor', 0.3870496153831482),
 ('entity', 0.3463446497917175З),
 ('mainstream', 0.2850078344345093),
 ('fora', 0.2819621562957763 7),
 ('representativeness', 0.27387499809265137),
 ('norms', 0.27328014373779297),
 ('interdependent', 0.2687690854072571),
 ('developmental', 0.2667452394962311),
 ('player', 0.26515331864356995),
 ('homogeneous', 0.2559206485748291)]
```

In [268…

```
spanish_gd = get_gender_dimension(spanish_differences)
```



In [269…

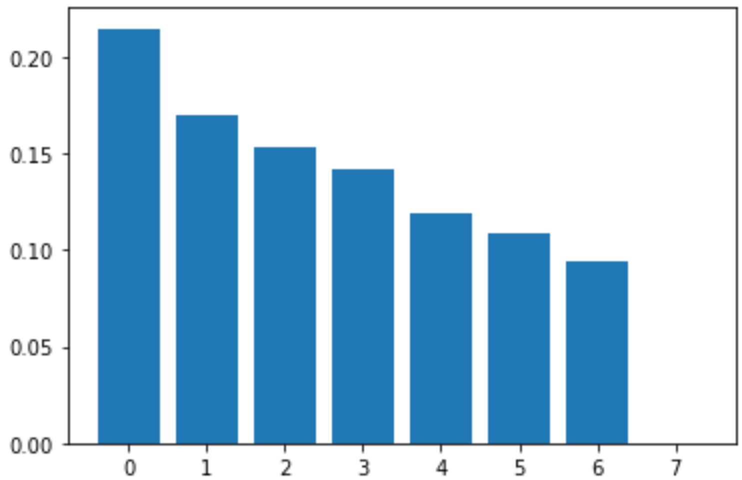
```
spanish_model.wv.similar_by_vector(spanish_gd)
```

Out[269…

```
[('el', 0.5803321003913879),
 ('del', 0.3509189188480377),
 ('de', 0.3069862127304077),
 ('—el', 0.3014705181121826),
 ('«el', 0.2934041619300842З),
 ('\xad', 0.2808428406715393),
 ('com2003', 0.2781440317630768),
 ('autorizó', 0.26634785532951355),
 ('¿el', 0.26501867175102234),
 ('y', 0.26461419463157654)]
```

In [270…

```
french_gd = get_gender_dimension(french_differences)
```



In [271…

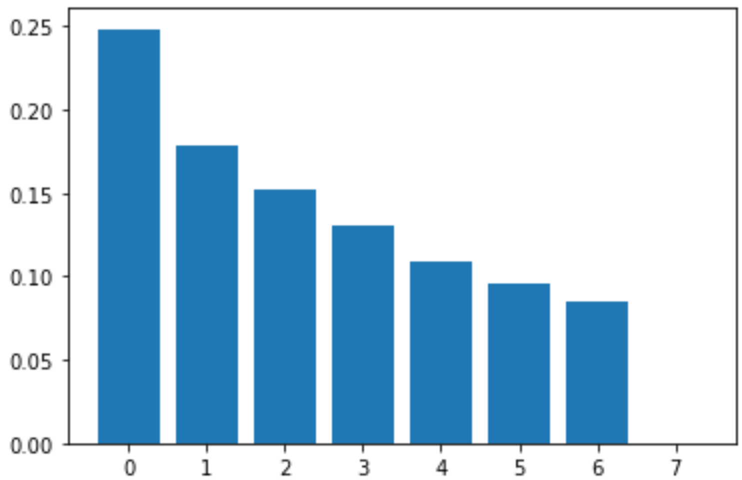
```
french_model.wv.similar_by_vector(french_gd)
```

Out[271…

```
[('acteur', 0.44209659099957886),
 ('scène', 0.28074365854263306),
 ('elle', 0.26503151655197144),
 ('influent', 0.2426709532737732),
 ('partenaire', 0.24154089391231537),
 ('concurrentiels', 0.21544647216796875),
 ('qu’acteur', 0.21181568503379822),
 ('quacteur', 0.2104436457157135),
 ('donateur', 0.21042898297309875),
 ('compétitifs', 0.20752541720867157)]
```

In [272…

```
german_gd = get_gender_dimension(german_differences)
```



In [273…

```
german_model.wv.similar_by_vector(german_gd)
```

Out[273…

```
[('mann', 0.5554859042167664),
 ('eingreiftruppe', 0.1988731324672699),
 ('truppe', 0.17532256245613098),
 ('verteidigung', 0.15899917483329773),
 ('starke', 0.1451280117034912),
 ('betrag', 0.14402683079242706),
 ('pro', 0.13702496886253357),
 ('gleichberechtigung', 0.1369360387325287),
 ('einheiten', 0.1359703689813614),
 ('bein', 0.1356247067451477)]
```

In [274…

```
english_embeddings = [english_model.wv[word.lower()] for word in english_words
spanish_embeddings = [spanish_model.wv[word.lower()] for word in spanish_words
french_embeddings = [french_model.wv[word.lower()] for word in french_words]
german_embeddings = [german_model.wv[word.lower()] for word in german_words]
```

In [275…

```
# Dictionary of words to normalized word embeddings
english_embed_dict = {word.lower(): english_model.wv[word.lower()]/np.linalg.n
spanish_embed_dict = {word.lower(): spanish_model.wv[word.lower()]/np.linalg.n
french_embed_dict = {word.lower(): french_model.wv[word.lower()]/np.linalg.no
german_embed_dict = {word.lower(): german_model.wv[word.lower()]/np.linalg.no
```

In [276…

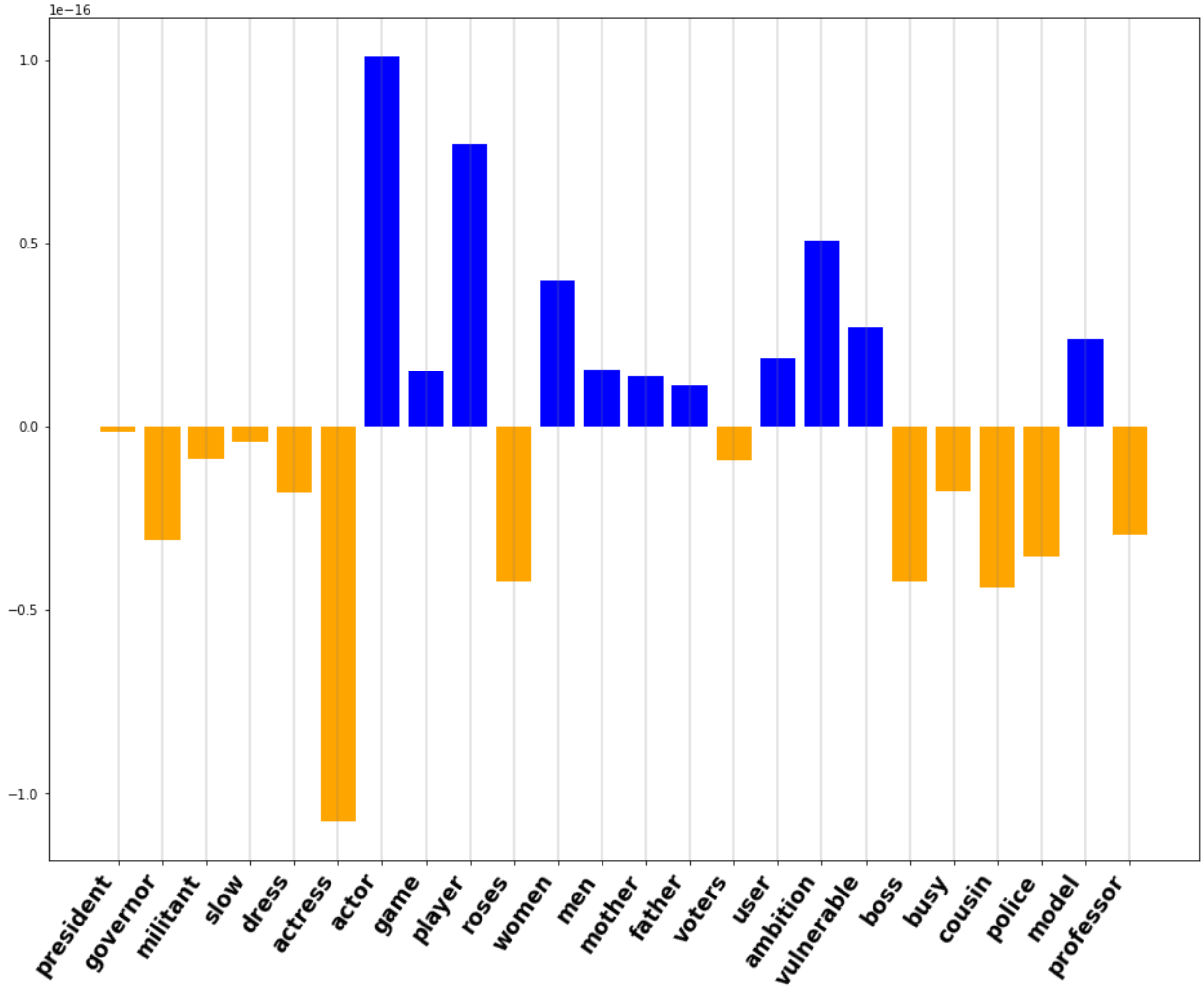
```
def gender_component(w, v, g):
    w_g = np.dot(w, g)*g
    w_perp = w-w_g
    w_perp_norm = np.linalg.norm(w_perp)

    v_g = np.dot(v, g)*g
    v_perp = v-v_g
    v_perp_norm = np.linalg.norm(v_perp)

    w_dot_v = np.dot(w, v)

    beta = (w_dot_v - np.dot(w_perp, v_perp)/(w_perp_norm*v_perp_norm))/w_dot_
    return beta
```

In [277…
```
gender_component(english_embed_dict['roses'], english_embed_dict['women'], en
```

Out[277… -0.26679698266679513

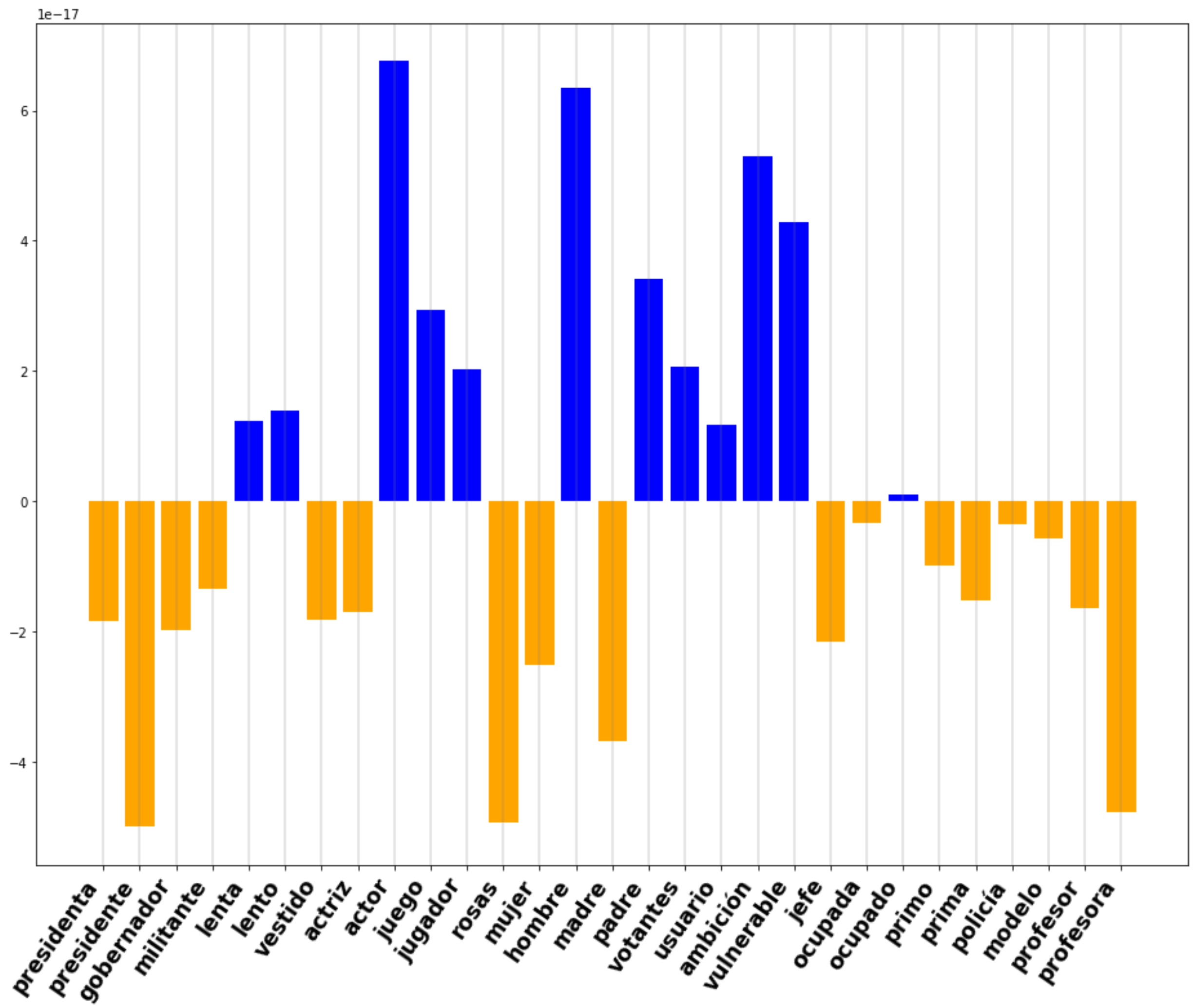
In [278…
```
def contribution_gender(w, g):
    w_g = np.dot(w, g)*g
    return w_g

def plot_gender_contribution_influence(embed_dict, gd, ):
    gender = [contribution_gender(embedding, gd) for embedding in embed_dict.v

    pca = PCA(n_components=2)
    pca.fit(gender)
    gender_transformed = pca.transform(gender)
    words = list(embed_dict.keys())
    y_pos = np.arange(len(words))

    plt.figure(figsize=(2.5*6.4, 2.5*4.8))
    plt.xticks(y_pos, words, color='black', rotation=55, fontweight='bold', fo
    plt.grid(axis = 'x',color = 'gray', linewidth = 0.4)
    for i in range(len(gender_transformed)):
        x = i
        y = gender_transformed[i][1]
        color = 'b'
        if y < 0:
            color = 'orange'
        plt.bar(x, y, color=color)
    plt.show()
```

In [279…
```
plot_gender_contribution_influence(english_embed_dict, english_gd)
```



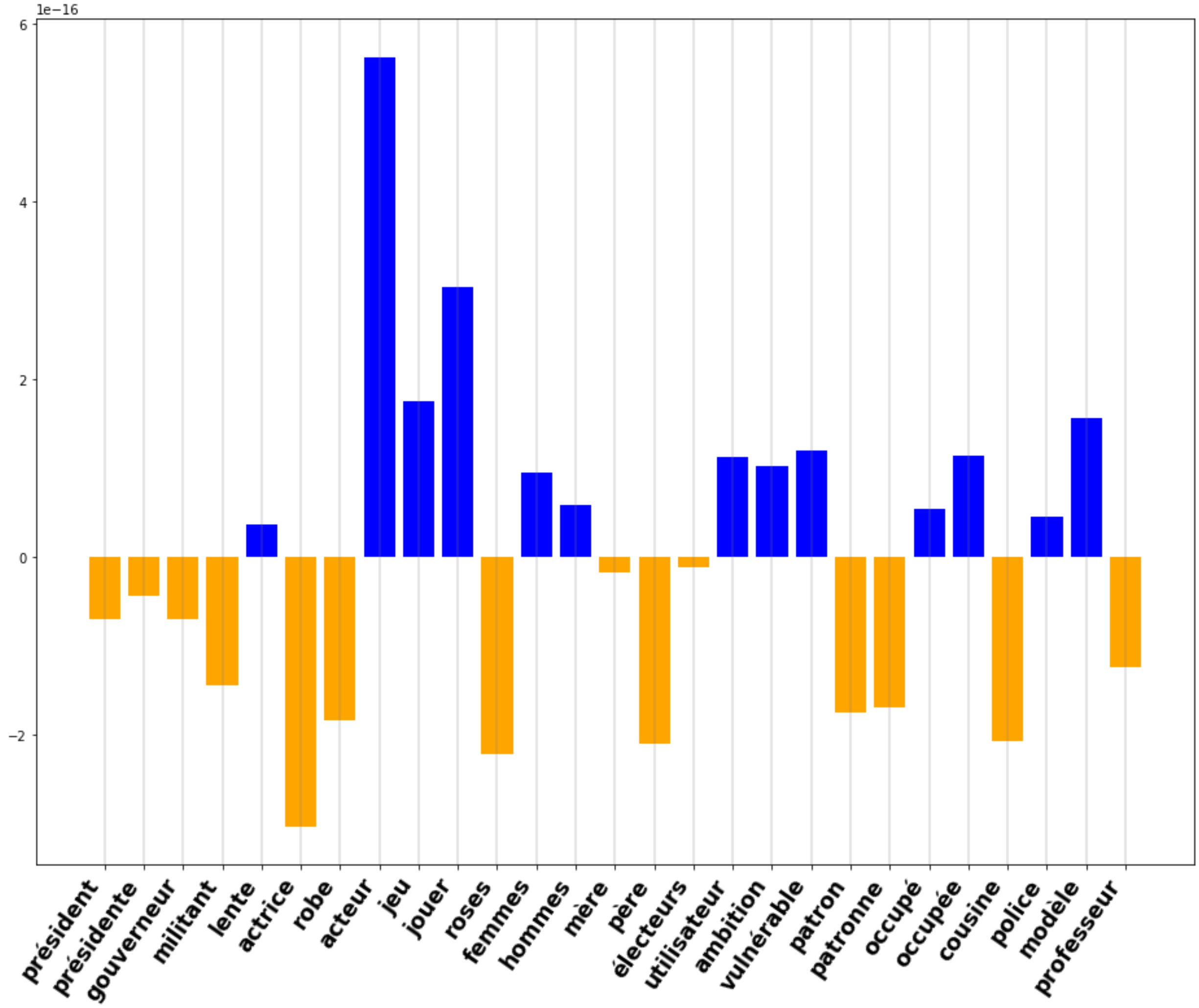
In [280…

```
plot_gender_contribution_influence(spanish_embed_dict, spanish_gd)
```



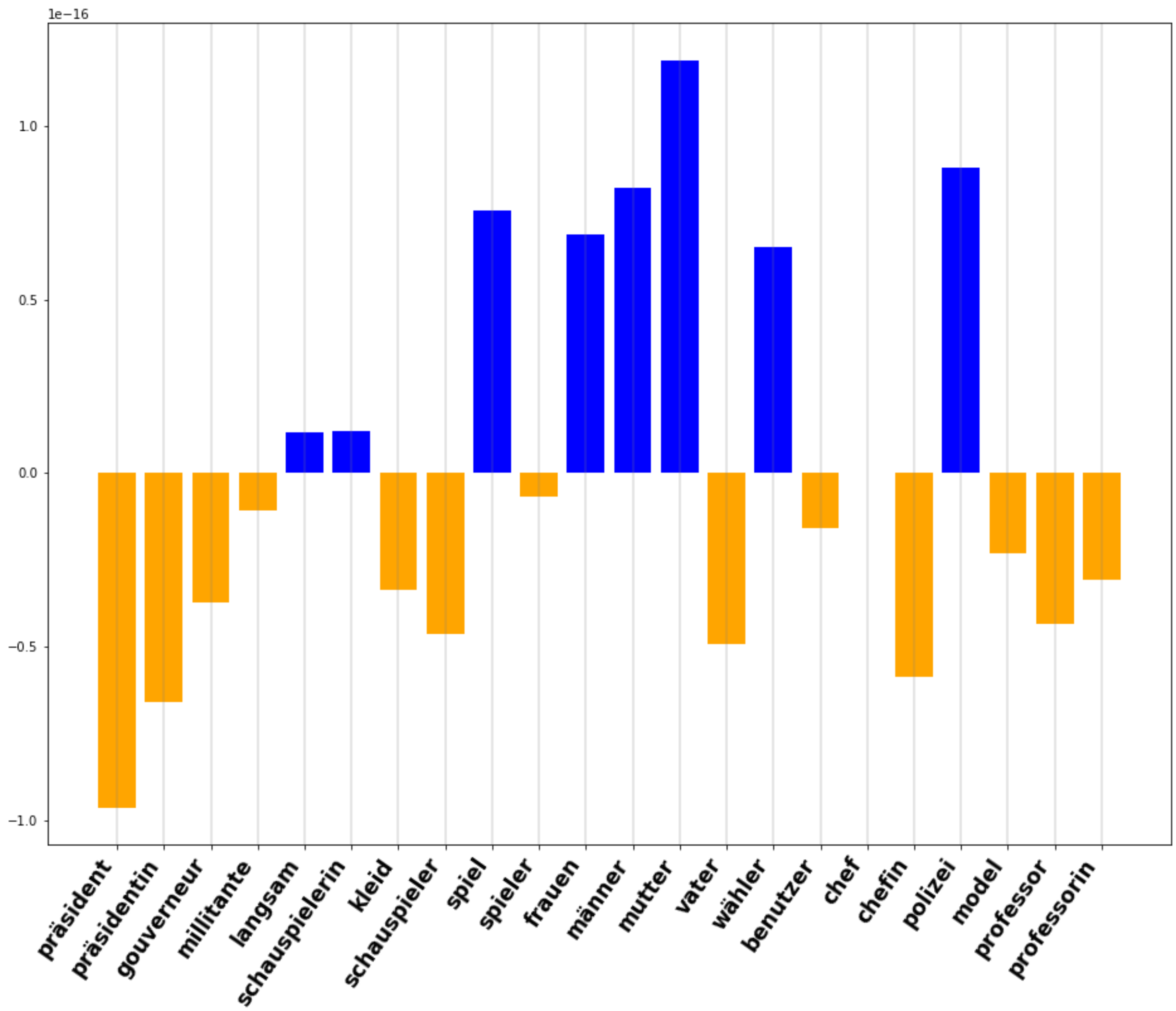
In [281…

```
plot_gender_contribution_influence(french_embed_dict, french_gd)
```



In [261…

```
plot_gender_contribution_influence(german_embed_dict, german_gd)
```

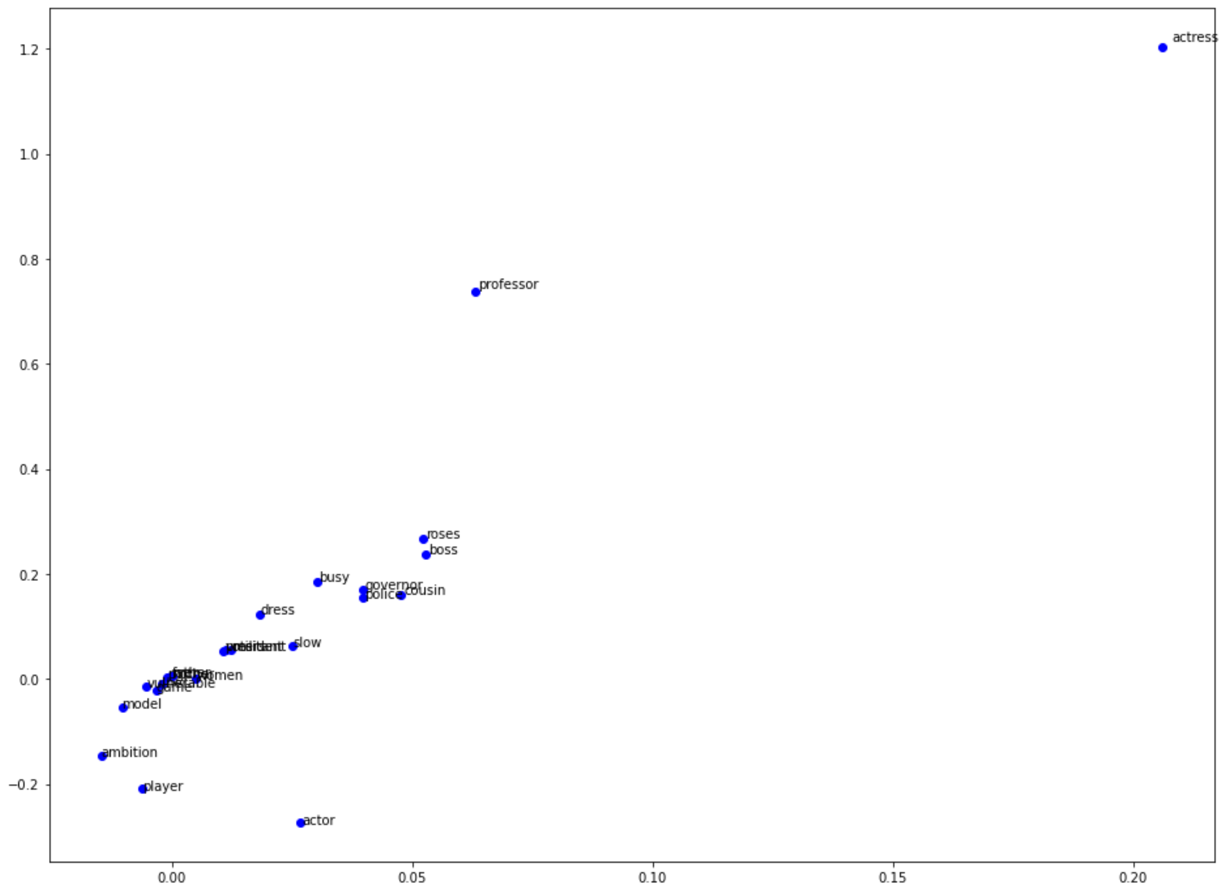


In [262…

```
def plot_gender_component_influence(embed_dict, gd, female_word, male_word):
    women = [-gender_component(embedding, embed_dict[female_word], gd) for emb
    men = [-gender_component(embedding, embed_dict[male_word], gd) for embedd:

    words = list(embed_dict.keys())
    plt.figure(figsize=(2.5*6.4, 2.5*4.8))
    for i in range(len(women)):
        x = men[i]
        y = women[i]
        plt.plot(x, y, 'bo')
        plt.text(x * (1 + 0.01), y * (1 + 0.01) , words[i], fontsize=10)
    plt.show()
```

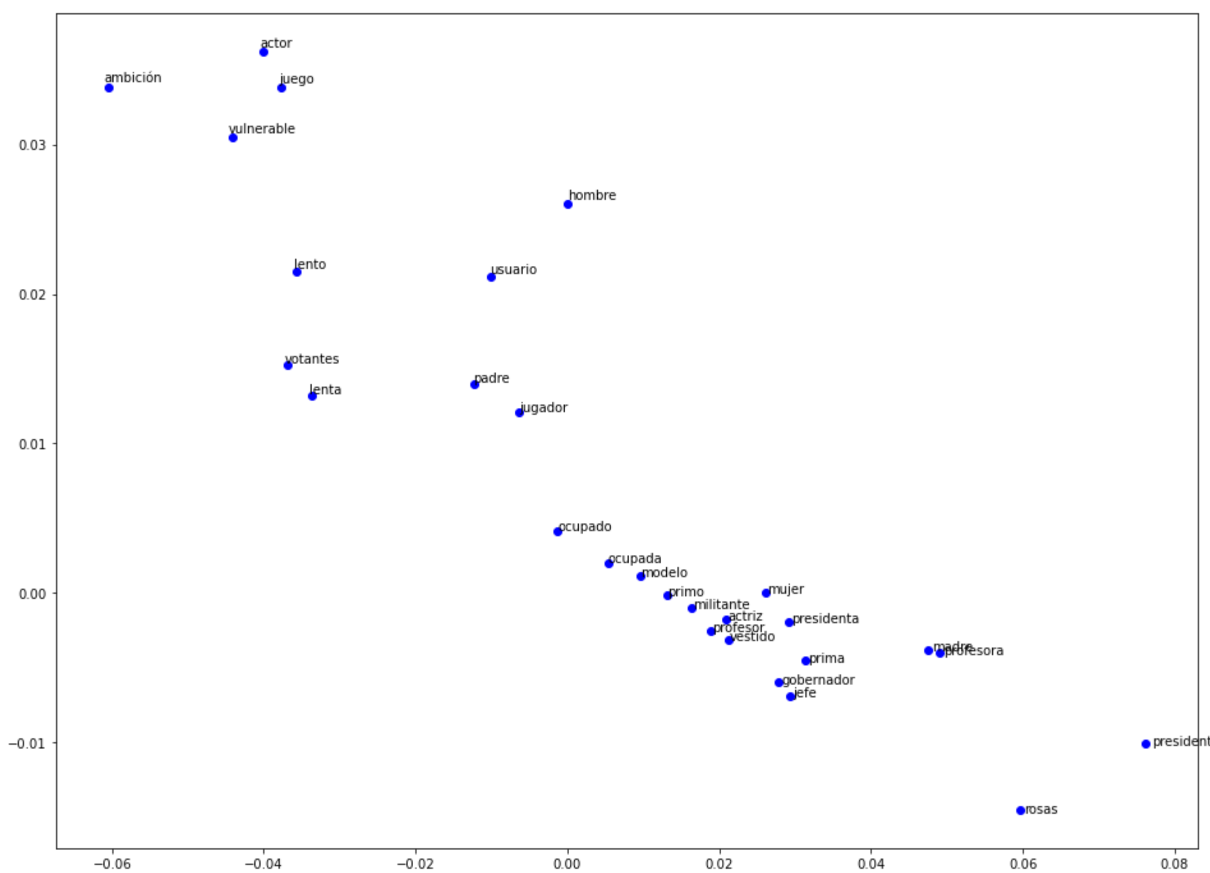
In [239…

```
plot_gender_component_influence(english_embed_dict, english_gd, 'women', 'men
```

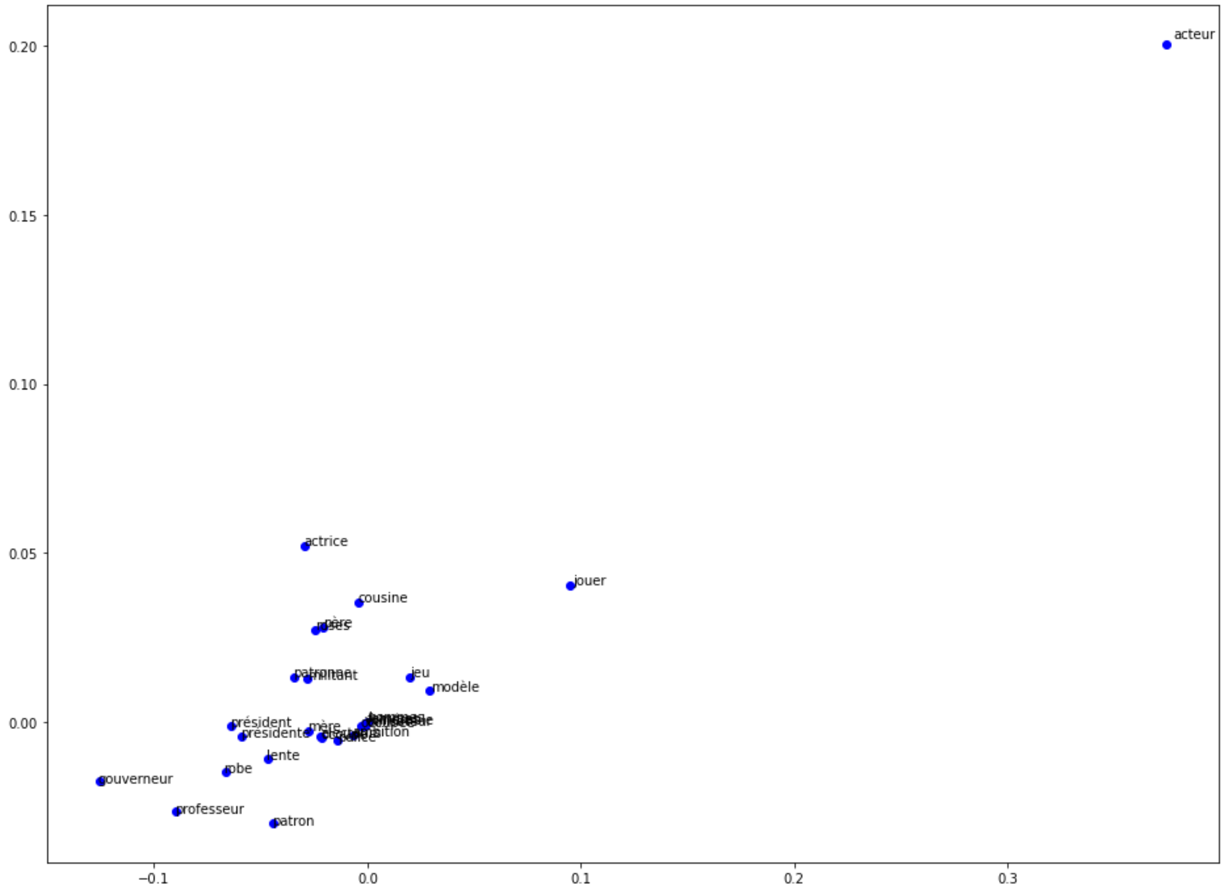


In [84]:

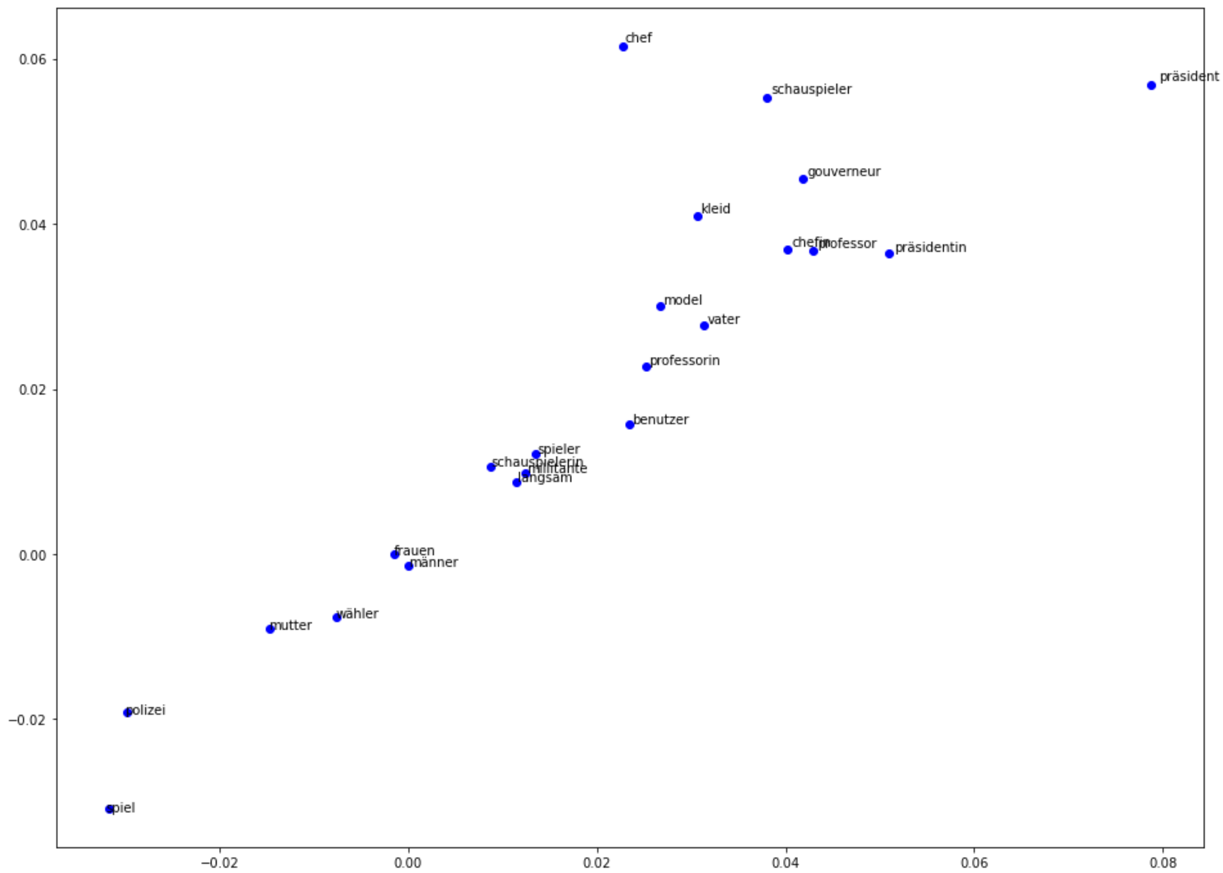
```
plot_gender_component_influence(spanish_embed_dict, spanish_gd, 'mujer', 'homb
```



In [85]:
```
plot_gender_component_influence(french_embed_dict, french_gd, 'femmes', 'homme
```



In [86]:
```
plot_gender_component_influence(german_embed_dict, german_gd, 'frauen', 'männe
```



Unused Data Exploration:

In [32]:

```
for word, embedding in english_embed_dict.items():
    for word2, embedding2 in english_embed_dict.items():
        gender = gender_component(embedding, embedding2, english_gd)
        if abs(round(gender, 2)) > 0:
            print(word, word2, round(gender, 5))
```

```
president militant 0.01215
president slow 0.01818
president actress -0.0223
president actor -0.18214
president game -0.00902
president dress 0.02755
president player -0.11293
president women -0.03087
president voters 0.01208
president user 0.14263
president ambition -0.0447
president vulnerable -0.03722
president boss 0.0122
president busy 0.01301
president police 0.09959
president model -0.01626
president professor 0.01173
governor militant 0.02366
governor slow 0.08933
governor actress 0.05835
governor actor -0.35534
governor game -0.06186
governor dress 0.0808
governor player -0.29927
governor roses 0.08612
governor women -0.14581
```

```
governor men -0.02556
governor mother -0.02564
governor father -0.00814
governor voters 0.0364
governor user -0.13645
governor ambition -0.41064
governor vulnerable -0.284
governor boss 0.05241
governor busy 0.09507
governor cousin 0.04169
governor police 0.10115
governor model -0.11048
governor professor 0.04965
militant president 0.01215
militant governor 0.02366
militant slow 0.37123
militant actress -0.02153
militant actor -0.18316
militant game -0.01326
militant dress 0.01503
militant player -0.1586
militant roses 0.02063
militant women -0.04025
militant men -0.00534
militant voters 0.0143
militant user -0.02546
militant ambition -0.11763
militant vulnerable -0.02932
militant boss 0.00889
militant busy 0.04283
militant police 0.02991
militant model -0.03717
militant professor 0.03325
slow president 0.01818
slow governor 0.08933
slow militant 0.37123
slow actress 0.77582
slow actor 0.70752
slow game -0.01438
slow dress 0.2023
slow player -0.18512
slow roses 0.04836
slow women -0.05236
slow men -0.00974
slow mother -0.01398
slow father 2.52957
slow voters 0.04754
slow user -0.03213
slow ambition -0.09161
slow vulnerable -0.02338
slow boss 0.66174
slow busy 0.01523
slow cousin 0.05471
slow police 0.06994
slow model -0.0268
slow professor 0.90474
actress president -0.0223
actress governor 0.05835
actress militant -0.02153
actress slow 0.77582
actress actor -0.75497
actress game -0.20001
actress dress -0.02899
actress player -0.69818
actress roses 0.05073
actress women -1.04595
actress men -0.17298
actress mother -0.1628
actress father -0.12299
actress voters 0.05514
actress user -0.23252
actress ambition -2.09581
```

```
actress vulnerable -1.19154
actress boss 0.0422
actress busy 0.05672
actress cousin 0.03425
actress police 0.24947
actress model -0.31615
actress professor 0.04645
actor president -0.18214
actor governor -0.35534
actor militant -0.18316
actor slow 0.70752
actor actress -0.75497
actor game -0.05442
actor dress -0.22954
actor player 0.04206
actor roses -0.42624
actor women 0.19308
actor men -0.06332
actor mother -0.06705
actor father -0.1007
actor voters -0.30415
actor user -0.0227
actor ambition 0.13614
actor vulnerable 0.24015
actor boss -0.38232
actor busy -0.34363
actor cousin -0.36192
actor police -1.05314
actor professor -0.32706
game president -0.00902
game governor -0.06186
game militant -0.01326
game slow -0.01438
game actress -0.20001
game actor -0.05442
game dress -0.01732
game player -0.02004
game roses -0.03964
game women 0.01906
game voters -0.01024
game vulnerable 0.0222
game boss -0.06206
game busy -0.01433
game cousin -0.04486
game police -0.17039
game model 0.01
game professor -0.18243
dress president 0.02755
dress governor 0.0808
dress militant 0.01503
dress slow 0.2023
dress actress -0.02899
dress actor -0.22954
dress game -0.01732
dress player -0.19784
dress roses 0.02023
dress women -0.10503
dress men -0.01172
dress mother -0.01059
dress voters 0.04802
dress user -0.02942
dress ambition -0.23587
dress vulnerable -0.1458
dress boss 0.0295
dress busy 0.0244
dress cousin 0.01522
dress police 0.15414
dress model -0.04179
dress professor 0.05797
player president -0.11293
player governor -0.29927
player militant -0.1586
```

```
player slow -0.18512
player actress -0.69818
player actor 0.04206
player game -0.02004
player dress -0.19784
player roses -0.37634
player women 0.15427
player men -0.02348
player mother -0.0236
player father -0.05955
player voters -0.16597
player ambition 0.13177
player vulnerable 0.62125
player boss -0.3977
player busy -0.20227
player cousin -0.30562
player police -0.92639
player model 0.03104
player professor -0.35727
roses governor 0.08612
roses militant 0.02063
roses slow 0.04836
roses actress 0.05073
roses actor -0.42624
roses game -0.03964
roses dress 0.02023
roses player -0.37634
roses women -0.21576
roses men -0.03353
roses mother -0.03166
roses father -0.01381
roses voters 0.02706
roses user -0.06202
roses ambition -0.20126
roses vulnerable -0.16835
roses boss 0.05421
roses busy 0.03368
roses cousin 0.02796
roses police 0.31417
roses model -0.08936
roses professor 0.07934
women president -0.03087
women governor -0.14581
women militant -0.04025
women slow -0.05236
women actress -1.04595
women actor 0.19308
women game 0.01906
women dress -0.10503
women player 0.15427
women roses -0.21576
women father -0.01392
women voters -0.03345
women user 0.00792
women ambition 0.11356
women vulnerable 0.01068
women boss -0.19192
women busy -0.12802
women cousin -0.13347
women police -0.12683
women model 0.04243
women professor -0.57386
men governor -0.02556
men militant -0.00534
men slow -0.00974
men actress -0.17298
men actor -0.06332
men dress -0.01172
men player -0.02348
men roses -0.03353
men ambition -0.00603
men boss -0.0347
```

```
men busy -0.0113
men cousin -0.034
men police -0.02645
men professor -0.02842
mother governor -0.02564
mother slow -0.01398
mother actress -0.1628
mother actor -0.06705
mother dress -0.01059
mother player -0.0236
mother roses -0.03166
mother voters -0.00501
mother boss -0.0333
mother busy -0.0115
mother cousin -0.0314
mother police -0.03146
mother professor -0.01954
father governor -0.00814
father slow 2.52957
father actress -0.12299
father actor -0.1007
father player -0.05955
father roses -0.01381
father women -0.01392
father user -0.00627
father ambition -0.03036
father vulnerable -0.02217
father boss -0.01602
father busy 0.01038
father cousin -0.01927
father police 0.03221
father model -0.00847
voters president 0.01208
voters governor 0.0364
voters militant 0.0143
voters slow 0.04754
voters actress 0.05514
voters actor -0.30415
voters game -0.01024
voters dress 0.04802
voters player -0.16597
voters roses 0.02706
voters women -0.03345
voters mother -0.00501
voters user -0.02178
voters ambition -0.08489
voters vulnerable -0.03067
voters boss 0.03732
voters busy 0.02433
voters cousin 0.02011
voters police 0.03672
voters model -0.03018
voters professor 0.15981
user president 0.14263
user governor -0.13645
user militant -0.02546
user slow -0.03213
user actress -0.23252
user actor -0.0227
user dress -0.02942
user roses -0.06202
user women 0.00792
user father -0.00627
user voters -0.02178
user ambition 0.06234
user vulnerable 0.00505
user boss -0.07511
user busy -0.02744
user cousin -0.07226
user police -0.06605
user model 0.00908
user professor -0.06544
```

```
ambition president -0.0447
ambition governor -0.41064
ambition militant -0.11763
ambition slow -0.09161
ambition actress -2.09581
ambition actor 0.13614
ambition dress -0.23587
ambition player 0.13177
ambition roses -0.20126
ambition women 0.11356
ambition men -0.00603
ambition father -0.03036
ambition voters -0.08489
ambition user 0.06234
ambition vulnerable 0.13702
ambition boss -0.35066
ambition busy -0.13292
ambition cousin -0.23774
ambition police -0.24071
ambition model 0.01414
ambition professor -0.27258
vulnerable president -0.03722
vulnerable governor -0.284
vulnerable militant -0.02932
vulnerable slow -0.02338
vulnerable actress -1.19154
vulnerable actor 0.24015
vulnerable game 0.0222
vulnerable dress -0.1458
vulnerable player 0.62125
vulnerable roses -0.16835
vulnerable women 0.01068
vulnerable father -0.02217
vulnerable voters -0.03067
vulnerable user 0.00505
vulnerable ambition 0.13702
vulnerable boss -0.30854
vulnerable busy -0.05092
vulnerable cousin -0.0923
vulnerable police -0.11778
vulnerable model 0.02229
vulnerable professor 0.50979
boss president 0.0122
boss governor 0.05241
boss militant 0.00889
boss slow 0.66174
boss actress 0.0422
boss actor -0.38232
boss game -0.06206
boss dress 0.0295
boss player -0.3977
boss roses 0.05421
boss women -0.19192
boss men -0.0347
boss mother -0.0333
boss father -0.01602
boss voters 0.03732
boss user -0.07511
boss ambition -0.35066
boss vulnerable -0.30854
boss busy 0.06005
boss cousin 0.03033
boss police 0.16896
boss model -0.2064
boss professor 0.0394
busy president 0.01301
busy governor 0.09507
busy militant 0.04283
busy slow 0.01523
busy actress 0.05672
busy actor -0.34363
busy game -0.01433
```

```
busy dress 0.0244
busy player -0.20227
busy roses 0.03368
busy women -0.12802
busy men -0.0113
busy mother -0.0115
busy father 0.01038
busy voters 0.02433
busy user -0.02744
busy ambition -0.13292
busy vulnerable -0.05092
busy boss 0.06005
busy cousin 0.03093
busy police 0.1088
busy model -0.07515
busy professor 0.25811
cousin governor 0.04169
cousin slow 0.05471
cousin actress 0.03425
cousin actor -0.36192
cousin game -0.04486
cousin dress 0.01522
cousin player -0.30562
cousin roses 0.02796
cousin women -0.13347
cousin men -0.034
cousin mother -0.0314
cousin father -0.01927
cousin voters 0.02011
cousin user -0.07226
cousin ambition -0.23774
cousin vulnerable -0.0923
cousin boss 0.03033
cousin busy 0.03093
cousin police 0.1571
cousin model -0.09093
cousin professor 0.04808
police president 0.09959
police governor 0.10115
police militant 0.02991
police slow 0.06994
police actress 0.24947
police actor -1.05314
police game -0.17039
police dress 0.15414
police player -0.92639
police roses 0.31417
police women -0.12683
police men -0.02645
police mother -0.03146
police father 0.03221
police voters 0.03672
police user -0.06605
police ambition -0.24071
police vulnerable -0.11778
police boss 0.16896
police busy 0.1088
police cousin 0.1571
police model -0.10945
police professor 0.25209
model president -0.01626
model governor -0.11048
model militant -0.03717
model slow -0.0268
model actress -0.31615
model game 0.01
model dress -0.04179
model player 0.03104
model roses -0.08936
model women 0.04243
model father -0.00847
model voters -0.03018
```

```
model user 0.00908
model ambition 0.01414
model vulnerable 0.02229
model boss -0.2064
model busy -0.07515
model cousin -0.09093
model police -0.10945
model professor -0.06897
professor president 0.01173
professor governor 0.04965
professor militant 0.03325
professor slow 0.90474
professor actress 0.04645
professor actor -0.32706
professor game -0.18243
professor dress 0.05797
professor player -0.35727
professor roses 0.07934
professor women -0.57386
professor men -0.02842
professor mother -0.01954
professor voters 0.15981
professor user -0.06544
professor ambition -0.27258
professor vulnerable 0.50979
professor boss 0.0394
professor busy 0.25811
professor cousin 0.04808
professor police 0.25209
professor model 0.06897
```

In [174…

```python
for word, embedding in spanish_embed_dict.items():
    for word2, embedding2 in spanish_embed_dict.items():
        gender = round(gender_component(embedding, embedding2, spanish_gd), 2
        if abs(gender) > 0:
            print(word, word2, gender)
```

```
presidenta jugador -0.1
presidenta señor -0.1
presidenta madre -0.1
presidenta votantes -0.1
presidenta modelo -0.1
presidente gobernador -0.1
presidente lenta -0.1
presidente lento -0.1
presidente vestido -0.2
presidente actriz -0.1
presidente actor -0.1
presidente juego -0.2
presidente jugador -0.3
presidente rosas -0.1
presidente señora -0.2
presidente señor -0.3
presidente madre -0.3
presidente padre -0.1
presidente votantes -0.3
presidente usuario -0.2
presidente ambición -0.1
presidente vulnerable -0.1
presidente ocupada -0.1
presidente ocupado -0.1
presidente primo -0.1
presidente prima -0.2
presidente modelo -0.3
presidente profesor -0.1
presidente profesora -0.1
gobernador presidente -0.1
gobernador señor -0.1
militante señor -0.1
militante votantes -0.1
```

```
militante modelo -0.1
lenta presidente -0.1
lento presidente -0.1
lento jefe -0.1
vestido presidente -0.2
vestido jefe -0.1
actriz presidente -0.1
actor presidente -0.1
actor jefe -0.1
juego presidente -0.2
juego jefe -0.1
jugador presidenta -0.1
jugador presidente -0.3
jugador jefe -0.2
rosas presidente -0.1
rosas jefe -0.1
señora presidente -0.2
señora jefe -0.1
señor presidenta -0.1
señor presidente -0.3
señor gobernador -0.1
señor militante -0.1
señor jefe -0.2
señor profesor -0.1
madre presidenta -0.1
madre presidente -0.3
madre jefe -0.2
padre presidente -0.1
padre jefe -0.1
votantes presidenta -0.1
votantes presidente -0.3
votantes militante -0.1
votantes jefe -0.2
usuario presidente -0.2
usuario jefe -0.1
ambición presidente -0.1
ambición jefe -0.1
vulnerable presidente -0.1
vulnerable jefe -0.1
jefe lento -0.1
jefe vestido -0.1
jefe actor -0.1
jefe juego -0.1
jefe jugador -0.2
jefe rosas -0.1
jefe señora -0.1
jefe señor -0.2
jefe madre -0.2
jefe padre -0.1
jefe votantes -0.2
jefe usuario -0.1
jefe ambición -0.1
jefe vulnerable -0.1
jefe ocupada -0.1
jefe ocupado -0.1
jefe prima -0.1
jefe modelo -0.2
jefe profesora -0.1
ocupada presidente -0.1
ocupada jefe -0.1
ocupado presidente -0.1
ocupado jefe -0.1
primo presidente -0.1
prima presidente -0.2
prima jefe -0.1
modelo presidenta -0.1
modelo presidente -0.3
modelo militante -0.1
modelo jefe -0.2
profesor presidente -0.1
profesor señor -0.1
profesora presidente -0.1
```

```
profesora jefe -0.1
```

In [175…

```
for word, embedding in french_embed_dict.items():
    for word2, embedding2 in french_embed_dict.items():
        gender = round(gender_component(embedding, embedding2, french_gd), 2)
        if abs(gender) > 0:
            print(word, word2, gender)
```

```
président militant 0.01
président lente 0.01
président robe 0.01
président actrice 0.01
président acteur 0.01
président jeu 0.02
président jouer 0.01
président roses 0.01
président femmes 0.01
président mère 0.01
président père 0.01
président utilisateur 0.01
président ambition 0.01
président patron 0.01
président patronne 0.01
président occupé 0.01
président occupée 0.01
président cousine 0.01
président police -0.02
président modèle 0.01
présidente jeu -0.01
présidente jouer -0.01
présidente père -0.01
présidente professeur -0.01
gouverneur jeu -0.01
gouverneur jouer -0.01
gouverneur père -0.01
gouverneur professeur -0.01
militant président 0.01
militant hommes -0.01
militant police -0.02
lente président 0.01
lente jeu -0.01
lente jouer -0.01
lente police -0.01
robe président 0.01
robe police -0.02
actrice président 0.01
actrice hommes -0.01
actrice police -0.02
acteur président 0.01
acteur hommes -0.01
acteur électeurs -0.01
acteur police -0.02
jeu président 0.02
jeu présidente -0.01
jeu gouverneur -0.01
jeu lente -0.01
jeu femmes -0.01
jeu hommes -0.02
jeu mère -0.01
jeu père 0.02
jeu électeurs -0.02
jeu utilisateur -0.01
jeu vulnérable -0.01
jeu police -0.05
jeu professeur 0.01
jouer président 0.01
jouer présidente -0.01
jouer gouverneur -0.01
jouer lente -0.01
```

```
jouer femmes -0.01
jouer hommes -0.02
jouer mère -0.01
jouer père 0.01
jouer électeurs -0.02
jouer vulnérable -0.01
jouer police -0.04
roses président 0.01
roses hommes -0.01
roses police -0.02
femmes président 0.01
femmes jeu -0.01
femmes jouer -0.01
femmes police -0.01
hommes militant -0.01
hommes actrice -0.01
hommes acteur -0.01
hommes jeu -0.02
hommes jouer -0.02
hommes roses -0.01
hommes père -0.02
hommes occupé -0.01
hommes cousine -0.01
hommes modèle -0.01
hommes professeur -0.01
mère président 0.01
mère jeu -0.01
mère jouer -0.01
mère police -0.01
père président 0.01
père présidente -0.01
père gouverneur -0.01
père jeu 0.02
père jouer 0.01
père hommes -0.02
père électeurs -0.01
père vulnérable -0.01
père police -0.04
électeurs acteur -0.01
électeurs jeu -0.02
électeurs jouer -0.02
électeurs père -0.01
électeurs occupé -0.01
électeurs professeur -0.01
utilisateur président 0.01
utilisateur jeu -0.01
utilisateur police -0.01
ambition président 0.01
ambition police -0.02
vulnérable jeu -0.01
vulnérable jouer -0.01
vulnérable père -0.01
vulnérable police -0.01
patron président 0.01
patron police -0.01
patronne président 0.01
patronne police -0.01
occupé président 0.01
occupé hommes -0.01
occupé électeurs -0.01
occupé police -0.02
occupée président 0.01
occupée police -0.02
cousine président 0.01
cousine hommes -0.01
cousine police -0.02
police président -0.02
police militant -0.02
police lente -0.01
police robe -0.02
police actrice -0.02
police acteur -0.02
```

```
police jeu -0.05
police jouer -0.04
police roses -0.02
police femmes -0.01
police mère -0.01
police père -0.04
police utilisateur -0.01
police ambition -0.02
police vulnérable -0.01
police patron -0.01
police patronne -0.01
police occupé -0.02
police occupée -0.02
police cousine -0.02
police modèle -0.02
police professeur -0.03
modèle président 0.01
modèle hommes -0.01
modèle police -0.02
modèle professeur 0.01
professeur présidente -0.01
professeur gouverneur -0.01
professeur jeu 0.01
professeur hommes -0.01
professeur électeurs -0.01
professeur police -0.03
```

In [176…

```
for word, embedding in german_embed_dict.items():
    for word2, embedding2 in german_embed_dict.items():
        gender = round(gender_component(embedding, embedding2, german_gd), 2)
        if abs(gender) > 0:
            print(word, word2, gender)
```

```
präsident präsidentin -0.14
präsident gouverneur -0.1
präsident millitante -0.16
präsident langsam -0.13
präsident kleid -0.11
präsident schauspielerin -0.07
präsident schauspieler -0.05
präsident spiel -0.05
präsident spieler -0.12
präsident frauen -0.31
präsident männer -0.2
präsident mutter -0.16
präsident vater -0.06
präsident wähler -0.12
präsident benutzer -0.2
präsident chef -0.1
präsident chefin -0.14
präsident polizei -0.07
präsident model -0.15
präsident professor -0.08
präsident professorin -0.12
präsidentin präsident -0.14
präsidentin schauspielerin -0.01
präsidentin schauspieler -0.01
präsidentin spiel -0.01
präsidentin männer 0.01
präsidentin mutter 0.01
präsidentin vater -0.01
präsidentin polizei -0.01
präsidentin professor -0.01
gouverneur präsident -0.1
gouverneur schauspieler -0.01
gouverneur spiel -0.01
gouverneur frauen -0.02
gouverneur männer -0.01
gouverneur benutzer -0.01
```

```
millitante präsident -0.16
millitante schauspielerin -0.01
millitante schauspieler -0.02
millitante spiel -0.02
millitante mutter 0.01
millitante vater -0.01
millitante polizei -0.01
millitante professor -0.01
langsam präsident -0.13
langsam schauspielerin -0.01
langsam schauspieler -0.01
langsam spiel -0.01
langsam frauen -0.01
langsam vater -0.01
kleid präsident -0.11
kleid schauspieler -0.01
kleid spiel -0.01
kleid frauen -0.02
kleid männer -0.01
kleid vater -0.01
kleid benutzer -0.01
schauspielerin präsident -0.07
schauspielerin präsidentin -0.01
schauspielerin millitante -0.01
schauspielerin langsam -0.01
schauspielerin frauen -0.05
schauspielerin männer -0.02
schauspielerin mutter -0.01
schauspielerin benutzer -0.02
schauspielerin chefin -0.01
schauspielerin model -0.01
schauspieler präsident -0.05
schauspieler präsidentin -0.01
schauspieler gouverneur -0.01
schauspieler millitante -0.02
schauspieler langsam -0.01
schauspieler kleid -0.01
schauspieler spieler -0.01
schauspieler frauen -0.06
schauspieler männer -0.03
schauspieler mutter -0.02
schauspieler wähler -0.01
schauspieler benutzer -0.03
schauspieler chef -0.01
schauspieler chefin -0.01
schauspieler model -0.01
schauspieler professorin -0.01
spiel präsident -0.05
spiel präsidentin -0.01
spiel gouverneur -0.01
spiel millitante -0.02
spiel langsam -0.01
spiel kleid -0.01
spiel spieler -0.01
spiel frauen -0.06
spiel männer -0.03
spiel mutter -0.02
spiel wähler -0.01
spiel benutzer -0.03
spiel chef -0.01
spiel chefin -0.01
spiel model -0.01
spiel professorin -0.01
spieler präsident -0.12
spieler schauspieler -0.01
spieler spiel -0.01
spieler frauen -0.02
spieler vater -0.01
frauen präsident -0.31
frauen gouverneur -0.02
frauen langsam -0.01
frauen kleid -0.02
```

```
frauen schauspielerin -0.05
frauen schauspieler -0.06
frauen spiel -0.06
frauen spieler -0.02
frauen mutter -0.01
frauen vater -0.05
frauen wähler -0.02
frauen chef -0.02
frauen chefin -0.01
frauen polizei -0.05
frauen professor -0.04
frauen professorin -0.01
männer präsident -0.2
männer präsidentin 0.01
männer gouverneur -0.01
männer kleid -0.01
männer schauspielerin -0.02
männer schauspieler -0.03
männer spiel -0.03
männer vater -0.02
männer chef -0.01
männer polizei -0.02
männer model 0.01
männer professor -0.01
mutter präsident -0.16
mutter präsidentin 0.01
mutter millitante 0.01
mutter schauspielerin -0.01
mutter schauspieler -0.02
mutter spiel -0.02
mutter frauen -0.01
mutter vater -0.01
mutter polizei -0.01
mutter model 0.01
mutter professor -0.01
vater präsident -0.06
vater präsidentin -0.01
vater millitante -0.01
vater langsam -0.01
vater kleid -0.01
vater spieler -0.01
vater frauen -0.05
vater männer -0.02
vater mutter -0.01
vater wähler -0.01
vater benutzer -0.02
vater chefin -0.01
vater model -0.01
vater professorin -0.01
wähler präsident -0.12
wähler schauspieler -0.01
wähler spiel -0.01
wähler frauen -0.02
wähler vater -0.01
benutzer präsident -0.2
benutzer gouverneur -0.01
benutzer kleid -0.01
benutzer schauspielerin -0.02
benutzer schauspieler -0.03
benutzer spiel -0.03
benutzer vater -0.02
benutzer chef -0.01
benutzer polizei -0.02
benutzer professor -0.01
chef präsident -0.1
chef schauspieler -0.01
chef spiel -0.01
chef frauen -0.02
chef männer -0.01
chef benutzer -0.01
chefin präsident -0.14
chefin schauspielerin -0.01
```

```
chefin schauspieler -0.01
chefin spiel -0.01
chefin frauen -0.01
chefin vater -0.01
chefin polizei -0.01
chefin professor -0.01
polizei präsident -0.07
polizei präsidentin -0.01
polizei millitante -0.01
polizei frauen -0.05
polizei männer -0.02
polizei mutter -0.01
polizei benutzer -0.02
polizei chefin -0.01
polizei model -0.01
model präsident -0.15
model schauspielerin -0.01
model schauspieler -0.01
model spiel -0.01
model männer 0.01
model mutter 0.01
model vater -0.01
model polizei -0.01
professor präsident -0.08
professor präsidentin -0.01
professor millitante -0.01
professor frauen -0.04
professor männer -0.01
professor mutter -0.01
professor benutzer -0.01
professor chefin -0.01
professorin präsident -0.12
professorin schauspieler -0.01
professorin spiel -0.01
professorin frauen -0.01
```

In [165…

```python
gender_diff = english_embed_dict['men']-english_embed_dict['women']

for word, embedding in english_embed_dict.items():
    for word2, embedding2 in english_embed_dict.items():
        if word != word2 and 'men' not in word and 'men' not in word2:
            norm = np.linalg.norm(embedding-embedding2)
            if norm < 1:
                print(word, word2, np.dot(gender_diff, embedding-embedding2))
```

```
president governor -0.0019425792
president militant -0.006145278
president slow 0.03657881
president dress 0.04175341
president actress 0.03923607
president actor -0.03137803
president game 0.13183418
president roses 0.04731539
president father 0.01987448
president voters 0.036900222
president ambition 0.0029110303
president boss -0.0021079471
president busy 0.052831825
president cousin 0.010584817
president police -0.11488187
president professor -0.0015583369
governor president 0.0019425792
governor militant -0.0042026965
governor slow 0.038521394
governor dress 0.043695994
governor actress 0.041178647
governor actor -0.02943545
governor game 0.13377675
```

```
governor player 0.0706764
governor roses 0.049257964
governor mother 0.039010264
governor father 0.021817062
governor voters 0.0388428
governor user 0.06615415
governor ambition 0.00485361
governor vulnerable 0.0282825
governor boss -0.00016536599
governor busy 0.054774404
governor cousin 0.012527395
governor police -0.11293929
governor model 0.1739713
governor professor 0.00038424158
militant president 0.006145278
militant governor 0.0042026965
militant slow 0.04272409
militant dress 0.047898687
militant actress 0.045381345
militant actor -0.025232755
militant game 0.13797945
militant player 0.074879095
militant roses 0.053460665
militant mother 0.043212965
militant father 0.02601976
militant voters 0.0430455
militant user 0.07035685
militant ambition 0.009056307
militant vulnerable 0.032485195
militant boss 0.004037331
militant busy 0.0589771
militant cousin 0.016730092
militant police -0.10873659
militant model 0.178174
militant professor 0.004586938
slow president -0.03657881
slow governor -0.038521394
slow militant -0.04272409
slow dress 0.005174599
slow actress 0.002657254
slow actor -0.06795684
slow game 0.09525537
slow player 0.032155003
slow roses 0.0107365735
slow mother 0.0004888703
slow father -0.01670433
slow voters 0.00032140757
slow user 0.027632765
slow ambition -0.03366778
slow vulnerable -0.010238895
slow boss -0.03868676
slow busy 0.016253008
slow cousin -0.025994
slow police -0.15146068
slow model 0.13544992
slow professor -0.038137153
dress president -0.04175341
dress governor -0.043695994
dress militant -0.047898687
dress slow -0.005174599
dress actress -0.0025173482
dress actor -0.07313145
dress game 0.09008077
dress player 0.026980408
dress roses 0.005561974
dress mother -0.004685729
dress father -0.021878928
dress voters -0.004853192
dress user 0.02245816
dress ambition -0.03884238
dress vulnerable -0.015413491
dress boss -0.04386136
```

```
dress busy 0.01107841
dress cousin -0.031168593
dress police -0.15663528
dress model 0.13027531
dress professor -0.04331176
actress president -0.03923607
actress governor -0.041178647
actress militant -0.045381345
actress slow -0.002657254
actress dress 0.0025173482
actress actor -0.0706141
actress game 0.09259811
actress player 0.02949775
actress roses 0.008079319
actress mother -0.0021683848
actress father -0.019361585
actress voters -0.0023358455
actress user 0.024975507
actress ambition -0.036325037
actress vulnerable -0.012896147
actress boss -0.041344013
actress busy 0.013595754
actress cousin -0.028651252
actress police -0.15411794
actress model 0.13279265
actress professor -0.04079441
actor president 0.03137803
actor governor 0.02943545
actor militant 0.025232755
actor slow 0.06795684
actor dress 0.07313145
actor actress 0.0706141
actor game 0.16321221
actor player 0.10011185
actor roses 0.07869342
actor mother 0.06844571
actor father 0.051252514
actor voters 0.06827825
actor user 0.09558961
actor ambition 0.034289062
actor vulnerable 0.05771795
actor boss 0.029270085
actor busy 0.08420985
actor cousin 0.041962847
actor police -0.08350384
actor model 0.20340677
actor professor 0.029819692
game president -0.13183418
game governor -0.13377675
game militant -0.13797945
game slow -0.09525537
game dress -0.09008077
game actress -0.09259811
game actor -0.16321221
game player -0.06310036
game roses -0.0845188
game mother -0.0947665
game father -0.111959696
game voters -0.09493396
game user -0.0676226
game ambition -0.12892315
game vulnerable -0.10549426
game boss -0.13394213
game busy -0.07900235
game cousin -0.12124937
game police -0.24671605
game model 0.04019455
game professor -0.13339251
player governor -0.0706764
player militant -0.074879095
player slow -0.032155003
player dress -0.026980408
```

```
player actress -0.02949775
player actor -0.10011185
player game 0.06310036
player roses -0.021418434
player mother -0.031666134
player father -0.048859335
player voters -0.031833597
player user -0.0045222426
player ambition -0.06582279
player vulnerable -0.042393897
player boss -0.07084176
player busy -0.015901996
player cousin -0.058149002
player model 0.10329491
roses president -0.04731539
roses governor -0.049257964
roses militant -0.053460665
roses slow -0.0107365735
roses dress -0.005561974
roses actress -0.008079319
roses actor -0.07869342
roses game 0.0845188
roses player 0.021418434
roses mother -0.010247701
roses father -0.027440904
roses voters -0.010415166
roses user 0.016896188
roses ambition -0.044404358
roses vulnerable -0.020975467
roses boss -0.049423333
roses busy 0.005516436
roses cousin -0.036730573
roses police -0.16219726
roses model 0.12471335
roses professor -0.048873723
mother governor -0.039010264
mother militant -0.043212965
mother slow -0.0004888703
mother dress 0.004685729
mother actress 0.0021683848
mother actor -0.06844571
mother game 0.0947665
mother player 0.031666134
mother roses 0.010247701
mother father -0.017193202
mother voters -0.00016746111
mother user 0.027143892
mother ambition -0.034156654
mother vulnerable -0.010727767
mother boss -0.03917563
mother busy 0.015764136
mother cousin -0.026482869
mother police -0.15194955
mother model 0.13496104
mother professor -0.038626023
father president -0.01987448
father governor -0.021817062
father militant -0.02601976
father slow 0.01670433
father dress 0.021878928
father actress 0.019361585
father actor -0.051252514
father game 0.111959696
father player 0.048859335
father roses 0.027440904
father mother 0.017193202
father voters 0.017025739
father user 0.044337086
father ambition -0.016963452
father vulnerable 0.0064654388
father boss -0.02198243
father busy 0.03295734
```

```
father cousin -0.009289668
father police -0.13475636
father model 0.15215424
father professor -0.021432824
voters president -0.036900222
voters governor -0.0388428
voters militant -0.0430455
voters slow -0.00032140757
voters dress 0.004853192
voters actress 0.0023358455
voters actor -0.06827825
voters game 0.09493396
voters player 0.031833597
voters roses 0.010415166
voters mother 0.00016746111
voters father -0.017025739
voters user 0.027311353
voters ambition -0.03398919
voters vulnerable -0.010560302
voters boss -0.039008167
voters busy 0.0159316
voters cousin -0.026315406
voters police -0.1517821
voters model 0.1351285
voters professor -0.03845856
user governor -0.06615415
user militant -0.07035685
user slow -0.027632765
user dress -0.02245816
user actress -0.024975507
user actor -0.09558961
user game 0.0676226
user player 0.0045222426
user roses -0.016896188
user mother -0.027143892
user father -0.044337086
user voters -0.027311353
user ambition -0.061300546
user vulnerable -0.037871655
user boss -0.066319525
user busy -0.011379754
user cousin -0.05362676
user model 0.10781715
user professor -0.06576991
ambition president -0.0029110303
ambition governor -0.00485361
ambition militant -0.009056307
ambition slow 0.03366778
ambition dress 0.03884238
ambition actress 0.036325037
ambition actor -0.034289062
ambition game 0.12892315
ambition player 0.06582279
ambition roses 0.044404358
ambition mother 0.034156654
ambition father 0.016963452
ambition voters 0.03398919
ambition user 0.061300546
ambition vulnerable 0.02342889
ambition boss -0.0050189765
ambition busy 0.04992079
ambition cousin 0.007673786
ambition police -0.117792904
ambition model 0.16911769
ambition professor -0.004469368
vulnerable governor -0.0282825
vulnerable militant -0.032485195
vulnerable slow 0.010238895
vulnerable dress 0.015413491
vulnerable actress 0.012896147
vulnerable actor -0.05771795
vulnerable game 0.10549426
```

```
vulnerable player 0.042393897
vulnerable roses 0.020975467
vulnerable mother 0.010727767
vulnerable father -0.0064654388
vulnerable voters 0.010560302
vulnerable user 0.037871655
vulnerable ambition -0.02342889
vulnerable boss -0.028447866
vulnerable busy 0.026491903
vulnerable cousin -0.015755102
vulnerable police -0.14122179
vulnerable model 0.14568882
vulnerable professor -0.027898256
boss president 0.0021079471
boss governor 0.00016536599
boss militant -0.004037331
boss slow 0.03868676
boss dress 0.04386136
boss actress 0.041344013
boss actor -0.029270085
boss game 0.13394213
boss player 0.07084176
boss roses 0.049423333
boss mother 0.03917563
boss father 0.02198243
boss voters 0.039008167
boss user 0.066319525
boss ambition 0.0050189765
boss vulnerable 0.028447866
boss busy 0.05493977
boss cousin 0.0126927635
boss police -0.112773925
boss model 0.17413667
boss professor 0.00054960744
busy president -0.052831825
busy governor -0.054774404
busy militant -0.0589771
busy slow -0.016253008
busy dress -0.01107841
busy actress -0.013595754
busy actor -0.08420985
busy game 0.07900235
busy player 0.015901996
busy roses -0.005516436
busy mother -0.015764136
busy father -0.03295734
busy voters -0.0159316
busy user 0.011379754
busy ambition -0.04992079
busy vulnerable -0.026491903
busy boss -0.05493977
busy cousin -0.042247005
busy police -0.1677137
busy model 0.11919691
busy professor -0.054390162
cousin president -0.010584817
cousin governor -0.012527395
cousin militant -0.016730092
cousin slow 0.025994
cousin dress 0.031168593
cousin actress 0.028651252
cousin actor -0.041962847
cousin game 0.12124937
cousin player 0.058149002
cousin roses 0.036730573
cousin mother 0.026482869
cousin father 0.009289668
cousin voters 0.026315406
cousin user 0.05362676
cousin ambition -0.007673786
cousin vulnerable 0.015755102
cousin boss -0.0126927635
```

```
cousin busy 0.042247005
cousin police -0.1254667
cousin model 0.16144392
cousin professor -0.012143156
police president 0.11488187
police governor 0.11293929
police militant 0.10873659
police slow 0.15146068
police dress 0.15663528
police actress 0.15411794
police actor 0.08350384
police game 0.24671605
police roses 0.16219726
police mother 0.15194955
police father 0.13475636
police voters 0.1517821
police ambition 0.117792904
police vulnerable 0.14122179
police boss 0.112773925
police busy 0.1677137
police cousin 0.1254667
police professor 0.11332353
model governor -0.1739713
model militant -0.178174
model slow -0.13544992
model dress -0.13027531
model actress -0.13279265
model actor -0.20340677
model game -0.04019455
model player -0.10329491
model roses -0.12471335
model mother -0.13496104
model father -0.15215424
model voters -0.1351285
model user -0.10781715
model ambition -0.16911769
model vulnerable -0.14568882
model boss -0.17413667
model busy -0.11919691
model cousin -0.16144392
professor president 0.0015583369
professor governor -0.00038424158
professor militant -0.004586938
professor slow 0.038137153
professor dress 0.04331176
professor actress 0.04079441
professor actor -0.029819692
professor game 0.13339251
professor roses 0.048873723
professor mother 0.038626023
professor father 0.021432824
professor voters 0.03845856
professor user 0.06576991
professor ambition 0.004469368
professor vulnerable 0.027898256
professor boss -0.00054960744
professor busy 0.054390162
professor cousin 0.012143156
```

```
In [ ]:
```