

A Prior Analysis

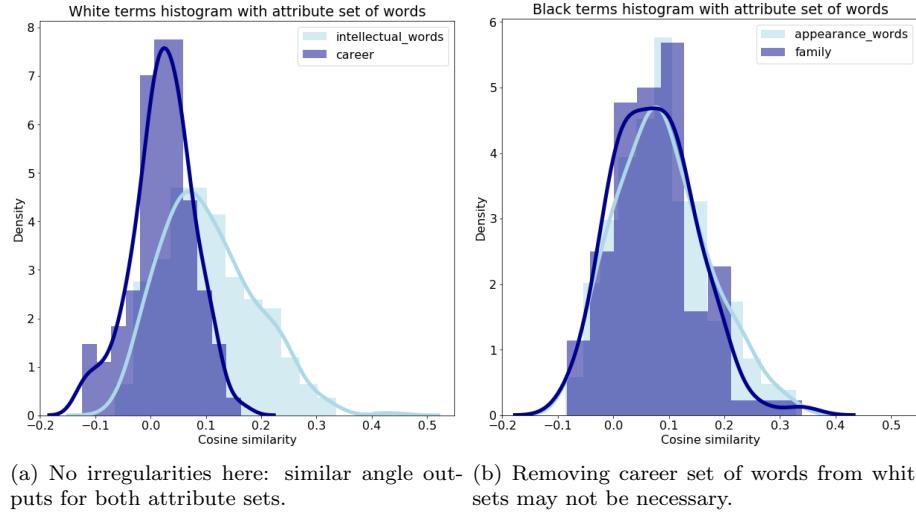


Figure 1: Kernel density estimate of cosine similarities between black, white word sets and their corresponding attribute word sets ready for debiasing (Word2Vec)

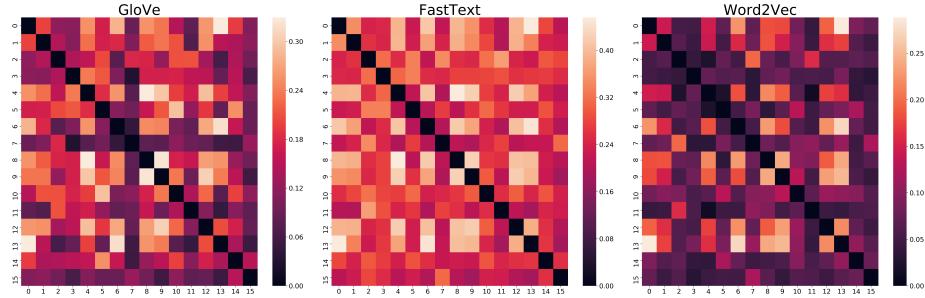


Figure 2: Median cosine similarity value between each pair of attribute sets (Not measured between words within the same set due to easier visibility).

B Bias results

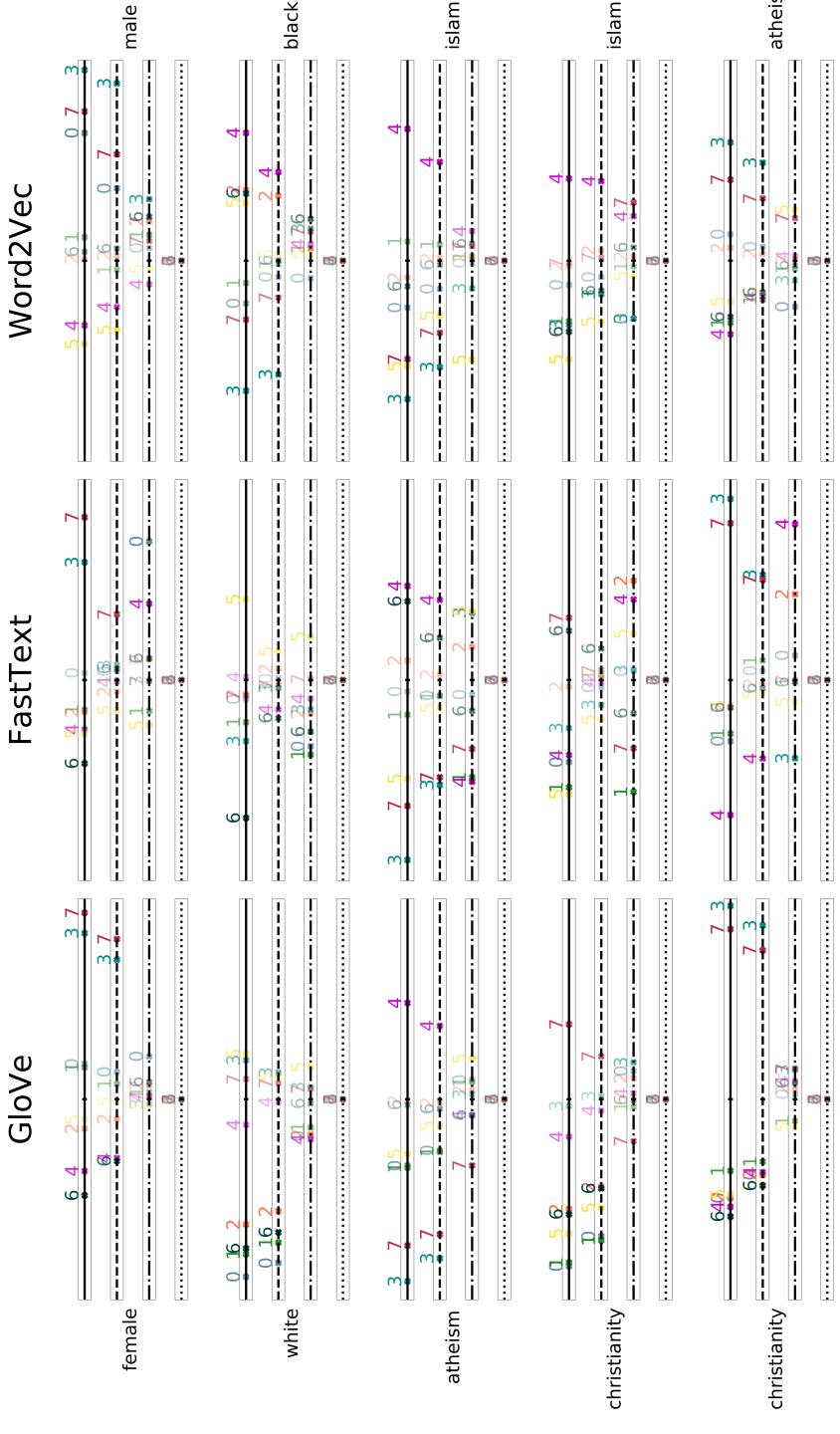


Figure 1: WEAT results before Regular Embedding and after debiasing (SoftWEAT $\lambda = 0.2$, HardWEAT $\lambda = 1$) and HardWEAT. Target words pair X is on the left, Y on the right, whereas attribute pairs A, B are numbers, indexed as: 0: likable vs unlikeable, 1: competent vs incompetent, 2: shy vs aggressive, 3: intellectual vs appearance, 4: family vs career, 5: instruments vs weapons, 6: pleasant vs unpleasant, 7: science vs artIf the number is on the left side of the scale, it suggest negative d value (between -1.55 and 0) and $Y - A, X - B$ relationship. In case of positive value (between 0 and 1.55) $X - A, Y - B$.

C Quality of Embeddings

	Regular	HardWEAT	SoftWEAT $\lambda = 0.2$	SoftWEAT $\lambda = 1$
RG65	76.031*	<u>63.422</u>	75.677	71.425
WS	73.804	69.731	73.997*	70.336
RW	46.147*	46.093	46.146	45.939
MEN	80.131	<u>77.515</u>	80.339*	78.738
MTurk	71.513*	69.785	71.251	68.635
SimLex	40.881	40.437	41.464	42.185*
SimVerb	28.735	28.744	28.897	29.776*
Mikolov	0.652	0.635	0.652*	0.639

Table 1: **Quality tasks on GloVe:** In 5 out of 8 tests, our methods maintain/increase quality of embeddings. HardWEAT makes a significant drop with RG65.

	Regular	HardWEAT	SoftWEAT $\lambda = 0.2$	SoftWEAT $\lambda = 1$
RG65	86.713*	<u>72.653</u>	86.136	<u>76.897</u>
WS	72.204*	68.279	72.175	<u>64.411</u>
RW	57.114	56.84	57.43*	56.283
MEN	81.35*	79.343	81.245	76.848
MTurk	75.101	73.757	75.137*	70.238
SimLex	47.153	46.219	47.517*	45.209
SimVerb	38.216	38.238*	38.2	38.1
Mikolov	0.853*	0.833	0.851	0.842

Table 2: **Quality tasks on FastText:** In half of the tests, quality is maintained/improved. Significant drop seen with RG65 and WS with HardWEAT and SoftWEAT with $\lambda = 1$.

	Regular	HardWEAT	SoftWEAT $\lambda = 0.2$	SoftWEAT $\lambda = 1$
RG65	74.943*	<u>64.025</u>	74.86	<u>69.69</u>
WS	69.998	65.943	70.128*	69.325
RW	53.394*	53.119	53.356	52.954
MEN	77.068*	75.307	77.025	76.304
MTurk	67.139*	66.326	66.999	66.184
SimLex	44.255	43.954	44.301	44.302*
SimVerb	36.749	36.758*	36.745	36.673
Mikolov	0.74	0.722	0.74*	0.737

Table 3: **Quality tasks on Word2vec:** Similar output as with FastText, on half tests were results maintained/improved, with RG65 achieving lower quality on HardWEAT and SoftWEAT with $\lambda = 1$.

D Sensitivity Analysis

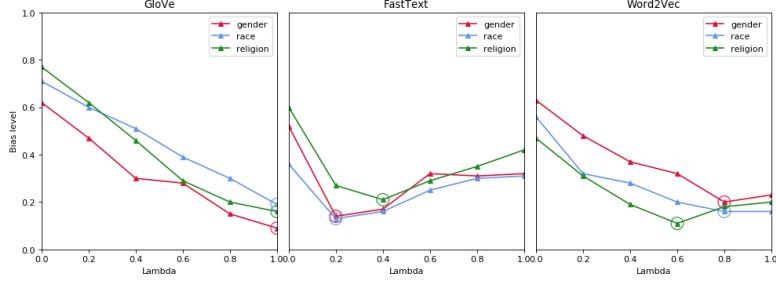


Figure 1: **WEAT levels SoftWEAT:** SoftWEAT leads to bias decrease, however not always in complete correlation with λ , like in GloVe.

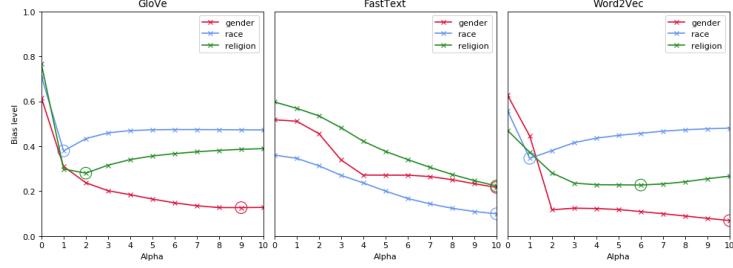


Figure 2: **WEAT levels Conceptor:** Similarly as with SoftWEAT, higher method's parameter does not always α lead to less of bias levels.

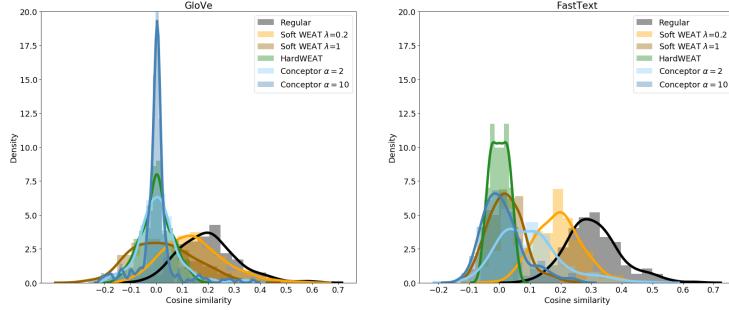


Figure 3: **Kernel Density Estimate of cosine similarity values between words of pairs of sets: atheism - science, christianity - art:** While Conceptor does reduce overall angles between target and attribute sets of words, it also decreases angles between words of actual target sets. We performed summation of sums (double sum) of cosine similarity values between each word pair within each target set. Results are following, before and after Conceptor Debiasing ($\alpha = 2$): GloVe ($1745 \rightarrow 260$), FastText ($1558 \rightarrow 490$), Word2Vec ($438 \rightarrow 85$). These values remain the same when applying SoftWEAT.

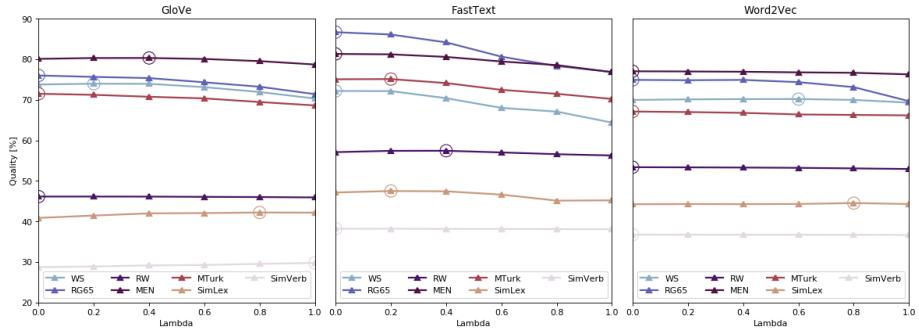


Figure 4: Quality explained via Similarity Task - SoftWEAT

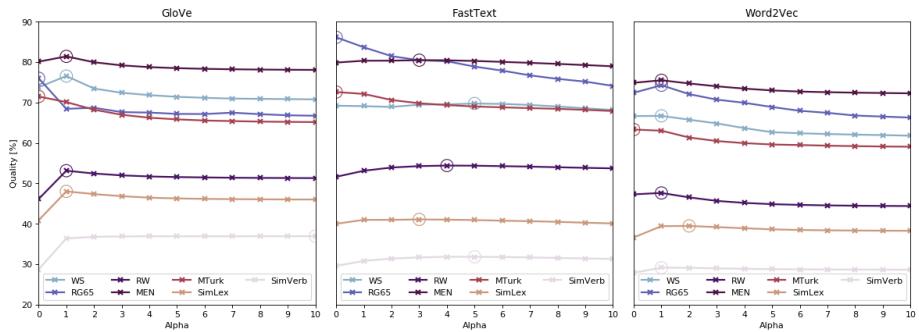


Figure 5: Quality explained via Similarity Task - Conceptor

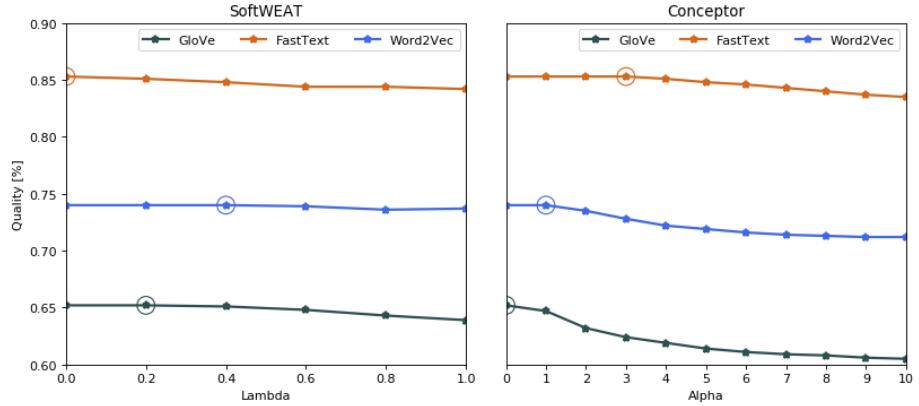


Figure 6: Comparison of Mikolov analogy task based on different SoftWEAT λ and Conceptor's α values

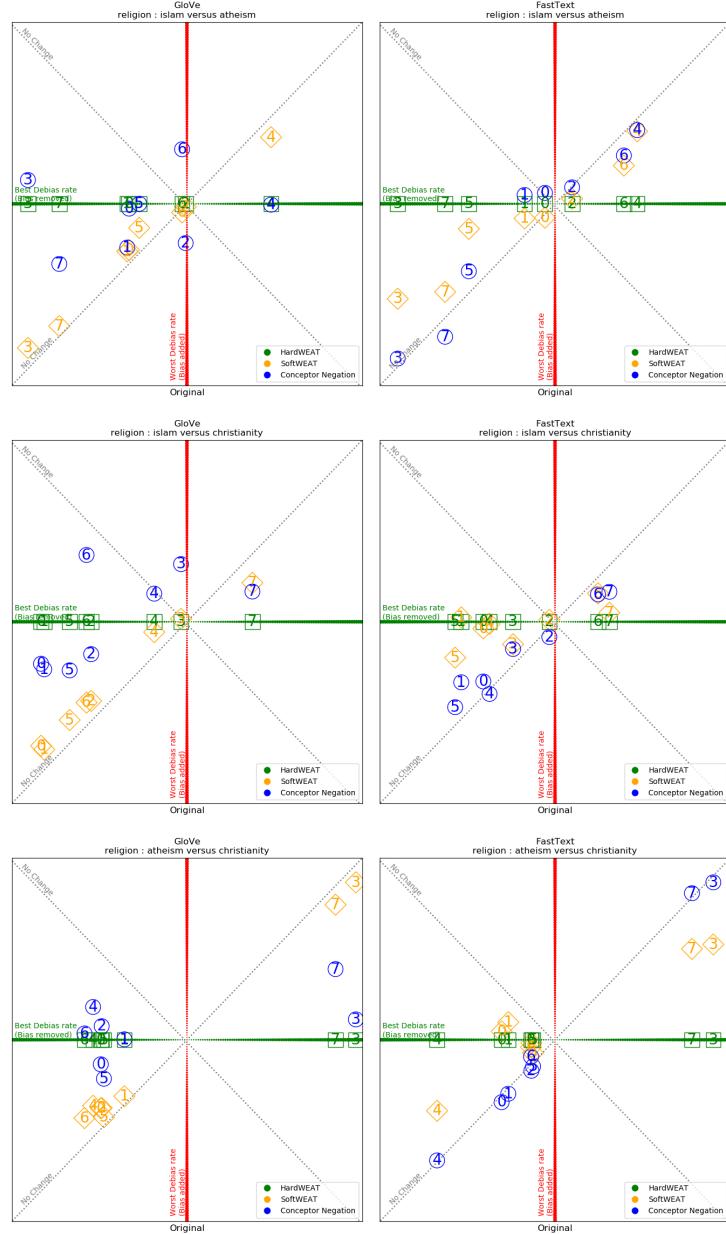


Figure 7: Before and after debiasing for HardWEAT, SoftWEAT ($\lambda = 0.2$ and Conceptor $\alpha = 2$)

E Sentiment Analysis

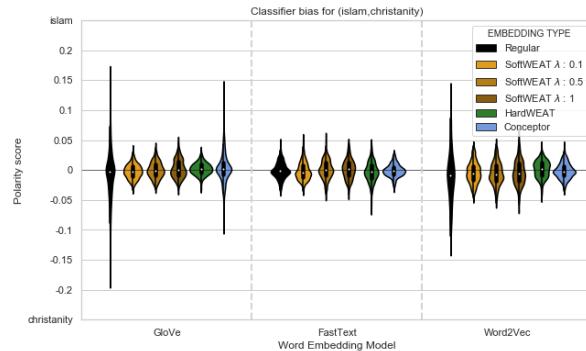


Figure 1: Classifier Bias on (islam, christianity) words

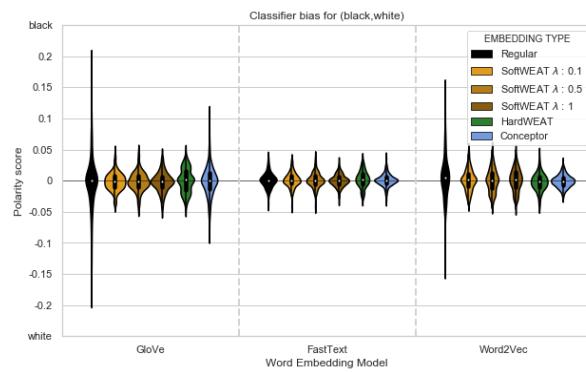


Figure 2: Classifier Bias on (black, white) words:

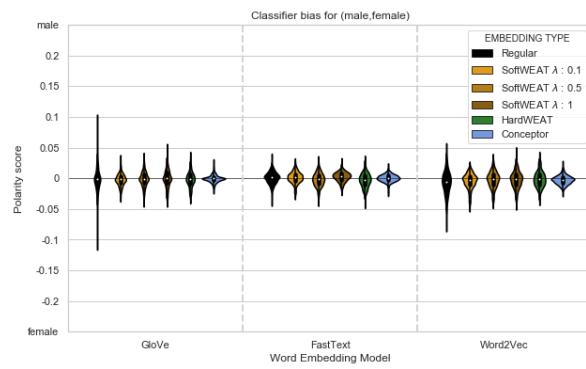


Figure 3: Classifier Bias on (male, female) set of words

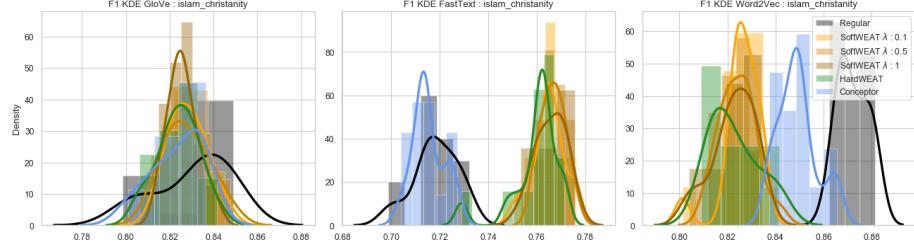


Figure 4: Kernel density estimate on F1 scores for (islam, christianity) modified embeddings.

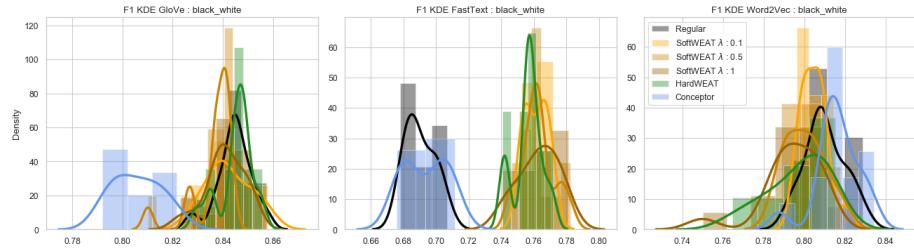


Figure 5: Kernel density estimate on F1 scores for (black, white) modified embeddings.

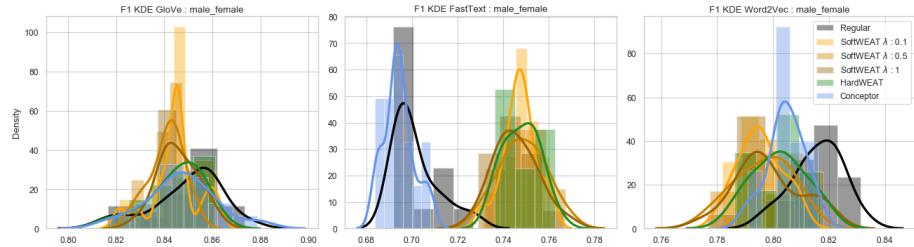


Figure 6: Kernel density estimate on F1 scores for (male, female) modified embeddings.

F Target attribute sets for debiasing within SoftWEAT.

- GloVe** : Male terms [science, intellectual, unpleasant]
Female terms [pleasant, appearance, art]
- Black names [aggressive, unlikable, unpleasant, incompetent]
White names [competent, likable, pleasant, shy]
- Islam terms [unlikable, art, weapons, family, incompetent, appearance, aggressive, unpleasant]
- Atheism terms [unlikable, science, intellectual, weapons, career, aggressive, unpleasant]

Christianity terms [competent, pleasant, art, shy, family, instruments, likable, appearance]

Word2Vec : Male terms [science, intellectual, weapons, likable]

Female terms [instruments, unlikable, appearance, art]

Black names [family, appearance]

White names [intellectual, career]

Islam terms [weapons, family, appearance, art]

Atheism terms [science, career, instruments, intellectual]

Christianity terms [career, instruments, appearance, art]

Fasttext : Male terms [science, intellectual, unpleasant]

Female terms [pleasant, appearance, art]

Black names [instruments, unpleasant]

White names [weapons, pleasant]

Islam terms [unlikable, pleasant, art, weapons, family, incompetent, appearance]

Atheism terms [science, intellectual, instruments, career, unpleasant]

Christianity terms [competent, art, family, instruments, likable, appearance]

Number of changed words within SoftWEAT

Embedding	Subclass	Male terms		Female terms		Black names		White names		Islam words		Atheism words		Christianity words	
GloVe		50	47	156	244	80	146	102							
Word2Vec		31	34	108	92	47	52	39							
Fasttext		57	54	470	254	126	157	120							

Table 4: Number of changed target set words within SoftWEAT.

G Sets

Target sets

male[1] = {'male', 'man', 'boy', 'brother', 'he', 'him', 'his', 'son', 'father', 'uncle', 'grandfather'}

female[1] = {'female', 'woman', 'girl', 'sister', 'she', 'her', 'hers', 'daughter', 'mother', 'aunt', 'grandmother'}

white[1] = {adam, chip, harry, josh, roger, alan, frank, ian, justin, ryan, andrew, fred, jack, matthew, stephen, brad, greg, jed, paul, todd, brandon, hank, jonathan, peter, wilbur, amanda, courtney, heather, melanie, sara, amber, crystal, katie, meredith, shannon, betsy, donna, kristin, nancy, stephanie, bobbie-sue, ellen, lauren, peggy, sue-ellen, colleen, emily, megan, rachel, wendy, bren-dan, geoffrey, brett, jay, neil, anne, carrie, jill, laurie, kristen, sarah}

black[1] = {alonzo, jamel, lerone, percell, theo, alphonse, jerome, leroy, rasaan, torrance, darnell, lamar, lionel, rashawn, tyree, deion, lamont, malik, terrence, tyrone, everol, lavon, marcellus, terry, wardell, aiesha, lashelle, nichelle, shereen, temeka, ebony, latisha, shaniqua, tameisha, teretha, jasmine, latonya, shanise, tanisha, tia, lakisha, latoya, sharise, tashika, yolanda, lashandra, malika, shavonn, tawanda, yvette, hakim, jermaine, kareem, jamal, rasheed, aisha, keisha, kenya, tamika}

christianity[2] = {baptism, messiah, catholicism, resurrection, christianity, sal-vation, protestant, gospel, trinity, jesus, christ, christian, cross, catholic, church}

islam[2] = {allah, ramadan, turban, emir, salaam, sunni, koran, imam, sultan, prophet, veil, ayatollah, shiite, mosque, islam, sheik, muslim, muhammad}

atheism[3] = {atheism, atheist, atheistic, heliocentric, evolution, darwin, galilei, agnostic, agnosticism, pagan, science, disbelief, scepticism, philosophy, university, kopernikus}

Attribute sets

science[1] = {math, algebra, geometry, calculus, equations, computation, numbers, addition, science, technology, physics, chemistry, einstein, nasa, experi-ment, astronomy}

art[1] = {poetry, art, dance, literature, novel, symphony, drama, sculpture, shakespeare}

intellectual[3] = {precocious, luminous, brilliant, stupid, logical, idiotic, trivial, analytical, thoughtful, reflective, astute, inquiring, venerable, dull, resource-ful, ingenious, smart, discerning, sagacious, clever, wise, inventive, unintelligent, adaptable, sage, judicious, imaginative, intuitive, unwise, naive, dumb, apt, clumsy, foolish, shrewd, inquisitive, genius, intelligent}

appearance[2] = {alluring, voluptuous, blushing, homely, plump, sensual, gor-geous, slim, bald, athletic, fashionable, stout, ugly, muscular, slender, feeble, handsome, healthy, attractive, fat, weak, thin, pretty, beautiful, strong}

career[1] = {executive, management, professional, corporation, salary, office, business, career}

family[1] = {home, parents, children, family, cousins, marriage, wedding, relatives}

pleasant[1] = caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest, lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation, joy, wonderful}

unpleasant[1] = abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred, pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison, terrible, horrible, nasty, evil, war, awful, failure}

shy[5] = {soft, quiet, compromising, rational, calm, kind, agreeable, servile, pleasant, cautious, friendly, supportive, nice, mild, demure, passive, indifferent, submissive}

aggressive[5] = {shrill, loud, argumentative, irrational, angry, abusive, obnoxious, controlling, nagging, brash, hostile, emasculating, mean, harsh, sassy, aggressive, opinionated, domineering}

shy[5] = {soft, quiet, compromising, rational, calm, kind, agreeable, servile, pleasant, cautious, friendly, supportive, nice, mild, demure, passive, indifferent, submissive}

aggressive[5] = {shrill, loud, argumentative, irrational, angry, abusive, obnoxious, controlling, nagging, brash, hostile, emasculating, mean, harsh, sassy, aggressive, opinionated, domineering}

competent[5] = {competent, productive, effective, ambitious, active, decisive, strong, tough, bold, assertive]}

incompetent[5] = {incompetent, unproductive, ineffective, unambitious, passive, indecisive, weak, gentle, timid, unassertive}

likable[5] = {agreeable, fair, honest, trustworthy, selfless, accommodating, likable, liked}

unlikable[5] = {abrasive, conniving, manipulative, dishonest, selfish, pushy, unlikable, unliked}

flowers[5] = {aster, clover, hyacinth, marigold, poppy, azalea, crocus, iris, orchid, rose, bluebell, daffodil, lilac, pansy, tulip, buttercup, daisy, lily, peony, violet, carnation, gladiola, magnolia, petunia, zinnia}

insects[5] = {ant, caterpillar, flea, locust, spider, bedbug, centipede, fly, maggot, tarantula, bee, cockroach, gnat, mosquito, termite, beetle, cricket, hornet, moth, wasp, blackfly, dragonfly, horsefly, roach, weevil}

Extended non-neutral words list for HardWEAT

male[7] = {countryman, fraternal, wizards, manservant, fathers, divo, actor, bachelor, papa, dukes, barman, countrymen, brideprice, hosts, airmen, andropause, penis, prince, governors, abbot, men, widower, gentlemen, sorcerers, sir, bridegrooms, baron, househusbands, gods, nephew, widowers, lord, brother, grooms, priest, adultors, andrology, bellboys, his, marquis, princes, emperors, stallion, chairman, monastery, priests, boyhood, fellas, king, dudes, daddies, manservant, semen, spokesman, tailor, cowboys, dude, bachelors, barbershop, emperor, daddy, masculism, guys, enchanter, guy, fatherhood, androgen, cameramen, godfather, strongman, god, patriarch, uncle, chairmen, sir, brotherhood,

host, testosterone, husband, dad, steward, males, cialis, spokesmen, pa, beau, stud, bachelor, wizard, sir, nephews, fathered, bull, beaus, councilmen, landlords, grandson, fiances, stepfathers, horsemen, grandfathers, adulter, schoolboy, rooster, grandsons, bachelor, cameraman, dads, him, master, lad, policeman, monk, actors, salesmen, boyfriend, councilman, fellas, statesman, paternal, chap, landlord, brethren, lords, blokes, fraternity, bellboy, duke, ballet_dancer, dudes, fiance, colts, husbands, suitor, paternity, he, businessman, masseurs, hero, deer, busboys, boyfriends, kings, brothers, masters, stepfather, grooms, son, studs, cowboy, gentleman, sons, baritone, salesman, paramour, male_host, monks, menservants, mr., headmasters, lads, congressman, airman, househusband, priest, barmen, barons, abbots, handyman, beard, fraternities, stewards, colt, czar, stepsons, himself, boys, lions, gentleman, penis, his, masseur, bulls, uncles, bloke, beards, hubby, lion, sorcerer, macho, father, gays, male, waiters, sperm, prostate, stepson, prostatic_utricle, businessmen, heir, waiter, headmaster, man, governor, god, bridegroom, grandpa, groom, dude, gay, gents, boy, grandfather, gelding, paternity, roosters, prostatic_utricle, priests, manservants, stailor, busboy, heros}

female[7] = {countrywoman, sororal, witches, maidservant, mothers, diva, actress, spinster, mama, duchesses, barwoman, countrywomen, dowry, hostesses, airwomen, menopause, clitoris, princess, governesses, abbess, women, widow, ladies, sorceresses, madam, brides, baroness, housewives, godesses, niece, widows, lady, sister, brides, nun, adultresses, obstetrics, bellgirls, her, marchioness, princesses, empresses, mare, chairwoman, convent, priestesses, girlhood, ladies, queen, gals, mommies, maid, female_ejaculation, spokeswoman, seamstress, cowgirls, chick, spinsters, hair_salon, empress, mommy, feminism, gals, enchantress, gal, motherhood, estrogen, camerawomen, godmother, strongwoman, goddess, matriarch, aunt, chairwomen, ma'am, sisterhood, hostess, estradiol, wife, mom, stewardess, females, viagra, spokeswoman, ma, belle, minx, maiden, witch, miss, nieces, mothered, cow, belles, councilwomen, landladies, granddaughter, fiancees, stepmothers, horsewomen, grandmothers, adultrress, schoolgirl, hen, granddaughters, bachelorette, camerawoman, moms, her, mistress, lass, police-woman, nun, actresses, saleswomen, girlfriend, councilwoman, lady, stateswoman, maternal, lass, landlady, sistren, ladies, wenches, sorority, bellgirl, duchess, ballerina, chicks, fiancee, fillies, wives, suitress, maternity, she, businesswoman, masseuses, heroine, doe, busgirls, girlfriends, queens, sisters, mistresses, step-mother, brides, daughter, minxes, cowgirl, lady, daughters, mezzo, saleswoman, mistress, hostess, nuns, maids, mrs., headmistresses, lasses, congresswoman, airwoman, housewife, priestess, bar-women, barnoesses, abbesses, handywoman, toque, sororities, stewardesses, filly, czarina, stepdaughters, herself, girls, lionesses, lady, vagina, hers, masseuse, cows, aunts, wench, toques, wife, lioness, sorceress, effeminate, mother, lesbians, female, waitresses, ovum, skene_gland, stepdaughter, womb, businesswomen, heiress, waitress, headmistress, woman, governess, godess, bride, grandma, bride, gal, lesbian, ladies, girl, grandmother, mare, maternity, hens, uterus, nuns, maidservants, seamstress', busgirl, heroines}

gender[6] = {cowboy, cowgirl, cowboys, cowgirls, camerawomen, cameramen,

cameraman, camerawoman, busboy, busgirl, busboys, busgirls, bellboy, bellgirl, bellboys, bellgirls, barman, barwoman, barmen, barwomen, tailor, seamstress, tailors, seamstress', prince, princess, princes, princesses, governor, governess, governors, governesses, adulteror, adulteress, adultors, adultresses, god, goddess, gods, goddesses, host, hostess, hosts, hostesses, abbot, abbess, abbots, abbesses, actor, actress, actors, actresses, bachelor, spinster, bachelors, spinsters, baron, baroness, barons, baroesses, beau, belle, beaus, belles, bridegroom, bride, bridegrooms, brides, brother, sister, brothers, sisters, duke, duchess, dukes, duchesses, emperor, empress, emperors, empresses, enchanter, enchantress, father, mother, fathers, mothers, fiance, fiancee, fiances, fiancees, priest, nun, priests, nuns, gentleman, lady, gentlemen, ladies, grandfather, grandmother, grandfathers, grandmothers, headmaster, headmistress, headmasters, headmistresses, hero, heroine, heros, heroines, lad, lass, lads, lasses, landlord, landlady, landlords, landladies, male, female, males, females, man, woman, men, women, manservant, maidservant, manservants, maidservants, marquis, marchioness, masseur, masseuse, masseurs, masseuses, master, mistress, masters, mistresses, monk, nun, monks, nuns, nephew, niece, nephews, nieces, priest, priestess, priests, priestesses, sorcerer, sorceress, sorcerers, sorceresses, stepfather, stepmother, stepfathers, stepmothers, stepson, stepdaughter, stepsons, stepdaughters, steward, stewardess, stewards, stewardesses, uncle, aunt, uncles, aunts, waiter, waitress, waiters, waitresses, widower, widow, widowers, widows, wizard, witch, wizards, witches}

religion[4] = {synagogue, synagogues, altar, altars, parish, parishes, biblical, bishop, bishops, jihadist, clergy, bible, bibles, mosque, mosques, mullah, church, churches, sermon, sermons, papacy, imam, pew, chancel, pope, priest, priests, baptism, jihad, confessional, holy_eucharist, evangelical, jesus, burqa, vicar, vicars, judaism, christianity, islam, jew, christian, muslim, torah, quran, rabbi}

References

- [1] Caliskan, A., Bryson, J.J., Narayanan, A.: Semantics derived automatically from language corpora contain human-like biases. *Science* (2017)
- [2] Garg, N., Schiebinger, L., Jurafsky, D., Zou, J.: Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences* (2018)
- [3] Knoche, M., Popović, R., Lemmerich, F., Strohmaier, M.: Identifying biases in politically biased wikis through word embeddings. In: *Proceedings of the 30th ACM Conference on Hypertext and Social Media*. p. 253–257 (2019)
- [4] Manzini, T., Lim, Y.C., Tsvetkov, Y., Black, A.W.: Black is to criminal as caucasian is to police: Detecting and removing multiclass bias in word embeddings. *CoRR* **abs/1904.04047** (2019), <http://arxiv.org/abs/1904.04047>
- [5] May, C., Wang, A., Bordia, S., Bowman, S.R., Rudinger, R.: On measuring social biases in sentence encoders. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. pp. 622–628. Association for Computational Linguistics, Minneapolis, Minnesota (Jun 2019), <https://www.aclweb.org/anthology/N19-1063>
- [6] Zhao, J., Wang, T., Yatskar, M., Ordonez, V., Chang, K.: Gender bias in coreference resolution: Evaluation and debiasing methods. *CoRR* **abs/1804.06876** (2018), <http://arxiv.org/abs/1804.06876>
- [7] Zhao, J., Zhou, Y., Li, Z., Wang, W., Chang, K.: Learning gender-neutral word embeddings. *CoRR* **abs/1809.01496** (2018), <http://arxiv.org/abs/1809.01496>