Measuring social bias in knowledge graph embeddings

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Abstract

It has recently been shown that word embeddings encode social biases, with a harmful impact on downstream tasks. However, to this point there has been no similar work done in the field of knowledge graph embeddings. We present the first study on social bias in knowledge graph embeddings, and propose a new metric suitable for measuring such bias. We conduct experiments on Wikidata and Freebase, and show that, as with word embeddings, harmful social biases related to professions are encoded in knowledge graph embeddings with respect to gender, religion, ethnicity and nationality. For example, knowledge graph embeddings encode the information that men are more likely to be bankers, and women more likely to be homekeepers. As knowledge graph embeddings become increasingly utilized, we suggest that it is important the existence of such biases are understood and steps taken to mitigate their impact.

1 Introduction

Recent work in the word embeddings literature has shown that embeddings encode gender and racial biases, (Bolukbasi et al., 2016; Caliskan et al., 2017; Garg et al., 2017). These biases can have harmful effects in downstream tasks including coreference resolution, (Zhao et al., 2018a) and machine translation, (Stanovsky et al., 2019), leading to the development of a range of methods to try to mitigate such biases, (Bolukbasi et al., 2016; Zhao et al., 2018b). In an adjacent literature, learning embeddings of knowledge graph entities and relations is becoming an increasingly common first step in utilizing knowledge graphs for a range of tasks, from missing link prediction, (Bordes et al., 2013; Trouillon et al., 2016), to more recent methods integrating learned embeddings into language models, (Zhang et al., 2019; IV et al., 2019; Peters et al., 2019).

A natural question to ask is "do knowledge graph embeddings encode social biases in similar fashion to word embeddings"? We show that existing methods for identifying bias in word embeddings are not suitable for knowledge graph embeddings, and present an approach to overcome this using embedding finetuning. We demonstrate (perhaps unsurprisingly) that unequal distributions of people of different genders, ethnicities, religions and nationalities in the Freebase and Wikidata knowledge graphs result in biases related to professions being encoded in knowledge graph embeddings, such as that men are more likely to be bankers and women more likely to be homekeepers.

Such biases are potentially harmful when knowledge graph embeddings are used in downstream applications. For example, if embeddings are used in a fact checking task[1], they would make it less likely that we accept facts that a female entity is a politician as opposed to a male entity. Alternatively, as knowledge graph embeddings get utilized as input to language models (Zhang et al., 2019; IV et al., 2019; Peters et al., 2019), such biases can impact all downstream NLP tasks, as has been the case with bias in word embeddings.

We begin in Section 2 by providing the interpretation of bias in embeddings used in this paper, before introducing knowledge graph embedding methods, and discussing how the commonly used method of measuring bias in word embeddings is not applicable to knowledge graph embeddings. In Section 3 we present our proposed alternative approach for identifying bias in graph embeddings. Section 4 then presents results for Wikidata with TransE embeddings, and for FB3M with ComplEx embeddings, with further results provided in the Appendix.

[1] Where we evaluate the likelihood that a new triple is correct before adding it to a knowledge base.

2 Background

2.1 Defining bias in embeddings

Bias can be thought of as "prejudice in favor or against a person, group, or thing that is considered to be unfair" (Jones, 2019). Because definitions of fairness have changed over time, algorithms which are trained on "real-world" data[2] may pick up associations which existed historically (or still exist), but which are considered undesirable. In the word embedding literature, one common idea is to analyse relationships which embeddings encode between professions and gender, race, ethnicity or nationality. We follow this approach in this paper, though note that our method is equally applicable to measuring the encoded relationship between any set of entities in a knowledge graph.[3].

2.2 Knowledge Graph Embeddings

Knowledge graph embeddings are a vector representation of dimension d of all entities and relations in a knowledge graph. To learn these representations, we define a score function $g(.)$ which takes as input the embeddings of a fact in triple form and outputs a score, denoting how likely this triple is to be correct.

$$s = \mathbf{g}(e_1, r_1, e_2)$$

where $e_{1/2}$ are the dimension d embeddings of entities 1/2, and r_1 is the dimension d embedding of relation 1. The score function is composed of a transformation, which takes as input one entity embedding and the relation embedding and outputs a vector of the same dimension, and a similarity function, which calculates the similarity or distance between the output of the transformation function and the other entity embedding.

Many transformation functions have been proposed, including TransE (Bordes et al., 2013), ComplEx (Trouillon et al., 2016) and RotatE (Sun et al., 2019). In this paper we use the TransE and ComplEx functions, and the dot product similarity metric, though emphasize that our approach is applicable to any score function.

TransE:

$$s = ((e_1 + r_1), \bar{e_2})$$

[2]Such as news articles or a knowledge graph

[3]For example, we could consider the encoded relationship between a person's nationality and their chances of being a CEO etc.

ComplEx:

$$s = Re(< e_1, r_1, \bar{e_2} >)$$

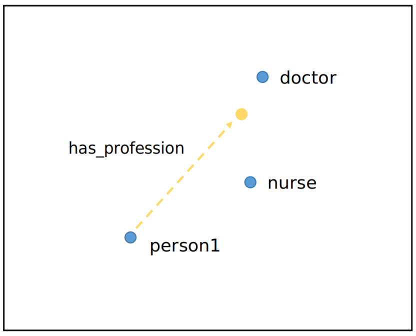
We use embeddings of dimension 200, and sample 1000 negative triples per positive, by randomly permuting the lhs or rhs entity. We pass the 1000 negatives and single positive through a softmax function, and train using the cross entropy loss. All training is implemented using the PyTorch-BigGraph library (Lerer et al., 2019).

2.3 Measuring bias in word embeddings

The most common technique for exposing bias in word embeddings, the "Word Embedding Association Test" (Caliskan et al., 2017), measures the cosine distance between entity embeddings and the average entity embeddings of two sets of attribute words (where the sets of attribute words could correspond to e.g. male vs. female). They give a range of examples of biases according to this metric, including that science related words are more associated with "male", and art related words with "female". In a similar vein, in (Bolukbasi et al., 2016), the authors use the direction between vectors to expose stereotypical analogies, claiming that the direction between man::doctor is analogous to that of woman::nurse. Despite (Nissim et al., 2019) exposing some technical shortcomings in this approach, it remains the case that distance metrics appear to be appropriate in at least exposing bias in word embeddings, which has then been shown to clearly propagate to downstream tasks, (Zhao et al., 2018a; Stanovsky et al., 2019).

We suggest that distance-based metrics are not suitable for measuring bias in knowledge graph embeddings. Figure 1 provides a simple demonstration of the reasoning behind this. Visualizing in a two dimensional space, the embedding of person1 is closer to nurse than to doctor. However, knowledge graph embedding models do not use distance between two entity embeddings when making predictions, but rather the distance between some transformation of one entity embedding with the relation embedding.

Figure 1: Unsuitability of distance based metrics for measuring bias in knowledge graph embeddings



In the simplest case of TransE (Bordes et al., 2013) this transformation is a summation, which could result in a vector positioned at the yellow dot in Figure 1, when making a prediction of the profession of person1. As the transformation function becomes more complicated, (Trouillon et al., 2016; Sun et al., 2019) etc., the distance metric becomes increasingly less applicable, as associations in the distance space become less and less correlated with associations in the score function space.

3 Method

When presenting measures of bias for knowledge graph embeddings, we define the sensitive attribute we are interested in, denoted g, and two alternative values of this attribute, denoted a and b. For the purposes of our example we use gender as the sensitive attribute g, and male and female as the alternative values a and b. We are interested in measuring the influence of the sensitive attribute (gender) on the model's predictions of the likelihood of a person having a profession p, defined by the score function:

$$s_{j,p} = \mathbf{g}(e_j, r_p, e_p)$$

where e_j is the entity embedding of person j, r_p is the embedding of the relation corresponding to "has_profession", and e_p is the entity embedding of profession p.

3.1 Comparing pairs of entities

Taking into account the discussion of bias in word embeddings, one potential starting point for a bias measure in graph embeddings is to look at the model's scores $s_{j,p}$ for a male entity j, and compare them to the scores $s_{i,p}$ for a female entity i. For example, we can calculate the scores that the entity "Barack Obama" has each profession in the knowledge graph, and the scores that the entity "Michelle Obama" has each profession, and use the difference between the two as a measure of bias, denoted b_p:

$$b_p = \mathbf{g}(e_{barack}, r_p, e_p) - \mathbf{g}(e_{michelle}, r_p, e_p)$$

Table 1: Top 20 male professions in Wikidata relative to female using Barack Obama vs. Michelle Obama

Profession	B_p	C_{male}	$C_{fem.}$
zoologist	8.10	5355	754
President of the U.S.	7.71	1	0
police officer	6.85	2765	203
ornithologist	6.56	2283	151
geographer	6.46	3922	390
entomologist	5.67	4775	544
darts player	5.36	681	57
caricaturist	5.11	1303	63
child actor	5.03	978	1074
theater director	5.01	6256	1563
biochemist	5.00	2136	564
playwright	4.96	9293	1730
rikishi	4.88	398	2
geologist	4.86	4911	402
supervillain	4.85	59	29
cartoonist	4.84	2380	464
animator	4.78	2354	410
rakugoka	4.78	181	19
ballet dancer	4.71	1126	1738
psychiatrist	4.58	3351	471

Table 2: Top 20 female professions in Wikidata relative to male using Barack Obama vs. Michelle Obama

Profession	B_p	$C_{fem.}$	C_{male}
lawyer	8.66	5691	55205
printer	7.91	78	1785
typographer	7.42	19	442
publisher	7.30	582	6376
astronomer	6.73	565	5543
fashion photogr.	6.60	49	227
digital artist	6.58	18	57
visual artist	6.51	1203	2002
performance artist	6.27	181	203
architectural photogr.	6.26	16	83
military commander	6.02	0	1077
photojournalist	6.02	215	918
Hofmeister	5.90	13	125
notary	5.89	34	874
attorney at law	5.82	14	89
editor	5.74	1177	5488
count	5.74	13	102
advocate	5.70	110	486
painter	5.69	16514	87371
translator	5.64	6298	21045

Table 1 shows the top 20 "male" professions in Wikidata using this metric, and Table 2 the top 20 "female" professions using the inverse metric. Alongside the score we present the counts of humans in the knowledge graph which have this profession, split by attributes. For example, the top rows of column C_{male} and $C_{fem.}$ in Table 1 shows that there are 5355 male entities in Wikidata with the profession "zoologist", and 754 female entities with this profession.[4]

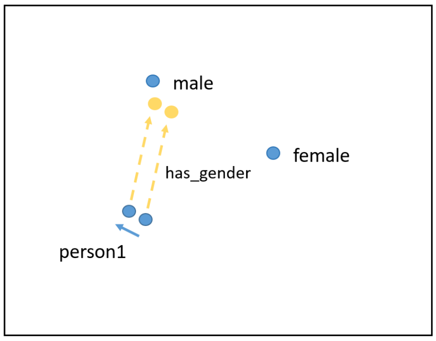
The top professions, whilst in some cases amusing ("supervillain" and "ballet dancer" for Obama!) appear uncorrelated with the male/female counts in Wikidata; for example "military commander" is in the top 20 female professions by this measure whilst having no female observations and 1077 male observations. In general, we find this corresponds to a pattern with knowledge graph embeddings that measures based on a single entities' embeddings are highly noisy, and depending significantly on the particular set of triples which the corresponding entity is included in. To illustrate this, Tables 9 and 10 in Appendix A.1 show the same measure, but using Donald and Melania Trump. The results have very little overlap with those in Tables 1 and 2, suggesting they depend more on the particular entities chosen than the model's representation of gender relative to professions.

A potential alternative to this is to average such comparisons across multiple pairs of male/female entities. However, as we know that the distribution of human entities for each profession in real-world knowledge graphs with sensitive attributes is not balanced (there are, as we have seen, many more male "military commanders" in Wikidata than female), the resulting measure would simply represent whether the model is able to give higher scores to people's correct professions. Instead, we are interested in analysing if the trained embeddings of professions encode the information that they are more male/female, or put another way, if the model is likely to attribute a higher likelihood to an entity having a particular profession purely on the basis of their gender.

3.2 Proposed metric

In light of this discussion, we propose the following metric. We take a trained embedding of a human entity, j, denoted e_j and calculate an update to this embedding which increases the score that they have attribute a (male), and decreases the score that they have attribute b (female). In other words, we finetune the embedding to make the person "more male" according to the model's own encoding of masculinity. This is visualized for TransE in Figure 2, where we shift person1's embedding so that the transformation between person1 and the relation has_gender moves closer to male and away from female.

Figure 2: Finetuning of embedding along gender axis



Mathematically, we define function $\mathbf{m}$ as the difference between the score that person j has sensitive attribute a (male) and that they have sensitive attribute b (female). We then differentiate $\mathbf{m}$ wrt the embedding of person j, e_j, and update the embedding to increase this score function.

$$\mathbf{m}(\theta) = \mathbf{g}(e_j, r_s, e_a) - \mathbf{g}(e_j, r_s, e_b) \qquad (1)$$

$$e'_j = e_j + \alpha \frac{\delta \mathbf{m}(\theta)}{\delta e_j}$$

where e'_j denotes the updated embedding for person j, r_g the embedding of the sensitive relation i (gender), and e_a and e_b the embeddings of attributes a and b (male and female). This is equivalent to providing the model with a batch of two triples, (e_j, r_g, e_a) and (e_j, r_g, e_b), and taking a step with the basic gradient descent algorithm with learning rate α.[5]

We then analyse the change in the models scores for each profession. That is, we calculate whether, according to the model's score function, making an entity more male increases or decreases the likelihood that they have a particular profession, p:

$$\nabla_p = \mathbf{g}(e'_j, r_p, e_p) - \mathbf{g}(e_j, r_p, e_p)$$

where e_p denotes the entity embedding of the profession, p.

[4]Whilst for the majority of results tables we limit professions to those with at least 20 occurrences in the knowledge graph to reduce noise, we leave in professions such as "President of the United States" which have less observations than this but have Barack or Michelle as a left hand entity.

[5]In all experiments in the paper we set α to 0.01. For TransE, the linearity of the score function means the result is independent of $alpha$. For non-linear score functions, the value of α should be kept small to ensure the updated embeddings e'_j remain in the proximity of unchanged human embeddings in the knowledge graph.

Figure 3: Effect of finetuning on scores of professions

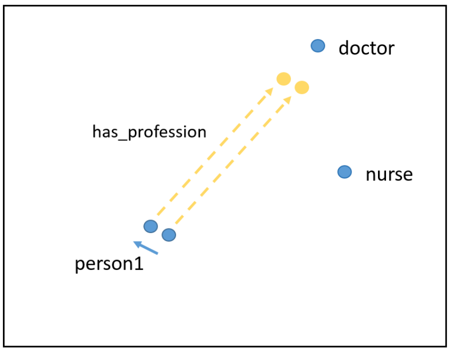


Figure 3 illustrates this. The adjustment to person1's embedding defined in Figure 2 results in the transformation of person1 and the relation has_profession moving closer to doctor and further away from nurse. That is, the score g(person1, has_profession, doctor) has increased, and the score g(person1, has_profession, nurse) has decreased. In other words, the embeddings in this case encode the bias that doctor is a profession associated with male rather than female entities.

We can then repeat the process for all humans in the knowledge graph and calculate the average changes, giving a bias score b_p for profession p:

$$b_p = \frac{1}{J}\sum_{j=1}^{J} \nabla_p$$

where J is the number of human entities in the knowledge graph. We calculate this score for each profession, $p = 1, ..., P$ and rank the results.

Importantly, this metric does not involve complementing/altering the training data or training procedure, meaning the results presented below are applicable to knowledge graph embeddings as trained in the standard fashion in the literature. In addition, the measure can be calculated for/averaged across all human entities in the graph, and as such, does not depend on the particular entity/set of entities chosen.

4 Results

We provide results in the main paper for Wikidata using TransE (Bordes et al., 2013) embeddings, and for FB3M using ComplEx embeddings, providing a demonstration of our method for two transformation functions and two knowledge graphs. Additional results for Wikidata are provided in Appendix A.2 for bias along religious and national lines, and for FB3M in Appendix A.3 for bias along gender, ethnic, religious and national lines. In all results tables, we limit to professions which have at least 20 observations in the knowledge graph.

4.1 TransE embeddings (Wikidata)

Table 3: Top 20 male professions in Wikidata relative to female using TransE embeddings

Profession	B_p	C_{male}	$C_{fem.}$
baritone	0.132	44	0
military commander	0.128	1077	0
banker	0.121	6664	280
racing driver	0.106	3152	139
engineer	0.103	27333	1124
explorer	0.102	5360	315
luthier	0.101	261	0
chess composer	0.101	614	4
F1 driver	0.100	681	3
prelate	0.099	1573	2
forestry scientist	0.097	147	1
count	0.095	102	13
military leader	0.093	5029	33
motorcycle racer	0.091	2855	89
jockey	0.091	1327	89
priest	0.089	21781	270
pastor	0.088	2565	85
structural engineer	0.088	212	3
local historian	0.088	970	52
legal historian	0.088	748	49

Table 4: Top 20 female professions in Wikidata relative to male using TransE embeddings

Profession	B_p	$C_{fem.}$	C_{male}
nun	0.174	1754	8
feminist	0.145	1441	26
soprano	0.138	110	2
Suffragette	0.126	1073	0
mezzo-soprano	0.126	28	0
salonniere	0.126	444	16
homekeeper	0.120	322	1
princess	0.118	128	0
queen consort	0.115	21	0
activist	0.110	2102	1344
nurse	0.108	1896	212
woman of letters	0.107	165	10
abbess	0.103	98	0
suffragist	0.101	689	54
textile artist	0.101	714	195
prostitute	0.101	195	23
maid	0.100	51	1
rhythmic gymnast	0.099	915	1
AV Idol	0.099	2176	1
fashion model	0.098	1670	17

Tables 3 and 4 present the results for gender, with attribute a being male and b female. Whilst the discrepancies in counts are of interest in themselves (Wagner et al., 2015) our main aim in this paper is to show that these differences propagate to the learned embeddings. Table 3 confirms this; although it includes a number of professions which are potentially male by definition, such as "baritone",[6] there are also many which we may wish

[6]The decision over which professions should be allowed to vary with gender/religion etc. is difficult, and dependent on

to be neutral, such as "banker" and "engineer". Whilst there is a strong correlation between the counts and B_p, it is not perfect. For example, there are more male and less female priests than there are bankers, but we get a higher score according to the model for banker than we do priest. The interconnected nature of graphs makes diagnosing the reason for this difficult, but there is clearly a difference in representation of the male entities in the graph who are bankers relatives to priests, which plays out along gender lines.

Table 4 presents the most female professions relative to male for Wikidata (i.e. we reverse a and b from Table 3). As with the most male case, there are a mixture of professions which are female by definition, such as "nun", and those which we may wish to be neutral, such as "nurse" and "homekeeper". This story is supported by Tables 15 and 16 in the Appendix, which give the same results but for the FB3M dataset.

Table 5: Top 20 most Jewish professions in Wikidata relative to ethnicity African American with TransE embeddings

Profession	Score	$C_{Jew.}$	$C_{AfAm.}$
opinion journalist	0.217	22	2
rabbi	0.206	71	5
theater director	0.190	9	32
sociologist	0.130	16	40
literary critic	0.123	34	19
publisher	0.122	16	18
translator	0.112	116	5
entrepreneur	0.108	50	66
economist	0.104	27	15
restaurateur	0.089	1	21
film score composer	0.088	10	25
editor	0.087	10	30
political scientist	0.081	8	13
engineer	0.079	27	54
biographer	0.078	12	25
stage actor	0.074	50	406
linguist	0.073	27	4
historian	0.072	68	82
inventor	0.070	19	58
computer scientist	0.065	13	15

We can also calculate biases for other sensitive relations such as ethnicity, religion and nationality. For each of these relations, we choose two attributes to compare, and finetune the embeddings to increase the score of the primary attribute whilst simultaneously reducing the score of the secondary attribute. In Table 5, we show the professions most associated with the ethnicity "Jewish" relative to "African American". As previously, the results include potentially harmful stereotypes,

the particular user/application. As such we defer from giving a fixed set of professions for which the likelihoods should be allowed to vary with each sensitive attribute in this paper.

Table 6: Top 20 most African American professions in Wikidata relative to ethnicity Jewish with TransE embeddings

Profession	Score	$C_{AfAm.}$	$C_{Jew.}$
Canadian football player	0.217	298	0
American football player	0.180	1661	1
head coach	0.175	41	0
baseball player	0.161	979	0
mixed martial artist	0.137	60	0
visual artist	0.132	57	1
dancer	0.122	186	7
civil rights advocate	0.121	73	0
motivational speaker	0.114	38	1
basketball coach	0.107	363	1
singer-songwriter	0.107	559	12
pornographic actor	0.103	61	9
boxer	0.101	149	1
jazz musician	0.101	698	5
sprinter	0.099	112	1
television actor	0.098	1123	50
academic	0.098	51	6
minister	0.097	49	1
guitarist	0.094	255	3
rapper	0.094	900	1

such as the "economist" and "entrepreneur" cases. It is interesting that these stereotypes play out in our measure, despite the more balanced nature of the counts [7]. In some extreme cases, such as for the profession "publisher" in Table 5, the count of people with "African American" ethnicity (18) is actually greater than the count for people with "Jewish" ethnicity (16), but the embeddings still encode this as a "Jewish" profession. Given the interconnected nature of knowledge graphs, it is difficult to precisely diagnose the reason for this, but it is clear that our finetuning based approach is able to identify some biases which would be missed with a simple count-based measure.

4.2 ComplEx embeddings (FB3M)

Our method is equally applicable to any transformation function. To demonstrate this, we trained embeddings of the same dimension on the FB3M dataset using the ComplEx transformation (Trouillon et al., 2016), and provide the results for gender in Tables 7 and 8 below (computational cost prohibited training of ComplEx embeddings on the full Wikidata knowledge graph).

FB3M contains a different set of professions to Wikidata, but the conclusion that ComplEx embeddings of professions encode potentially harmful social biases remains consistent with the TransE case. It is also clear that our proposed method of measuring this bias is effective at exposing the most gendered professions with the

[7] the balanced counts are themselves due to there being many more entities with ethnicity "African American" in Wikidata (16280) than ethnicity "Jewish" (1588).

Table 7: Top 20 male professions in FB3M relative to female using ComplEx embeddings

Profession	Score	C_{male}	$C_{fem.}$
/m/0513qg	0.186	160	8
detective	0.163	27	2
trumpeter	0.161	346	6
gangster	0.146	45	0
private investigator	0.142	18	4
assn. football manager	0.132	587	5
Trombonist	0.131	196	1
session musician	0.130	184	7
sailor	0.119	429	23
bodyguard	0.117	33	2
bandleader	0.115	533	32
assn. football player	0.115	13321	227
samurai	0.114	26	0
music director	0.114	643	29
mastering engineer	0.111	33	1
clergy	0.107	78	4
baseball umpire	0.107	88	0
rabbi	0.105	180	5
Mafioso	0.103	60	0
statistician	0.103	205	3

Table 8: Top 20 female professions in FB3M relative to male using ComplEx embeddings

Profession	Score	$C_{fem.}$	C_{male}
gravure idol	0.210	62	0
fitness professional	0.184	24	12
Nude Glamour Model	0.177	511	1
showgirl	0.171	41	0
nun	0.167	41	0
socialite	0.164	81	11
art model	0.157	22	2
Key Hair Stylist	0.157	43	11
jewellery designer	0.154	39	9
fashion model	0.153	508	32
nurse	0.152	185	20
supermodel	0.151	95	9
Memoirist	0.148	30	35
Adult model	0.147	24	1
pin-up girl	0.146	55	0
dialect coach	0.143	14	8
Prostitute	0.140	63	0
flight attendant	0.137	34	3
ballet dancer	0.135	237	104
Cheerleader	0.133	20	1

more sophisticated transformation function, where the WEAT would be even less applicable.

It would be interesting to carry out a comparison of the differences in how bias is encoded for different transformation functions, which we leave to future work, although a qualitative comparison is possible between the FB3M TransE embedding results for gender in Tables 15 and 16 (Appendix A.3) with the ComplEx embedding results for gender in Tables 7 and 8.

4.3 Discussion of the binary nature of comparisons

The metric and results presented are all based around a comparison between **two** values of a sensitive attribute (male vs. female, African American vs. Jewish etc.). This has two potential problems. Firstly, assigning people a fixed label for some attributes, such as gender, is potentially problematic. However, this is at present a limitation of the structure of knowledge graphs, and as such one which is inherited by any potential measure of bias. Secondly, for all the "sensitive attributes" discussed in this paper, there are more than two potential attributes, and for some cases, such as nationality, many hundreds. An individual human may have none, one or many of each of these attributes. Whilst the proposed method does not preclude this possibility, we only present the model's representation of the relationship between **any two** of these alternative values at a time, to keep the comparisons clear. However, if the researcher is interested in analysing the representation of a single nationality vs. all others, this is possible by updating Equation 1 to include the average score of all other nationalities instead of the score of single alternative attribute b. This measure will be highly dependent on the choice of nationalities chosen to compare against, [8] and as such, for clarity, we keep the comparisons in this paper between two attributes only.

5 Summary

We have presented the first study on social bias in knowledge graph embeddings, and proposed a new metric for measuring such bias. We demonstrated that differences in the distributions of entities in real-world knowledge graphs (there are many more male bankers in Wikidata than female) translate into harmful biases related to professions being encoded in embeddings. Given that knowledge graphs are formed of real-world entities, we cannot simply equalize the counts; it is not possible to correct history by creating female US Presidents, etc. In light of this, we suggest that care is needed when applying knowledge graph embeddings in NLP pipelines, and work needed to develop robust methods to debias such embeddings.

[8] As well as on the potential weighting required to account for some nationalities having very low counts and noisy embeddings.

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A Appendices

A.1 Wikidata Donald Trumps vs. Melania Trump gender bias scores

Table 9: Top 20 male professions in Wikidata relative to female using Donald Trump vs. Melania Trump

Profession	B_p	C_a	C_b
business executive	5.85	3466	539
zoologist	5.16	5355	754
autobiographer	4.7	1769	784
entomologist	4.42	4775	544
marketing	4.37	14	5
coach	4.29	3981	379
epidemiologist	4.25	409	174
ichthyologist	4.23	840	100
event rider	4.04	225	69
statistician	3.98	1625	379
whistleblower	3.88	33	7
entrepreneur	3.75	12958	1155
genealogist	3.72	648	42
film producer	3.72	16716	3468
character actor	3.67	254	49
cardiologist	3.57	596	65
pathologist	3.48	1069	121
ornithologist	3.41	2283	151
carcinologist	3.4	385	105
figure skating coach	3.39	386	298

Table 10: Top 20 female professions in Wikidata relative to male using Donald Trump vs. Melania Trump

Profession	B_p	C_a	C_b
partisan	10.63	178	1316
editor	10.54	1177	5488
cultural worker	10.09	24	119
opinion journalist	9.76	368	3126
political commissar	9.72	35	438
agricultural engineer	8.92	21	260
carver	7.96	6	122
slovenist	7.4	14	23
peasant	7.13	63	125
newspaper editor	7.08	122	942
interpreter	7.06	69	142
auxiliary bishop	7	0	57
polonist	6.82	31	16
taekwondo athlete	6.82	910	1302
oenologist	6.81	9	68
illuminator	6.78	21	387
Q23957323	6.74	7	22
disc jockey	6.73	418	3522
forestry engineer	6.7	1	92
rural municipality mayor	6.69	4	26

A.2 Wikidata additional results

We provide a sample of additional results for Wikidata, across ethnicity, religion and nationality. For each case we choose a pair of values (e.g. Catholic and Islam for religion) to compare.

The picture presented is similar to that in the main paper; the bias measure is highly correlated with the raw counts, with some associations being non-controversial, and others demonstrating potentially harmful stereotypes. Table 13 is interesting, as the larger number of US entities in Wikidata (390k) relative to UK entities (131k) means the counts are more balanced, and the correlation between counts and bias measure less strong.

Table 11: Top 20 Catholic professions in Wikidata relative to Islam with TransE embeddings

Profession	Score	$C_{Cat.}$	$C_{Isl.}$
Catholic priest	0.361	26860	0
Catholic bishop	0.323	189	0
editor	0.261	117	18
literary historian	0.240	25	7
church historian	0.233	198	0
archbishop	0.226	544	1
canon	0.223	264	0
presbyter	0.220	1099	0
Catholic religious	0.219	310	0
vicar general	0.217	106	0
medievalist	0.213	26	0
bishop	0.209	65	0
canon	0.205	133	0
auxiliary bishop	0.204	51	0
literary critic	0.191	100	55
brother	0.190	122	0
Prince-Bishop	0.189	89	0
titular bishop	0.186	63	0
classical philologist	0.185	28	0
father	0.181	53	0

Table 12: Top 20 Islamic professions in Wikidata relative to Catholic with TransE embeddings

Profession	Score	$C_{Isl.}$	$C_{Cat.}$
muhaddith	0.240	284	0
imam	0.207	173	0
Islamicist	0.204	57	5
faqih	0.194	317	0
Alim	0.181	94	0
mufti	0.148	48	0
Qari’	0.146	28	0
mufassir	0.127	114	0
qadi	0.127	80	0
human rights activist	0.125	59	42
record producer	0.122	47	8
religious leader	0.100	19	8
presenter	0.093	30	5
Akhoond	0.090	36	0
model	0.088	240	37
songwriter	0.081	112	24
Sufi	0.073	23	0
mystic	0.066	77	21
Terrorist	0.066	37	1
blogger	0.065	17	16

Table 13: Top 20 nationality "United Kingdom" professions in Wikidata relative to nationality "United States" using TransE embeddings

Profession	Score	C_{UK}	C_{US}
civil servant	0.100	150	226
stand-up comedian	0.095	107	189
comedian	0.084	939	829
life peer	0.081	1	37
barrister	0.080	5	260
bowls player	0.077	2	163
colonial administrator	0.066	5	31
rugby union player	0.063	195	2554
diplomat	0.063	2254	1093
television presenter	0.063	786	1848
guitarist	0.061	4049	1646
agronomist	0.061	26	7
solicitor	0.057	10	106
fashion designer	0.055	437	185
association football referee	0.055	45	159
college head	0.054	2	24
scientist	0.054	881	169
docent	0.053	21	13
mountaineer	0.053	211	129
medievalist	0.052	57	61

Table 14: Top 20 nationality "United States" professions in Wikidata relative to nationality "United Kingdom" using TransE embeddings

Profession	Score	C_{US}	C_{UK}
professional wrestler	0.132	1790	150
amateur wrestler	0.122	844	162
Canadian football player	0.106	2163	1
sportswriter	0.105	199	0
pornographic actor	0.103	1800	99
dancer	0.102	1283	163
baseball manager	0.097	146	0
manager	0.097	129	6
real estate developer	0.097	28	0
aikidoka	0.095	29	0
civil rights advocate	0.095	85	0
tribal chief	0.094	42	1
jockey	0.092	309	46
pastor	0.090	239	22
landscape architect	0.089	251	30
Playboy Playmate	0.087	317	6
abolitionist	0.087	81	2
urban planner	0.085	74	31
video game developer	0.084	75	11
gymnast	0.083	122	17

A.3 FB3M results

For comparison, we train TransE embeddings on FB3M of the same dimension, and present the corresponding results tables for gender, religion, ethnicity and nationality. The distribution of entities in FB3M is significantly different to that in Wikidata, resulting in a variety of different professions entering the top twenty counts. However, the broad conclusion is similar; the embeddings encode common and potentially harmful stereotypes related to professions.

Table 15: Top 20 male professions in FB3M relative to female using TransE embeddings

Profession	Score	C_{male}	$C_{fem.}$
baseball umpire	0.120	88	0
Holy Roman Emperor	0.119	23	0
Opera composer	0.115	77	0
Lighting Director	0.109	31	2
surveying	0.108	59	0
arranger	0.108	21	0
jockey	0.103	124	2
impresario	0.103	79	1
electrician	0.102	43	0
Nordic combined skier	0.102	65	0
Visual Effects Animator	0.098	27	2
Keytarist	0.097	35	3
Trombonist	0.097	196	1
Mafioso	0.097	60	0
Pirate	0.097	34	1
electronic musician	0.097	79	2
statistician	0.096	205	3
military engineering	0.096	21	0
chaplain	0.096	71	0
SEO Professional	0.095	99	5

Table 16: Top 20 female professions in FB3M relative to male using TransE embeddings

Profession	Score	$C_{fem.}$	C_{male}
gravure idol	0.091	0	62
Nude Glamour Model	0.081	1	511
nurse	0.075	20	185
fashion model	0.067	32	508
pin-up girl	0.060	0	55
socialite	0.058	11	81
model	0.057	1354	4680
housework	0.056	0	38
Hair Stylist	0.054	109	307
stripper	0.052	6	52
ballet dancer	0.050	104	237
Prostitute	0.047	0	63
Key Hair Stylist	0.047	11	43
supermodel	0.046	9	95
showgirl	0.046	0	41
Key Makeup Artist	0.044	9	29
Hair and Makeup Artist	0.042	4	24
secretary	0.041	11	43
registered nurse	0.041	6	22
Adult model	0.040	1	24

Table 17: Top 20 ethnicity Jewish professions in FB3M relative to ethnicity African American with TransE embeddings

Profession	Score	$C_{Jew.}$	$C_{AfAm.}$
rabbi	0.098	0	32
banker	0.081	2	27
economist	0.066	9	42
Talk show host	0.052	18	20
scientist	0.051	8	171
philosopher	0.050	10	92
playwright	0.050	72	80
physicist	0.049	5	84
film score composer	0.048	106	100
mathematician	0.048	5	86
political scientist	0.046	4	17
television director	0.046	85	108
theatrical producer	0.044	7	15
businessperson	0.043	133	253
patent inventor	0.042	12	19
historian	0.040	35	72
political activist	0.040	11	9
music video director	0.039	14	7
journalist	0.039	161	228
lyricist	0.036	29	34

Table 18: Top 20 ethnicity African American professions in FB3M relative to ethnicity Jewish with TransE embeddings

Profession	Score	$C_{AfAm.}$	$C_{Jew.}$
basketball player	0.096	1489	6
minister	0.073	23	0
pastor	0.055	26	1
American football player	0.054	525	8
rapper	0.050	337	11
professional wrestler	0.048	63	9
coach	0.047	225	7
basketball coach	0.042	55	2
sports commentator	0.037	23	4
/m/02h669_	0.034	46	11
keyboardist	0.033	30	11
bandleader	0.032	68	5
trumpeter	0.029	26	0
drummer	0.028	44	10
musician	0.024	1171	164
radio personality	0.023	31	25
Jazz Pianist	0.023	51	4
model	0.021	147	56
police officer	0.020	18	2
film editor	0.019	19	19

Table 19: Top 20 Catholic professions in FB3M relative to Islam with TransE embeddings

Profession	Score	$C_{Cat.}$	$C_{Isl.}$
priest	0.064	106	0
visual artist	0.052	44	4
Holy Roman Emperor	0.052	20	0
voice actor	0.045	195	11
playwright	0.044	56	6
theologian	0.043	25	5
essayist	0.037	26	2
lawyer	0.036	701	68
barrister	0.035	28	9
cardinal	0.034	20	0
television director	0.033	66	11
attorney at law	0.031	19	1
painter	0.029	37	6
teacher	0.023	149	39
diplomat	0.021	83	35
American football player	0.021	43	3
critic	0.019	22	2
television producer	0.018	181	23
fashion designer	0.018	27	4
baseball player	0.016	39	1

Table 20: Top 20 Islamic professions in FB3M relative to Catholic with TransE embeddings

Profession	Score	$C_{Isl.}$	$C_{Cat.}$
warlord	0.097	21	0
scientist	0.074	39	32
rapper	0.062	49	12
engineer	0.045	24	42
singer-songwriter	0.041	23	71
astronomer	0.040	16	11
basketball player	0.038	13	19
singer	0.035	114	250
record producer	0.035	40	49
professor	0.033	43	90
editor	0.032	11	37
lyricist	0.031	13	10
film director	0.030	63	148
film score composer	0.029	29	36
military officer	0.028	15	45
pundit	0.027	3	35
comedian	0.026	25	127
association football player	0.024	67	58
philosopher	0.024	57	134
Social activist	0.022	9	15

Table 21: Top 20 nationality "United Kingdom" professions in FB3M relative to nationality "United States" using TransE embeddings

Profession	Score	C_{UK}	C_{US}
barrister	0.074	142	3
solicitor	0.058	33	5
curler	0.044	11	14
field hockey player	0.042	16	16
broadcaster	0.041	66	57
radio producer	0.040	21	33
television presenter	0.040	877	949
Zoologist	0.038	8	12
Explorer	0.036	25	22
Rower	0.035	43	47
Equestrian	0.035	16	14
cricketer	0.035	86	7
geneticist	0.032	6	25
Radio Broadcaster	0.031	9	14
Civil servant	0.031	11	18
soldier	0.030	1170	637
art historian	0.030	17	41
botanist	0.030	52	87
Business magnate	0.029	13	36
Cross-country skier	0.028	3	21

Table 22: Top 20 nationality "United States" professions in FB3M relative to nationality "United Kingdom" using TransE embeddings

Profession	Score	C_{US}	C_{UK}
basketball coach	0.050	415	0
Talk show host	0.045	161	6
Televangelist	0.043	70	0
law enforcement officer	0.042	20	0
test pilot	0.042	20	0
ADR Director	0.042	41	1
Vaudeville Performer	0.039	83	4
veteran	0.039	20	1
American football player	0.038	7405	3
sheriff	0.037	30	0
Mafioso	0.036	57	0
cowboy	0.035	26	3
Football Coach	0.035	394	1
news presenter	0.034	241	4
Certified Public Accountant	0.033	33	0
TV Meteorologist	0.033	45	0
motivational speaking	0.032	102	6
police officer	0.031	151	10
Game Show Host	0.031	60	2
attorney at law	0.030	83	0