Bias in Word Embeddings

Ankit Pant 2018201035
Tarun Mohandas 2018201008
Team: *The Lost Linguists*

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Introduction

Introduction

- Word Embeddings (WE) - extensively used in NLP
- WE inherently contain various types of biases
- NLP models tend to amplify the biases
- Hence removing bias from WE increasingly crucial
- Project attempts to use existing debiasing techniques
- Shortcomings are highlighted and alternative proposed

Literature Review

Word Embeddings

- Word Embeddings
  - Most popular representation of document vocabulary
  - Captures context of words
  - Various models include *Word2Vec* and *GLoVe*
  - Both use neural network to form word representations

Types of Biases in Datasets

- Historical Bias:
  - Unwanted biases that were present in society years ago
- Representational Bias:
  - Certain parts of the input space are under-represented
- Measurement Bias:
  - Imperfect measuring of the data
  - assuming that the measured data is proxy of some other desired feature
- Aggregation Bias:
  - Same model is used for groups with different conditional distributions
- Evaluation Bias:
  - Evaluation and benchmark data for model does not represent actual target population

Social Bias in Datasets

- Gender Bias:
  - Biased due to associating stereotype to gender
  - Man is to computer programmer as woman is to homemaker
- Racial Bias:
  - Biased due to associating stereotype to race
  - Modern is to American as medieval is to Indian
- Religious Bias:
  - Biased due to associating stereotype to religion
  - Smart is to Christian as cheapskate is to Jew

Existing Debiasing Methods

- Post-processing debiasing (Bolukbasi et al.):
  - Make change to word vector to reduce encoded gender bias
  - Done by zeroing the gender projection of each word on a predefined gender direction
  - $\vec{W} = \frac{(\vec{w} - \vec{w_b})}{\left\|(\vec{w} - \vec{w_b})\right\|}$
  - Ensure all neutral words are equally close to the two words
- Train word embeddings from scratch (Zhao et al.)
  - Alter the loss of GloVe model
  - Concentrate most gender information to last coordinate of each vector
  - Use word representation excluding the gender coordinate
  - Representation of gender neutral words orthogonal to gender direction

Experimental Setup

Experimental Setup

- Various kinds of biases were identified in word embeddings
- Graphically projected to check clustering of biased words
- Applying debaising techniques
- Check result of debiasing quantitatively and graphically

Experiments and Results

Identifying Bias

- Gender Bias
  - manager is to man as mastercard is to woman
  - programmer is to man as nutritionist is to woman
- Racial Bias
  - filthy is to black as elitists is to white
  - manager is to American as barber is to Indian
- Religious Bias
  - rich is to Christian as homeless is to Muslim
  - smart is to Christian as cheapskate is to Jew

Bias in Professions- descending order (top 10) (man-woman)

('magician', 0.11574505)
('carpenter', 0.046477903)
('butcher', 0.035740647)
('gamer', 0.027397368)
('soldier', 0.018920997)
('servant', 0.00930707)
('barber', 0.007335724)
('engineer', -0.0022402927)
('player', -0.01447518)
('programmer', -0.016492786)

Bias in Misc. words - descending order (top 10) (man-woman)

('swear', 0.21706516)
('filthy', 0.20151067)
('sweet', 0.19195326)
('roar', 0.18197575)
('weep', 0.18006238)
('pretty', 0.17052722)
('beautiful', 0.15033276)
('think', 0.14811862)
('brave', 0.14424863)
('savage', 0.14332578)

Most biased words - Race i

Bias in Professions- descending order (top 10) (Indian-American)

('butcher', 0.30157873)
('barber', 0.20129806)
('florist', 0.18413721)
('nurse', 0.15209064)
('vet', 0.14899719)
('cashier', 0.1279751)
('tutor', 0.12523493)
('waiter', 0.11155586)
('chemist', 0.108406395)
('shopkeeper', 0.105821185)

Most biased words - Race ii

Bias in Misc. words - descending order (top 10) (Indian-American)

('lovely', 0.2813881)
('backpack', 0.25974354)
('bag', 0.20628145)
('cute', 0.19745344)
('purse', 0.19460957)
('sweet', 0.18077426)
('beautiful', 0.1678942)
('grumpy', 0.14973086)
('cool', 0.14963488)
('sassy', 0.14638355)

Most biased words - Religion i

Bias in Professions- descending order (top 10) (Muslim-Christian)

('vet', 0.12283135)
('cop', 0.11075719)
('soldier', 0.076730676)
('shopkeeper', 0.060545065)
('worker', 0.018872034)
('cashier', 0.016069816)
('butcher', -0.005377178)
('landlord', -0.00816943)
('nurse', -0.010036133)
('nanny', -0.011244484)

Most biased words - Religion ii

Bias in Misc. words - descending order (top 10) (Muslim-Christian)

('terrorist', 0.2741907)
('car', 0.10418006)
('fear', 0.10198632)
('bag', 0.07560906)
('creep', 0.06417281)
('brute', 0.057166893)
('yell', 0.041089058)
('poor', 0.04030589)
('roar', 0.039248332)
('mad', 0.038921878)

Clustering on Profession

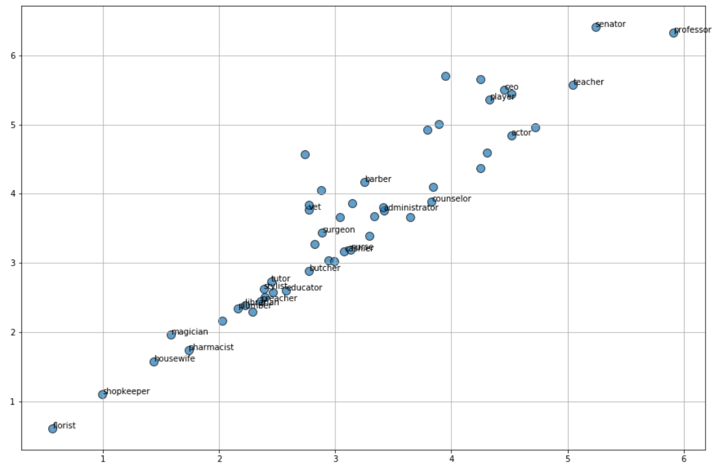

Figure 1: Result of clustering on male and female biased words

Clustering on Common Words

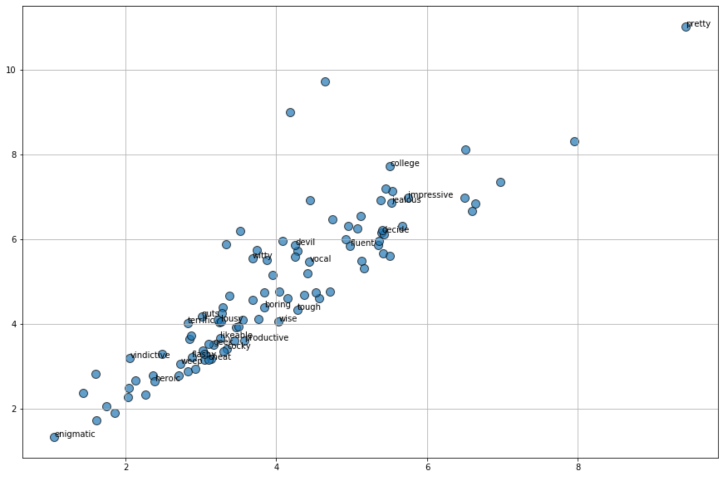

Figure 2: Result of clustering on male and female biased words

Debiasing Word Embeddings

Debiasing using neutralisation of hard-debiasing

Debiasing Professions – descending order
('magician', 0.11574504) ==> ('magician', 0.11456225)
('carpenter', 0.046477906) ==> ('carpenter', 0.045484226)
('gamer', 0.027397364) ==> ('gamer', 0.026887717)
('servant', 0.009307076) ==> ('servant', 0.008474963)
('barber', 0.0073357197) ==> ('barber', 0.006497547)

Debiasing Misc. words – descending order
('swear', 0.21706519) ==> ('swear', 0.21250035)
('filthy', 0.20151068) ==> ('filthy', 0.19604209)
('sweet', 0.19195326) ==> ('sweet', 0.18784045)
('roar', 0.18197575) ==> ('roar', 0.17574164)
('weep', 0.18006237) ==> ('weep', 0.17289506)

Clustering on Profession after Debiasing

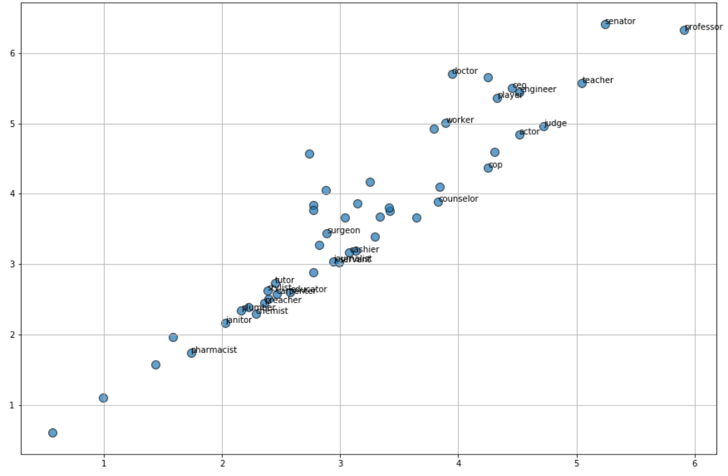

Figure 3: Result of clustering on male and female biased words

Clustering on Common Words after Debiasing

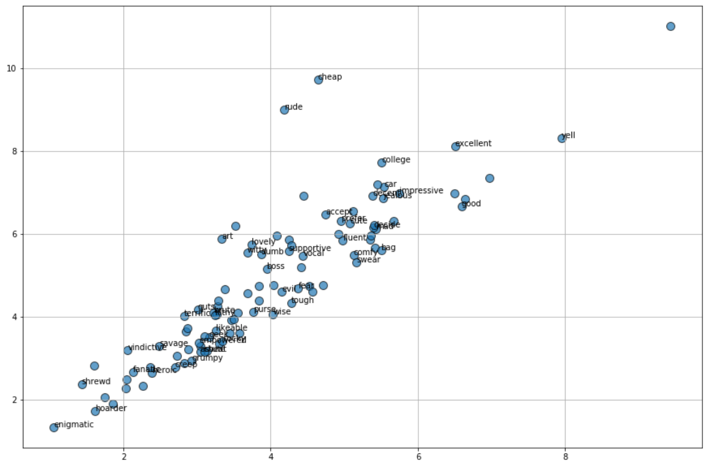

Figure 4: Result of clustering on male and female biased words

Proposed Algorithm

Proposed algorithm

- Pre-processing dataset –> add sentences by inverting the gender, races, religion, etc. –> appending them to create a new dataset.
- Debiasing during pre-processing as with (Zhao et al.)
- Analyse ‘biased’ words –> projecting them to biased sub-space and debias (Bolukbasi et al.)
- After identifying these words –> correlated with each other –> distances between the words clustering together should also be equalised.

Conclusion

Conclusion

- Project involved exploring various biases in word embeddings
- Word embeddings trained on the Reddit dataset were explored
- Attempt to debias using the traditional hard-debiasing method was done
- Debiasing happened on a superficial level
- Approach proposed that may address the issue

Future Scope

Future Scope

- Implement proposed algorithm
- Empirically test performance of proposed model
- Explore how biases are encoded in word embeddings

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