Embedding Freedom? An NLP Approach to Uncovering Pre- and Post-Abolition Racial Bias in Brazilian Literature

Stanford CS224N Custom Project

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Abstract

We use word embeddings trained with *word2vec* on 81 Brazilian literary works published in the periods before and after 1888, when slavery was abolished, to uncover the racial biases present at the time and how they evolved. We adapt the metric of bias that uses vector geometry proposed by Garg et al. (2018). First, we derive the bias for a set of concepts of towards Blacks or whites, finding that concepts such as ugly, submissive, and dirty are biased towards Blacks, with greater bias magnitude before abolition. Second, we analyze pairs of words, such as ugly and pretty, submissive and freed, and dirty and clean. The word vectors for Blacks are more biased towards the negative words in most pairs, with some biases accentuated post-abolition. Finally, we perform a leave-out analysis in which we rebuild the *word2vec* embeddings without the works of prominent authors from different literary movements, one author at a time. There is heterogeneity on the type and magnitude of bias that authors bring to the word embeddings, and the biases are not always a reflection of the author's values.

1 Key Information

- Mentor: Irena Gao (CS 224N)
- External Collaborators (if you have any): N/A
- Sharing project: N/A

2 Introduction

The mid-18^{th} and early 19^{th} century period in Brazil was marked by deep political, social, and artistic changes (see a timeline [1] in Figure 1). Brazil was the last country in the Americas to abolish slavery, in 1888 (Bergad, 2007). Up to this day, scholars, activists, and media outlets have differing views on how much progress was made in terms of racial equality since the end of slavery.

We attempt to contribute to this discussion by systematically reviewing written works of the time to derive insights on how racial bias changed. We use word embeddings trained with neural networks to draw insights from a large corpus of Brazilian literary works, to detect, quantify, and seek the source of racial bias in these texts.

[1] Dates drawn from the following websites, last accessed on March 20, 2023:
https://www.todamateria.com.br/movimentos-literarios/
https://mundoeducacao.uol.com.br/historiadobrasil/as-leis-abolicionistas.htm
https://pt.wikipedia.org/wiki/Periodiza%C3%A7%C3%A3o_da_hist%C3%B3ria_do_Brasil

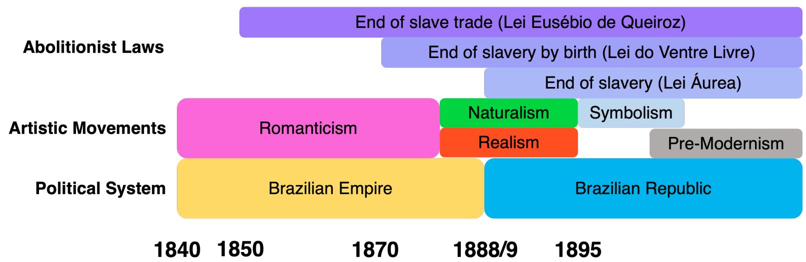

Figure 1: Timeline of main abolitionist laws, artistic movements, and political system changes in mid-18^{th} and early 19^{th} century Brazil.

Our guiding questions are:

- **Q1.** What were the biases associated with Black people before and after the abolition of slavery in Brazil?
- **Q2.** How much did these biases change after abolition?
- **Q3.** Can we detect the main sources of bias in our corpus?

Our main contributions with this project are:

- **Adapting and applying the computational social science framework that uses word embeddings to study bias in society in a novel setting.** To our best knowledge, this is the first study that uses word embeddings to quantify biases in the Brazilian setting, which could greatly benefit from the use NLP approaches in the social sciences, since structured historical data is less common than in countries such as the United States.
- **Unpacking the word embedding biases to identify its sources.** Tracing back the sources of bias on the input data is a valuable exercise for both computational social scientists and scholars seeking to explain and remove the biases in their NLP models.

We train *word2vec* word embeddings for pre-abolition and pos-abolition separately, and adapt the metric of bias proposed by Garg et al. (2018) to evaluate racial bias. We investigate the bias of a set of concepts such as ugly, incompetent, and dirty, towards Blacks and whites. Then, we explore whether the vectors for Blacks are more biased towards positive or negative words in word-pairs, such as submissive-freed. Finally, for the pre-abolition period, we re-run these analyses on word embeddings in which we leave-out all the works for a given author, to identify which authors, from which literary movements, are driving most of the bias on the original embedding.

Concepts of ugly, submissive, savage, and dirty are biased towards Blacks, with greater magnitude before abolition. Word vectors for Blacks are more biased towards the negative words in most pairs, with biases towards incompetent (vs. competent) and dirty (vs. clean) accentuated post-abolition. In our leave-out analysis, we find heterogeneity on the type and magnitude of bias that authors bring to the word embeddings. Removing the works of Machado de Assis, a Realist Black author, does not change embedding biases. Meanwhile, removing the works of Aluísio Azevedo, a Naturalist writer, reduces bias, and in certain cases, completely removes them; whereas the works of pro-slavery José de Alencar accentuate racial biases in certain cases, and reduces them in others. These findings paint a nuanced portrait of how racial biases arise in word embeddings.

3 Related Work

Technical Work. To our knowledge, Garg et al. (2018) were the first to propose using the bias in word embeddings to quantify stereotypes and biases in society, focusing on gender and ethnicity. They quantify over 100 years of stereotypes using vector geometry, and find that their proposed metric of bias of word embeddings for a given period is highly correlated with biases found in society at the same period. Their bias metric is a key idea we use and adapt in our work. Another related work is that of Lucy et al. (2020), which uses, among other Natural Language Processing strategies, word embeddings to analyze the content of textbooks with respect to gender, race, and ethnicity. We draw on their code to train the *word2vec* models in our own corpus and to recover some basic information on the embeddings, such as closest words to a set of vectors.

Historical Work. Our main historical reference is a paper by Borges (1993), which studies how discussions about race changed in the period around the time of abolition, until 1940. It argues that social thought in Brazil became medicalized and hygienist, dominated by an idea of "degeneration", which associated miscegenation to a decline in individual and social health and well-being. The idea of "degeneration" was tied to race, and the condition of Black and mixed race people was seen as pathological (Borges, 1993). We draw on this work and test whether in texts post-abolition, we can detect more bias towards Blacks for concepts such as dirty and unhealthy. Moreover, Borges (1993) draws his conclusions from some of the same literary texts in our corpus[2], so we can verify whether our results are aligned with his analysis.

4 Approach

Description In our project, we train from scratch two separate sets of word embeddings using *word2vec*, based on the work and code from Lucy et al. (2020), using data from Brazilian literary texts pre- and post-abolition of slavery. We then run three different analyses to evaluate and find the roots of racial bias in the embeddings.

Bias Measurement. Underlying all the analyses is our metric of bias. We adapt the metric proposed by Garg et al. (2018). Note that its range is [-2, 2]:

$$\text{bias} = \sum_{v_m \in M} \frac{1}{|M|} \left(\sum_{v_{g_1} \in G_1} \frac{1}{|G_1|} \text{cos-sim}\left(v_m, v_{g_1}\right) - \sum_{v_{g_2} \in G_2} \frac{1}{|G_2|} \text{cos-sim}\left(v_m, v_{g_2}\right) \right)$$

In which G_1 is the set of words related one group, G_2 is the set of words related to another group, and M is the set of words for a given concept. The formula averages the biases that each word in M has towards the words in G_1 and G_2, which is computed using cosine similarity. If the bias is positive, we say that M is more biased towards G_1. If the bias is negative, it is more biased towards G_2. If the bias is zero, then M is unbiased.

Note that we code this metric of bias ourselves, using `gensim`'s cosine similarity's method.

Analysis 1: Blacks vs. Whites Bias. In this first analysis, G_1 is the set of word vectors for Blacks, G_2 is the set of word vectors for whites, and M is the set of word vectors for each of the following concepts: **ugly, submissive, savage, dirty, and incompetent**. For "dirty" we include words for "dirty" and "unhealthy" on the same list. We include detail in Section 5 on how we created these wordlists. In this analysis, we obtain how biased each concept is towards Blacks and whites, and if the bias is positive (negative), the concept is more biased towards Blacks (whites). We compute these biases for pre- and post-abolition embeddings.

Analysis 2: Antonyms Bias for Blacks. In our second analysis, we have five paired concepts of antonyms: **pretty-ugly, freed-submissive, civilized-savage, clean-dirty, and competent-incompetent**. For each concept-pair, G_1 is the set of word vectors for the positive concept in the pair, G_2 is the set of word vectors for the negative concept in the pair, and M is the set of word vectors for Blacks. Hence, we obtain how biased the vectors for Blacks are towards positive and negative concepts of a given pair of antonyms. If the bias is positive (negative), the word vectors for Blacks are more biased towards the positive (negative) concept. We compute these biases for pre- and post-abolition embeddings.

Analysis 3: Author Leave-Out Embedding Bias. For our third analysis, we re-run analyses 1 and 2, but leaving out from the corpus all the works from a given authors. We focus on the pre-abolition embeddings, because there are more texts, and the period covers three different literary movements.

[2]One example is *O Cortiço*, by Aluísio Azevedo (1890).

We perform the leave-out analysis for Machado de Assis (Realist author), Aluísio Azevedo (Naturalist author), and José de Alencar (Romanticist author).

Baseline For analyses 1-3, we compare our estimates of bias against the null hypothesis, in which the bias equals zero.

5 Experiments

5.1 Data

Corpus. We use the Brazilian Portuguese Literature Corpus, which has 3.7 million words from 81 works of Brazilian literature from 1840 to 1908, provided by Rachel Tatman on Kaggle. There are 64 works from 1840-1887 and 17 works from 1888-1906. The texts include novels, theater plays, as well as collections of chronicles and short stories. There are works from seven different authors, many belonging to the Romanticist, Naturalist, or Realist phases of Brazilian literature. All authors are male, and out of the seven authors, only Machado de Assis is Black. The works on the original dataset were already in plain text format. For our leave-out analysis described in Section 5.3, we leave-out the pre-abolition works from **Machado de Assis** (Realist, 9 works), **Aluísio Azevedo** (Naturalist, 10 works), and **José de Alencar** (Romanticist, 24 works).

Wordlists. We compile the wordlists by starting from a concept, such as Blacks, whites, submissive, and freed, and search for similar words— the inital concepts were partly drawn from Garg et al. (2018) and from our reading of Borges (1993). For Blacks and whites, we remove the words "preto" and "branco", because they also refer to colors, and leave words that are more often associated only with race or nationality. In the list for whites, we include European nationalities that were considered white at the time. The complete wordlists and references can be found on the appendix.

5.2 Evaluation method

In Section 4, we describe how we compute bias. To evaluate whether the bias is different from the null hypothesis, we compute bootstrapped 95% confidence intervals, assuming a normal distribution for the sample mean bias. We then verify whether the null falls within the interval. We detail in Section 5.3 how we run the bootstrap analysis.

5.3 Experimental details

***Word2vec* embeddings** To train the *word2vec* embeddings, we use the `gensim` Python library's Continuous Bag of Words (CBOW) implementation, choosing a window size of 5, and a dimension size of 100, using the code from Lucy et al. (2020). We use the data described in Section 5.1, split between pre- and post-abolition periods. We stem the words before feeding them to the word2vec model, such that gendered words are (roughly) standardized to genderless stems.

Bootstrapping. For bootstrapping, we create for each period 50 separate *word2vec* word embeddings, each created from a random sample with replacement of all the sentences on the source texts, following Lucy et al. (2020). There are approximately 190k sentences in the pre-abolition corpus and 50k sentences on the post-abolition corpus.

5.4 Results

Results 1: Blacks vs. Whites Bias. In Figure 2, for the pre-abolition embedding, we find the following concepts are more biased towards Blacks: ugly (bias = +0.143), submissive (bias = +0.052), dirty (bias = +0.096), and savage (bias = +0.073), whereas incompetent is more biased towards whites (bias = -0.049). None of the intervals contains the null hypothesis. For the post-abolition embeddings, we find that the biases are reduced. Whereas all of the concepts have qualitatively the same direction of bias, their magnitude is smaller. None of the 95% confidence intervals contains the null, so the biases are still significant, albeit smaller.

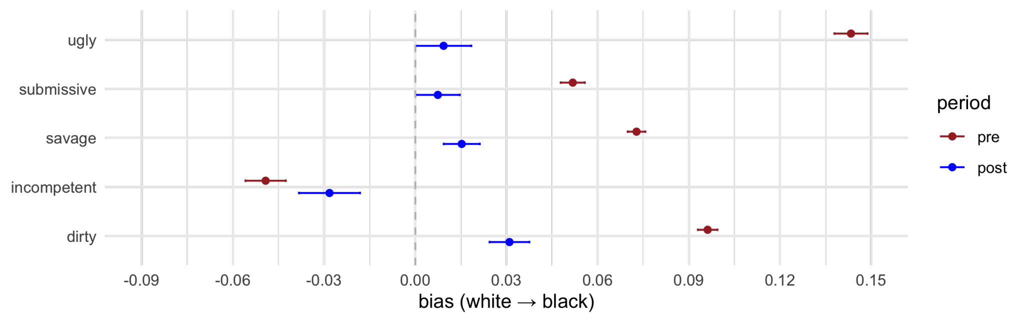

Figure 2: We report the measure of bias specified in Methods for pre- and post-abolition embeddings, using G_1 for words for Blacks, G_2 for words for whites, and M for words representing each concept on the y-axis. Bars represent bootstrapped 95% confidence intervals.

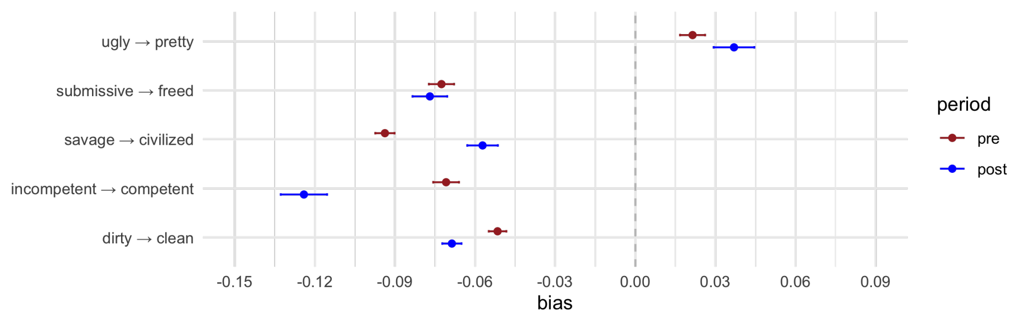

Figure 3: We report the measure of bias specified in Methods for pre- and post-abolition embeddings, using G_1 for positive words, G_2 for their respective opposite words, and M for words representing Blacks. Bars represent bootstrapped 95% confidence intervals.

Results 2: Antonyms Bias for Blacks. When we compare antonym concepts (Figure 3), we find that for the pre-abolition embeddings, word vectors for Blacks are more biased towards the following negative concepts: submissive (vs. freed, bias = -0.073), savage (vs. civilized, bias = -0.094), incompetent (vs. competent, bias = -0.071), and dirty (vs. clean, bias = -0.052). Post-abolition, the vectors for Blacks become less biased towards savage (bias = -0.057), but more biased towards incompetent (bias = -0.124), and dirty (bias = -0.069).

Analysis 3: Author Leave-Out Embedding Bias. For our analysis removing the works of one author in the pre-abolition embeddings, we find that removing the works of Machado de Assis, in most cases, leads to a similar bias. Overall, his works are the ones causing the least changes compared to José de Alencar and Aluísio Azevedo. For the Black and whites bias analysis, removing the works of Aluísio Azevedo makes the embedding be less biased towards Blacks for all concepts we report. For the antonyms analysis, removing Azevedo's work leads to null bias estimate for the incompetent-competent pair, and reduces the bias for the dirty-clean pair (bias = +0.028). When we remove Alencar's works from the Black and whites analysis, we see an increase in bias towards Blacks for submissive (bias = +0.090) and savage (bias = +0.091). Removing José de Alencar's works switches sign of the bias for the incompetent-competent pair (bias =+0.017), and also lowers the bias for the dirty-clean pair (bias = -0.025).

6 Discussion

Black vs. Whites Bias. Our results for Black and white bias are aligned with the expectation that biases between Blacks and whites are reduced post-abolition. It is unclear why "incompetent" becomes more associated with Blacks post-abolition. One hypothesis is the increased association of race with illness and degeneration in literary works, as described by Borges (1993).

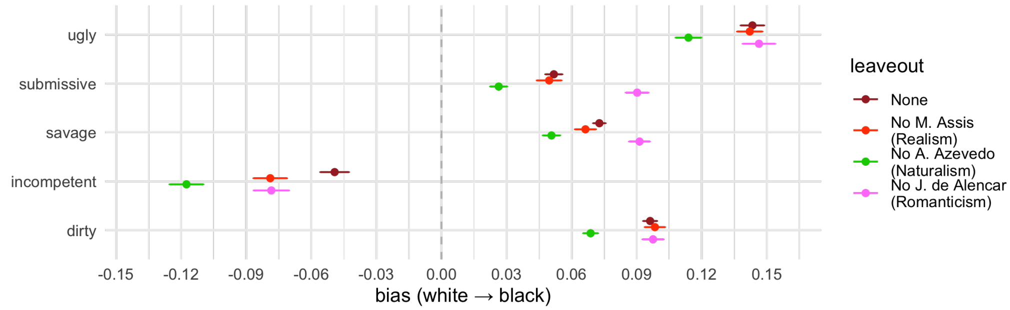

Figure 4: We report the measure of bias specified in Methods for pre-abolition embeddings, using G_1 for words for Blacks, G_2 for words for whites, and M for words representing each concept on the y-axis. We also include bias estimates where we leave-out the works of one of the following authors: Machado de Assis, Aluísio Azevedo, and José de Alencar. Bars represent bootstrapped 95% confidence intervals.

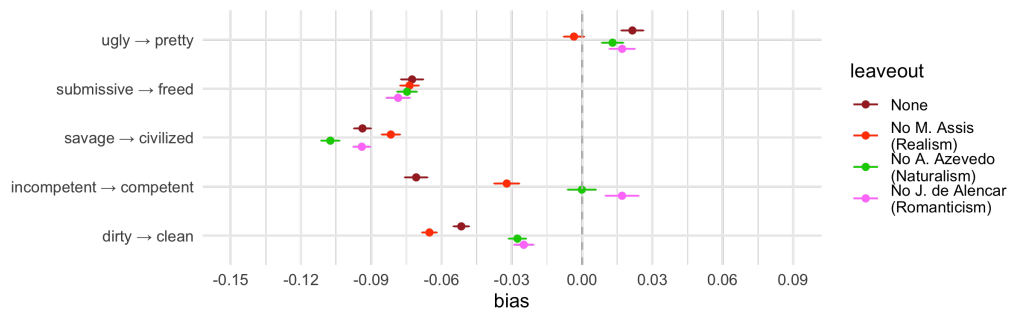

Figure 5: We report the measure of bias specified in Methods for pre-abolition embeddings, using G_1 for positive words, G_2 for their respective opposite words, and M for words representing Blacks. We also include bias estimates where we leave-out the works of one of the following authors: Machado de Assis, Aluísio Azevedo, and José de Alencar. Bars represent bootstrapped 95% confidence intervals.

Antonyms Bias for Blacks. It was more surprising to find that the antonyms biases in some cases increased in the direction of negative concepts. Again, an increased association of Blacks with "incompetent", as opposed to "competent", could be a product of the ideas of degeneration of the time. The same goes for dirty (and unhealthy[3]): the increase could be associated with a greater association of Blacks with illness than with health. We also see a decrease in the bias towards savage, as opposed to civilized, which likely reflects a certain level of increased humanization on the treatment of Blacks in literature. On the other hand, we barely see any changes in the bias for submissive and freed in the pre- and post-abolition periods.

Detecting Sources of Bias. First, it becomes clear from out leave-out analysis that different authors have different contributions to the embeddings biases. Some of these contributions are not obvious, and do not necessarily reflect the values and beliefs of the authors. Machado de Assis was Black man, and removing his texts from the embeddings makes only small differences in racial bias. Some argue that de Assis' work was constrained by the racism of the time (Nunes Martins, 2022), while others highlight Assis' efforts to confront racism[4]. Another interesting case is that of José de Alencar, who was in favor of slavery [5]. In certain cases, removing his texts increase the bias towards Blacks for words such as "submissive" and "savage", whereas one would expect it would decrease the bias. On the other hand, the effects of Aluísio Azevedo are more easily explainable. Azevedo often centered Black characters, such as in *O Cortiço* and *O Mulato*, and approached his writing from a Naturalistic perspective. Bergad (2007) cites Naturalism as tied to the ideas of medicalization

[3] In the list for dirty, we include words for "dirty" and "unhealthy"

[4] Such as Eduardo de Assis Duarte in his anthology *Machado de Assis: Afro-descendente*

[5] `https://www1.folha.uol.com.br/fsp/ilustrad/fq0810200808.htm`

and degeneration that became popular in Brazilian social thought— so it is less surprising that by removing Azevedo's Naturalist works, we see less bias towards Blacks (vs. whites) for concepts such as dirty (and unhealthy), savage, and ugly.

7 Conclusion

Key findings and Contributions. We find that biases between Blacks and whites are reduced after abolition, but still persist. Moreover, when we consider polar words (antonyms), we find that both before and after abolition, word vectors for Blacks are more biased towards the negative words in most cases, and for some concepts, the bias even increases post-abolition. Finally, we find that different authors have different effects on the type and magnitude of bias in a given embedding, and that these contributions not always reflect the values or beliefs of the author.

Limitations. The main limitations from our work are: (i) the selection of words in our wordlists, and the wordlists themselves, which might be missing important terms, as well as dimensions of bias; (ii) The lack of generalizability to non-literary texts to understand beliefs in broader Brazilian society at the time.

Future Work. We see two promising avenues for future work. First, we could extend our work to more efficiently detect the sources of embedding bias in the input text, since our leave-out approach is not cheaply scalable. Explaining and understanding the sources of bias could give greater insights for researchers and practitioners trying to build less biased models. A second extension would be using multi-modal models to detect quantify biases in more recent content (such as in news outlets) that includes text and pictures, which might not explicitly mention race in text, but might still be biased.

References

Laird W Bergad. 2007. *The comparative histories of slavery in Brazil, Cuba, and the United States*. Cambridge University Press New York.

Dain Borges. 1993. 'Puffy, ugly, slothful and inert': degeneration in Brazilian social thought, 1880–1940. *Journal of Latin American Studies*, 25(2):235–256.

Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16):E3635–E3644.

Li Lucy, Dorottya Demszky, Patricia Bromley, and Dan Jurafsky. 2020. Content analysis of textbooks via natural language processing: Findings on gender, race, and ethnicity in texas us history textbooks. *AERA Open*, 6(3):2332858420940312.

André Ricardo Nunes Martins. 2022. Análise: Machado de assis, o gênio na gaiola do racismo.

A Appendix

A.1 Wordlists in Portuguese

These wordlists were generated by the author, partly based on the lists on Garg et al. (2018) and on online dictionaries for the Portuguese language[6]:

Blacks. negro, negrinho, mulato, africano, crioulo, crioulinho, moreno, moreninho, pardo, mestiço, cafuzo

Whites. português, portuguesa, italiano, alemão, alemã, francês, francesa, europeu, europeia, caucasiano

Civilized. civilizado, culto, esclarecido, instruído, adestrado, alfabetizado, amestrado, disciplinado, doutrinado, ensinado, ilustrado, intelectualizado, preparado

Savage. selvagem, bárbaro, primitivo, gentio, nômade, arisco, bravio, indomável, indômito, indomesticado, bravo, fero, indócil, indisciplinado, desregrado, vândalo, rebelde, descontrolado, desordenado, feroz, cruel, mau, malvado, perverso, desumano, atroz, desapiedado, violento, brutal, bestial, brabo, grosseiro, descortês, mal-educado, indelicado, rude, bruto, estúpido, intratável, ignorante, impolido, incivil, incivilizado, inurbano, grosseirão, cavalgadura, brutamontes, tosco, bronco, alarve

Clean (and Healthy). abstergido, absterso, asseado, cuidado, descontaminado, despoluído, dessujo, higiênico, higienizado, imaculado, impoluto, inconspurcado, lavado, purificado, terso, rijo, sadio, bom, forte, são, vigoroso

Dirty (and Unhealthy). imundo, desasseado, encardido, porco, emporcalhado, porcalhão, enxovalhado, enodoado, manchado, sebento, nojento, poluído, espurco, sórdido, lambuzado, besuntado, besuntão, tramposo, emborralhado, embostelado, surrão, encarvoado, doente, enfermo, dodói, achacadiço, achacado, achacoso, adoentado, combalido, débil, debilitado, doentio, empalamado, enfermiço, enfermo, fraco, indisposto, insalubre, mórbid, abalado, alucinado, desorientado, inseguro, louco, perturbado

Freed. alforriado, libertado, manumitido, resgatado, emancipado, solto, livre

Submissive. submisso, servil, subserviente, subalterno, rasteiro, conformado, resignado, paciente, humilde, longânime, adulador, bajulador, escravo, vassalo, súdito, maleável, flexível, dúctil, dependente, subordinado, subjugado, submetido, conquistado, vencido, sujeito

Competent. competente, abalizado, capaz, apto, hábil, eficaz, bom, capacitado, eficiente, entendido, experiente, habilidoso, idôneo, inteligente, perito, prático, suficiente, versado

Incompetent. incompetente, incapaz, inábil, inapto, inepto, imperito, incapacitado, inabilitado, desqualificado, ineficiente, ineficaz, barbeiro, desajeitado, desazado

Pretty. bonito, belo, lindo, deslumbrante, formoso, airoso, gracioso, donairoso, apolíneo, elegante, charmoso, angélico, angelical, garboso, jeitoso, apolínico, deslumbrador, deslumbrativo, bem-parecido, bem-apresentado, bem-posto, bem-apessoado, bem-feito, bem-proporcionado, bem-composto, bem-conformado, bem-lançado, apessoado, proporcionado, catita, guapo, pulcro, venusto

Ugly. feio, disforme, desproporcionado, desengraçado, esquisito, fedo, feioso, hediondo, horroroso, mal-apanhado, mal-apessoado, malconformado, malfeito, malparecido, malproporcionado

[6] `https://www.dicio.com.br/`, `https://www.sinonimos.com.br/`

General Adjectives. adorável, afável, afetivo, agradável, ajuizado, alegre, altruísta, amável, amigável, amoroso, aplicado, assertivo, atencioso, atento, autêntico, aventureiro, bacana, benévolo, bondoso, brioso, calmo, carinhoso, carismático, caritativo, cavalheiro, cívico, civilizado, companheiro, compreensivo, comunicativo, confiante, confiável, consciencioso, corajoso, cordial, cortês, credível, criativo, criterioso, cuidadoso, curioso, decente, decoroso, dedicado, descontraído, desenvolto, determinado, digno, diligente, disciplinado, disponível, divertido, doce, educado, eficiente, eloquente, empático, empenhado, empreendedor, encantador, engraçado, entusiasta, escrupuloso, esforçado, esmerado, esperançoso, esplêndido, excelente, extraordinário, extrovertido, feliz, fiel, fofo, forte, franco, generoso, gentil, genuíno, habilidoso, honesto, honrado, honroso, humanitário, humilde, idôneo, imparcial, independente, inovador, íntegro, inteligente, inventivo, justo, leal, legal, livre, maduro, maravilhoso, meigo, modesto, natural, nobre, observador, organizado, otimista, ousado, pacato, paciente, perfeccionista, perseverante, persistente, perspicaz, ponderado, pontual, preocupado, preparado, prestativo, prestável, proativo, produtivo, prudente, racional, respeitador, responsável, sábio, sagaz, sensato, sensível, simpático, sincero, solícito, solidário, sossegado, ternurento, tolerante, tranquilo, transparente, valente, valoroso, verdadeiro, zeloso, agressivo, ansioso, antipático, antissocial, apático, apressado, arrogante, atrevido, autoritário, avarento, birrento, bisbilhoteiro, bruto, calculista, casmurro, chato, cínico, ciumento, colérico, comodista, covarde, crítico, cruel, debochado, depressivo, desafiador, desbocado, descarado, descomedido, desconfiado, descortês, desequilibrado, desleal, desleixado, desmazelado, desmotivado, desobediente, desonesto, desordeiro, despótico, desumano, discriminador, dissimulado, distraído, egoísta, estourado, estressado, exigente, falso, fingido, fraco, frio, frívolo, fútil, ganancioso, grosseiro, grosso, hipócrita, ignorante, impaciente, impertinente, impetuoso, impiedoso, imponderado, impostor, imprudente, impulsivo, incompetente, inconstante, inconveniente, incorreto, indeciso, indecoroso, indelicado, indiferente, infiel, inflexível, injusto, inseguro, insensato, insincero, instável, insuportável, interesseiro, intolerante, intransigente, irracional, irascível, irrequieto, irresponsável, irritadiço, malandro, maldoso, malicioso, malvado, mandão, manhoso, maquiavélico, medroso, mentiroso, mesquinho, narcisista, negligente, nervoso, neurótico, obcecado, odioso, oportunista, orgulhoso, pedante, pessimista, pé-frio, possessivo, precipitado, preconceituoso, preguiçoso, prepotente, presunçoso, problemático, quezilento, rancoroso, relapso, rigoroso, rabugento, rude, sarcástico, sedentário, teimoso, tímido, tirano, traiçoeiro, traidor, trapaceiro, tendencioso, trocista, vagabundo, vaidoso, vulnerável, vigarista, xenófobo