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Synchronic and Diachronic Predictors of Socialness Ratings of Words

Vladimir Bochkarev, **Anna Shevlyakova**, **Andrey Achkeev**

Kazan Federal University, Kazan, Russia

ABSTRACT

Introduction: In recent works, a new psycholinguistic concept has been introduced and studied that is socialness of a word. A socialness rating reflects word social significance and dictionaries with socialness ratings have been compiled using either a survey or machine method. Unfortunately, the size of the dictionaries with word socialness ratings created by a survey method is relatively small.

Purpose: The study objective is to compile a large dictionary with English word socialness ratings by using machine extrapolation, transfer the rating estimations to other languages as well as to obtain diachronic models of socialness ratings.

Method: The socialness ratings of words are estimated using multilayer direct propagation neural networks. To obtain synchronic estimates, pre-trained fasttext vectors were fed to the input. To obtain diachronic estimates, word co-occurrence statistics in a large diachronic corpus was used.

Results: The obtained Spearman`s correlation coefficient between human socialness ratings and machine ones is 0.869. The trained models allowed obtaining socialness ratings for 2 million English words, as well as a wide range of words in 43 other languages. An unexpected result is that the linear model provides highly accurate estimate of the socialness ratings, which can be hardly further improved. Apparently, this is due to the fact that in the space of vectors representing words there is a selected direction responsible for meanings associated with socialness driven by of social factors influencing word representation and use. The article also presents a diachronic neural network predictor of concreteness ratings using word co-occurrence vectors as input data. It is shown that using a one-year data from a large diachronic corpus Google Books Ngram one can obtain accuracy comparable to the accuracy of synchronic estimates.

Conclusion: The created large machine dictionary of socialness ratings can be used in psycholinguistic and cultural studies. Changes in socialness ratings can serve as a marker of word meaning change and be used in lexical semantic change detection.

KEYWORDS

Socialness, Psycholinguistics, Psycholinguistic data bases, Pre-trained word vectors, Neural networks, Lexical semantic change

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Correspondence:
Vladimir Bochkarev,
vbochkarev@mail.ru

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INTRODUCTION

Semantic knowledge is represented in different ways including natural language and its means. Language is directly connected with human perception of reality and cultural context. Therefore, various psycholinguistic parameters of words have been introduced that serve as key features in concept representation and have been widely studied in modern science. Among the mentioned parameters are word concreteness, imageability, valence etc. Social significance is also one of the key features in concept representation as socialness has a great impact on the concept structure and cognition. Socialness means the extent to which each word has social relevance by describing or referring to some socially relevant concept such as a social role, a social space, ideology etc. (Pexman et al., 2022). Recently, dictionaries of word psycholinguistic parameters, including word socialness, have been compiled, which can be employed for solving various practical tasks.

Survey and machine-based methods are used to study psycholinguistic word parameters. The size of the dictionaries compiled using the survey method is relatively small as this method is time- and labour-consuming. Creation of large text corpora and development of methods of natural language processing allowed creation of large dictionaries with word psycholinguistic ratings by machine extrapolation. In this case, the computational model is trained on a small number of words for which human ratings exist, and then the trained model is used to obtain machine ratings for a wide range of words. This approach has made it possible to obtain large machine dictionaries with concreteness ratings, affective ratings (Mohammad et al., 2013; Koper & Schulte im Walde, 2016), etc.

Some recent works have been devoted to estimation of word socialness ratings using the survey method. One of the works presented the first English dictionary of socialness ratings of 535 words was (Binder et al., 2016). Then, the work (Diveica et al., 2023) presented another dictionary which was compiled using the survey method and included 8838 words. It should be noted that the instructions used in (Diveica et al., 2023) were much more detailed than those used in (Binder et al., 2016). Similar study was conducted for the Chinese language (Wang et al., 2023). It was performed in several stages. First, a dictionary of socialness ratings for 17,940 Chinese words; was compiled using the survey method. Then, the ratings were extrapolated to 900 thousand Chinese words and the model was trained to obtain machine ratings for them. Finally, using the trained model and machine translation, a machine-based English dictionary was obtained by transferring Chinese ratings to English ones. A certain drawback of the dictionary presented in (Diveica et al., 2023) is its relatively small size, which may limit its use in practical tasks. This makes it relevant to create a computer model that would allow extrapolating socialness ratings to the largest possible range of words.

The purpose of this paper is to create a large English dictionary with word socialness ratings by using machine extrapolation, transfer the rating estimations to 43 other languages as well as to obtain diachronic models of socialness ratings. We use a model that allows predicting socialness ratings for 2 million English words. Unlike Wang et al. (2023), who transferred ratings from Chinese, we train our model on human judgments collected through surveys of native English speakers. This approach enhances the accuracy of socialness ratings for English words.

METHOD

Source Data

As a source of human ratings for training predictors, the dictionary described in (Diveica et al., 2023) is used. It contains ratings for 8,388 English words. The ratings given in the dictionary range from 1 to 7. High rating values indicate that the word has great social relevance, while low values indicate that the word, on the contrary, is not socially significant. The distribution mode of the of rating values lies in the middle of the range. Thus, the socialness rating scale in the dictionary is essentially bipolar. For convenience, we transformed the rating scale to the range from -1 to +1.

Used Sets of Vectors

To estimate psycholinguistic parameters of words, word vector representations developed within the framework of distributional semantics are employed. The general idea of distributional semantics is that distributional similarity and meaning similarity correlate with each other (Harris, 1970; Rubenstein & Goodenough, 1965; Firth, 1957). Therefore, word meaning can be revealed and estimated by the analysis of its distribution. There are different algorithms of distributional meaning acquisition. In early works, mainly representations based on co-occurrence vectors were used (Weeds et al., 2004; Pantel, 2005; Bullinaria & Levy, 2007; Gulordava & Baroni, 2011). In (Bullinaria & Levy, 2012), it was proposed to employ vectors constructed from Point Mutual Information (PMI). One of the reasons that hindered the effective application of early word embeddings was the high dimensionality of the resulting vectors. Various options for reducing the dimensionality of vector representations were considered, for example, using SVD (Turney & Pantel, 2010; Bullinaria & Levy, 2012). In 2013, an improved word embeddings technique using neural network approaches was proposed in (Mikolov et al., 2013; Bojanowski et al., 2017) that opened new horizons in this field of research. Recent advances in this area involve the use of contextualized word embeddings (Peters et al., 2018; Devlin et al., 2019). There is an overview of modern usage of low-dimensional word embeddings presented in (Worth, 2023; Pilehvar & Camacho-Collados, 2020). Currently, methods based on vector neural network models are applied in most cases. However, simpler representations based on explicit word vectors are also employed because their use has some advantages: the obtained results are easily interpreted (Basile & McGillivray, 2018), as well as the diachronic models can be easily constructed (Bochkarev et al., 2022). In this paper, we test both types of word embeddings in relation to the problem of predicting word socialness ratings.

Firstly, we selected two sets of pre-trained vectors trained on the largest corpora. One of them is the fasttext pre-trained vectors trained on the CommonCrawl corpus (Grave et al., 2018) with a total size of 650 billion words. In accordance with the recommendations by (Charbonnier & Wartena, 2019) and the results of our experiments, we used vectors trained without using subword information. Besides, we employed the Glove-840B pre-trained vectors also trained on the CommonCrawl corpus that included 840 billion words at the time of creating the vector set (Pennington, 2014).

Secondly, to obtain dictionaries for various languages (besides English), we used two multilingual sets of vectors. The fasttext project page provides embeddings for 44 languages, trained on Wikipedia texts as of 2017, aligned in a single vector space. The algorithm presented in (Juolin, 2018) was employed to align the vectors. The MuSE project page provides aligned embeddings for 29 languages. To create this multilingual dataset, as in the previous case, the fasttext vectors trained on Wikipedia texts were chosen as the initial ones, however, a different algorithm was used for the alignment (Conneau et al, 2017). All the above vector sets belong to the class of context-free models. As mentioned above, contextualized word embeddings are more promising. However, it should be noted that in the existing dictionary presented in the work (Diveica et al., 2023), only one value of the socialness rating is given for each word form. Moreover, it is not indicated for polysemantic words to which of its meanings the rating refers. In this case, contextualized embeddings may not show advantages over context-free models. It is also worth mentioning that all the above vector sets were obtained by training on synchronic corpora, and thus cannot be used to obtain diachronic estimates of socialness ratings.

Therefore, besides the low-dimensional vector representations mentioned above, we also employed explicit word vectors built according to the CFW (co-occurrence with the most frequent words) method. A detailed description of the method is proposed in (Xu & Kemp, 2015; Khristoforov et al., 2020). According to the CFW method, the vectors were composed of the values of regularized pointwise mutual information (in the form proposed in Bochkarev et al., 2021) for bigrams of the form *Wx* and *xW*, where *W* is the target word and *x* is one of the most frequent words. The frequency data on words and phrases required for constructing the vectors were extracted from the large diachronic corpus Google Books Ngram (Lin et al., 2012). To train the neural network, we use the frequency data averaged over the period 1900-2019. In this paper, following (Khristoforov et al., 2020), we use a list of 20 thousand most frequent words. Thus, a word is described by a vector of dimension 40,000.

Neural Network Predictors Training

The socialness degree of words was estimated using multilayer direct propagation neural networks. To maximize prediction accuracy, a number of network architectures with different numbers of layers and neurons per layer were tested. Each network was trained using several algorithms (adadelta, adagrad, adam, SGD) with different learning rate parameters. Tests were also conducted using L1 and L2 regularization and dropout regularization. Based on the tests, the following architecture of neural network predictors and learning parameters was selected for the case of low-dimensional vector representations:

(1) 3 dense layers of 3072 neurons with the ReLU activation function, the output layer of dimension 1 with linear activation;
(2) L2 regularization with coefficient $5 \cdot 10^{-4}$;
(3) The MSE metric for early stopping (no improvement greater than $1 \cdot 10^{-6}$ during 100 epochs)

Similarly, the following parameters were chosen for predictors that use explicit word vectors:

(1) 6 dense layers of 512 neurons with the ReLU activation function, the output layer of dimension 1 with linear activation;
(2) dropout-regularization – between dense layers with coefficient 0.02;
(3) The MSE metric for early stopping (no improvement greater than $1 \cdot 10^{-6}$ during 5 epochs).

In both cases, the best results were obtained using the MSE loss function and the SGD optimization algorithm.

Cross-Validation Procedure

Cross-validation has been used to improve reliability of the results and control the accuracy of the obtained estimates. Following (Bochkarev et al., 2024a), the list of words was divided into 6 groups including non-overlapping words. In each case, four groups out of six were used to train the model, and the remaining two groups were used as a test set. There are 15 different ways to select 4 groups out of 6, so for each word we get 15 independently trained models. In this case, for any word there are 5 models for which this word was in the test set, not the training set. Having several models allows us to further improve the accuracy by averaging the estimates, as well as to determine the standard deviation of the obtained estimate.

Training Linear Predictors

In addition to neural networks, we will also present the results for linear models for comparison. As for explicit word vectors, the relationship between individual vector components and meaningful characteristics of the word is obviously non-linear. Therefore, it makes sense to use linear predictors only for cases where low-dimensional vectors are fed to the input. Training a linear predictor is a linear regression task and is carried out using pseudo-inversion according to the L2 norm. Just as for neural network predictors, in this case a set of models is independently trained on 15 subsets of the sample. The estimates obtained from independently trained models can then be averaged in one way or another.

Transferring Ratings to Other Languages

The existence of freely available multilingual vector sets aligned in a single vector space makes it easy to transfer ratings from one language to another. There is a dictionary with human estimates of the socialness ratings for the English language. We train a socialness predictor using vectors for English words from a multilingual vector set as input data. By feeding word vectors for another language from the same set, we obtain a dictionary with socialness ratings for this language. It should be taken into account that errors in rating estimates associated with the imperfection of the model will be summed up with errors in vector alignment in two languages. Therefore, to solve the problem of transferring ratings in this paper, we use linear predictors, since in this case it is easier to predict the error value of the output value if errors in the input data are known.

RESULTS

We trained models of socialness ratings of English words using four sets of pre-trained vectors and one set of explicit word vectors. Neural network predictors were trained for each of these five sets of vectors. Also, linear predictors were trained for the four low-dimensional sets of vectors.

The estimates were obtained for the 5 models for which this word was in the test sample, and therefore was not presented to the neural network at the training stage. These estimates were averaged for each word. The Pearson`s and Spearman`s correlation coefficients between the averaged estimates obtained in this way and human ratings for different word representations and predictor architectures are given in Table 1. Averaging over a set of independently trained models allows one to increase the estimation accuracy. For example, for a set of pre-trained fasttext-CommonCrawl vectors, the average value of the Pearson`s and Spearman`s correlation coefficients between human ratings and their machine estimates for 15 models was 0.8531 and 0.8566, respectively. Averaging over independently trained models allowed us to increase the values of the correlation coefficients to the values of 0.8655 and 0.8688, respectively (Table 1).

First of all, it should be noted that the accuracy of linear predictors is very slightly inferior to the accuracy of neural network predictors using the same set of pre-trained vectors. At the same time, if linear predictors have a number of adjustable parameters equal to the dimension of the input vectors (in our case - 300 parameters), then neural network predictors using the same input data have 13.9 million weight coefficients (see Section 2). The model using explicit word vectors has even 21.8 million weight coefficients. Thus, this insignificant increase in the accuracy of neural network predictors is achieved by a colossal complication of the model, and a corresponding increase in training time.

It should also be noted that 15 linear models independently trained on different word subsets are highly consistent with each other. For a trained linear predictor, the gradient of the model output is constant throughout the vector space. Thus, the *i*-th model can be characterized by a unit direction vector v_i, the gradient normalized to unit length. For example, for the set of pre-trained fasttext-CommonCrawl vectors, the median value of the cosines of the angles between pairs of direction vectors of independently trained models was 0.9728. We can synthesize a single model from 15 independently trained models. To do this, we average the direction vectors of individual models, and normalizing the resulting vector to unit length, we obtain the direction vector of a single synthetic model *V*:

$$V = \frac{\sum_i v_i}{\|\sum_i v_i\|}$$

The median value of the projections of the direction vectors of the 15 models v_i onto the direction *V* for the set of

Table 1

Pearson`s (r) and Spearman`s (ρ) correlation coefficients between averaged estimates from independently trained models and human ratings

Used embeddings	Predictor type	r	ρ
fasttext-CommonCrawl	FNN	0.8655	0.8688
fasttext-CommonCrawl	linear	0.8411	0.8502
GloVe-840B	FNN	0.8541	0.8577
GloVe-840B	linear	0.8361	0.8418
fasttext-wiki	FNN	0.8390	0.8418
fasttext-wiki	linear	0.8179	0.8251
MuSE	FNN	0.8388	0.8414
MuSE	linear	0.8183	0.8255
Co-occurrence vectors (CFW)	FNN	0.8512	0.8540

pre-trained fasttext-CommonCrawl vectors is 0.9842. This proves the high degree of consistency of all 15 models.

Interestingly, using the synthetic model allows us to achieve a better accuracy compared to simple averaging of ratings. For example, the Spearman`s correlation coefficient between human ratings and the average machine rating for a set of pre-trained fasttext-CommonCrawl vectors equals 0.8354. It was obtained using simple averaging. The Spearman correlation coefficient obtained using the synthetic model is 0.8502. Therefore, Table 1 provides values of the correlation coefficients for linear predictors obtained using the synthetic model.

Let us also compare the accuracy of predictors using different sets of pre-trained vectors. The fasttext-wiki and MuSE embeddings were obtained by training using the Wikipedia text corpus, which has a much smaller size compared to the CommonCrawl corpus, therefore, the predictors employing these vectors show lower accuracy. It should be noted that a slightly lower result was obtained using the Glove-840B pre-trained vectors compared to fasttext-CommonCrawl, despite a larger size of the training corpus. A similar observation was described in (Wang et al., 2023). Apparently, this is due to a higher quality of embedding training using the fasttext algorithm.

Diachronic Predictor of Socialness Ratings of Words

As can be seen from Table 1, the use of explicit word vectors built using the CFW method allows us to obtain almost the same prediction accuracy as employing low-dimensional vectors trained on large-volume corpora. Despite a slightly lower accuracy, the CFW method has the great advantage of easily obtaining a diachronic model if we have an appropriate corpus (see, for example, (Bochkarev et al., 2022). To do this, we only need to build explicit word vectors for the target time intervals, using co-occurrence data of a target word in a diachronic corpus. Then, the obtained vectors are fed to the predictor input; thus, we obtain diachronic estimates of the socialness rating of the target word.

The Google Books Ngram corpus provides annual frequency data on words and phrases. Accordingly, we built vectors for each word present in the (Diveica et al., 2023) dictionary using the GBN corpus data for each year from 1870 to 2019 and calculated the corresponding socialness rating estimates of these words for each year. The Pearson`s and Spearman`s correlation coefficients between human ratings and machine estimates calculated using annual data are shown in Figure 1.

The highest value of the Spearman`s correlation coefficient is 0.8531 (in 2010), which is only a few ten-thousandths less than the value of the Spearman`s correlation coefficient given in Table 1 obtained using data of the entire time interval 1900-2019. No year in the interval 2000-2019 shows drop of the Spearman`s correlation coefficient value below 0.8480. The annual size of the English subcorpus of Google Books Ngram for these years is between 22.8 and 34.9 billion words. As can be seen from Figure 1 and the presented values such data size provides estimates that are no less accurate than those obtained using all available data. For earlier years, as can be seen from Figure 1, the correlation coefficients between human ratings and their machine estimates calculated from annual data are smaller. The main reason for this is the decrease in the annual corpus size for earlier years. In addition, language evolution can cause changes in the socialness ratings of words over time. Since human ratings are obtained as a result of surveys conducted in recent years, this phenomenon can also lead to a drop in the cor-

Figure 1

The Pearson`s (r) and Spearman`s (ρ) Correlation Coefficients between Human Ratings and Machine Estimates Calculated Using Annual Data

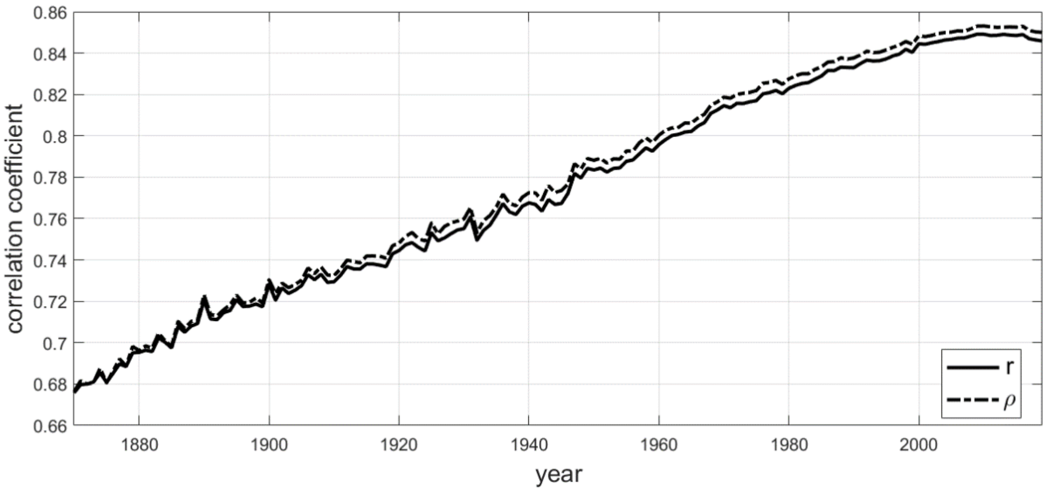
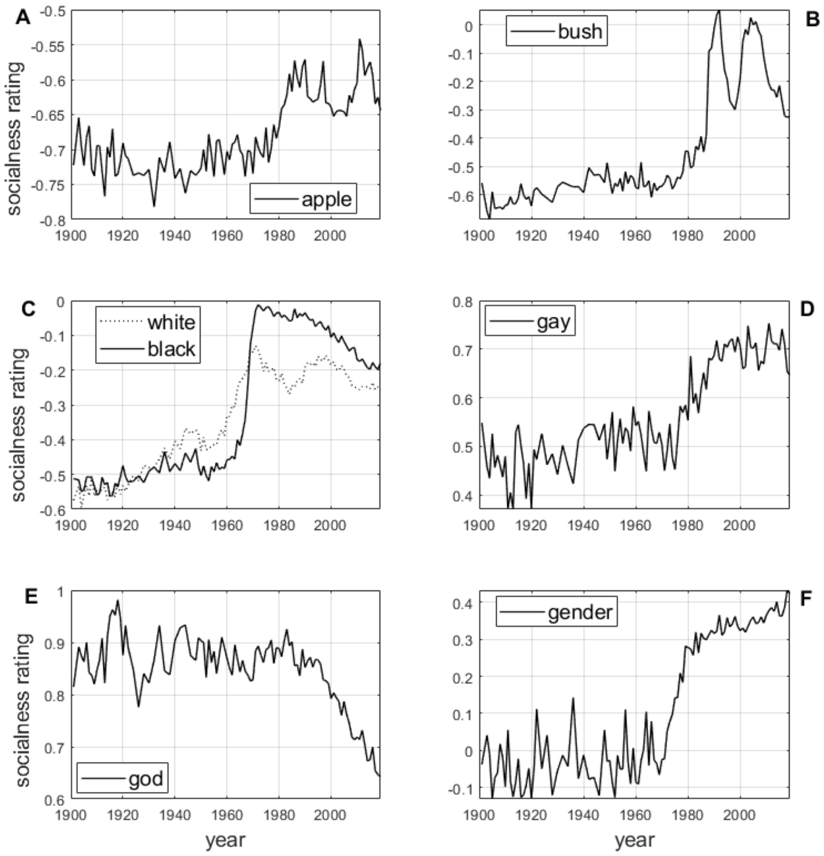


Figure 2

Examples of Words for which Socialness Ratings Change Over Time



relation coefficient between human socialness ratings and their machine estimates for earlier years.

Below we will analyse some examples of trends of socialness rating change trying to reveal possible regularities of rating change. The classification is not strict, just made for more convenient analysis.

The first example of socialness rating change is represented by a word *apple* (see Figure 2, A). Until the end of the 70s, the rating was negative and was fluctuating around -0.7. The graph shows a rapid growth of its ratings values since the end of 80s. This can be explained by the fact that *apple* traditionally denoting a kind of fruit gained a new denotata, which is a multinational corporation. The fastest growth in socialness ratings is observed at the time of the release of the Macintosh computer model, when Apple personal computers gained a wide popularity (Linzmayer, 2004). And now *Apple* is a world-famous brand associated with high social status. Thus, emergence of new meaning triggered changes of socialness ratings. The second burst on the graph is also not accidental; the growth of the socialness rating in this case coincides with the launching of families of mobile devices by Apple.

Another example is a word *bush*, which shows a similar tendency as the previous word (see Figure 2, B). The main meaning of this word is “woody-stemmed plant that grows much shorter and wider than a tree”. Therefore, the socialness rating of this word was initially negative for a long time remaining around the value of -0.6. However, this word also means a surname of German origin. In particular, this is a surname of a famous political dynasty in the USA (Schweizer & Schweizer, 2004). Starting with the time of the 2nd World War, one can see a gradual increase in the socialness rating of the word *bush*, associated with an increase in the percentage of use of this word as a proper name. The growth accelerated in the 70s. Career of a famous American politician George H. W. Bush started in 60s and was widely discussed in press. Particularly significant jumps in socialness ratings are observed in 1988 (when George H. W. Bush won the US presidential election) and in 2000 (when his son George W. Bush won the election).

More examples of words that have changed its socialness ratings are *white* and *black* (see Figure 2,C). Originally they denote colours. However, due to metonimical shift they also denote individuals, social groups of people distinguished by complexion. The below graphs show how socialness ratings of these words evolved. For the 19th century, the socialness ratings of both words range from -0.6 to -0.55. Tendency to the ratings growth has been observed since 1920, after the 1st World War with rapid jump in 60s. The peak can be explained by activation of the African American civil rights movement. It is interesting that the greatest change in the ratings occurred in 1968, when Martin Luther King, a prominent leader in the African American civil rights movement, was assassinated. This tragic event caused a huge resonance in American society.

One more example of meaning change that caused word rating change is the word *gay* (see Figure 2,D), which changed both denotata and reference to a particular part of speech (POS). *Gay* (cheerful) as an adjective has been a word with moderately low socialness ratings (in the range from 0.45 to 0.50). However, since the beginning of 80s one can observe their rapid growth. Also, being a noun, *gay*, denotes a homosexual person; and in this sense it is a "more social" concept. Though *gay* as a homosexual person appeared long ago, however, until recent times it was not widely used. The increase in the frequency of the word in the second meaning in the 1980s was associated with the social processes in the USA and triggered growth of socialness ratings.

There are some words denoting abstract notions and social concepts which socialness ratings change mostly due to the change of cultural context and perception. Let us consider the words *god* and *gender* (see Figures 2, E, F). *God* has always been a word with a high socialness rating. However, its ratings also fluctuate. The highest peaks are observed in 1914 – 1921 (the time or the 1st World War and some years after it) and slightly lower peak is detected in 1940 -1945 (the time of the 2nd World War). The maximum rating value of 0.982 was reached in 1918, while the annual rating values were mostly in the range of 0.85-0.9. An extremely interesting phenomenon is the current trend towards a decrease in the socialness rating of the word *god*. The trend has emerged since the last years of the 20th century. This issue requires additional research, however, it can be assumed that this is due to a tendency towards a more personal perception of the idea of god.

One more interesting example is the word *gender* that basically means sex. Its socialness ratings were almost neutral until 1970s. However, starting from the beginning of 1970s one can observe a rapid upgoing trend. According to the etymological dictionary[1], no new meanings for the word *gender* have emerged in the 20th century. However, as a result of public debate, its perception has been changing, and this concept is being rethought as more socially significant, which caused growing of socialness ratings.

Transferring of Socialness Ratings to Other Languages

Using trained linear predictors for the fasttext-wiki and MuSE pre-trained vector sets for English, we obtained machine dictionaries with socialness ratings for 43 and 28 other languages, respectively. The main challenge is to check the quality of the obtained socialness rating estimates for each of these languages.

This can be done, firstly, by selective manual check of the obtained machine ratings (total manual check is practically impossible due to the large size of the obtained dictionaries). We checked Russian words with the highest and lowest ratings. The checking showed that the model coped with the task very well. Words with high socialness ratings were at the top of the list, among them are *obshhestvennost', partnerstvo, druzhestvennost', vezhlivy, demokratichnost'* (public, partnership, friendliness, politeness, democracy). Words with low ratings are at the bottom of the list and include such words as *cellofan, bryzhejka, nubuk, struchok, peschanik* (cellophane, mesentery, nubuck, pod, sandstone).

Secondly, when both fasttext-wiki and MuSE pre-trained vectors are available for a language, we can compare ratings obtained using each of these two sets, which (to some extent) makes it possible to judge the quality of the obtained ratings. Table 2 shows the values of the Pearson`s and Spearman`s correlation coefficients between the socialness ratings obtained using the two sets of aligned pre-trained vectors.

Higher correlation coefficient values indicate a greater degree of similarity between the machine ratings obtained using two different sets of vectors, and thus indirectly indicate a greater degree of reliability of the results for a given language.

As for Chinese, only vectors from the fasttext-wiki multilingual dataset are available for it. However, independently obtained human socialness ratings for 17,940 Chinese words are available in (Wang et al., 2023). The Pearson`s and Spearman`s correlation coefficients between the human socialness ratings from that work and our machine ratings are 0.6010 and 0.6382, respectively. For 64,791 Chinese words, both the machine ratings available in (Wang et al., 2023) and our machine ratings are available. The Pearson and Spearman correlation coefficients between these two sets of ratings are 0.5828 and 0.5827, respectively. It should be noted that among the 64.8 thousand words mentioned,

[1] Online Etymology Dictionary. (n.d.). Gender. In Online Etymology Dictionary. Retrieved July 15, 2024, from https://www.etymonline.com/search?q=gender

Table 2

The Pearson`s (r) and Spearman`s (ρ) Correlation Coefficients between Socialness Ratings Obtained Using the Fasttext-Wiki and MuSE Aligned Pre-Trained Vector Sets

Language	*r*	*ρ*	Language	*r*	*ρ*
Bulgarian	0,8106	0,7910	Indonesian	0,8763	0,8638
Catalan	0,9111	0,9005	Italian	0,9409	0,9316
Czech	0,8730	0,8617	Macedonian	0,8221	0,8067
Danish	0,8818	0,8728	Dutch	0,9300	0,9201
German	0,9062	0,8959	Norwegian	0,9206	0,9137
Greek	0,8256	0,8032	Polish	0,8842	0,8745
English	0,9997	0,9996	Portuguese	0,9436	0,9386
Spanish	0,9492	0,9427	Romanian	0,8889	0,8775
Estonian	0,8922	0,8859	Russian	0,8649	0,8512
Finnish	0,8540	0,8420	Slovak	0,8240	0,8107
French	0,9259	0,9149	Slovenian	0,8357	0,8216
Hebrew	0,6948	0,6656	Swedish	0,9100	0,8922
Croatian	0,8901	0,8833	Turkish	0,8328	0,8162
Hungarian	0,8628	0,8528			

there is a significant percentage of rare and low-frequency words for which machine ratings are less accurate. This influenced the decrease in the correlation level.

DISCUSSION

The survey method used to create dictionaries with psycholinguistic ratings is rather labour-intensive. Therefore, dictionaries with human ratings are relatively small size. Development of natural language processing technologies triggered appearance of a significant number of works devoted to extrapolation of human ratings to a wide range of words. In this way, large machine dictionaries have been created for many psycholinguistic parameters, such as dictionaries of affective, concreteness and imageability ratings (Mohammad et al., 2013; Koper & Schulte im Walde, 2016; Charbonnier & Wartena, 2019).

At the same time, only one work is devoted to the recently introduced socialness rating, which attempts to build large machine dictionaries for Chinese and English. However, in this work, the ratings for English were obtained by transferring ratings from Chinese; and social weight of words from different languages may not be similar.

The following results were achieved in the present paper. Firstly, synchronic models of socialness ratings were trained for English and a dictionary with socialness ratings for 2 million words was compiled by using the obtained ratings. Secondly, a diachronic model of socialness ratings was also trained for English and examples of changes in the perception of words as related or not related to social were considered. Finally, using the aligned sets of pre-trained vectors, the obtained rating estimates were transferred to 43 other languages.

Synchronic Models

The constructed models allow obtaining estimates of the socialness ratings of English words with a fairly high accuracy. The best value of the Spearman`s correlation coefficient between human ratings and their estimates was 0.8688. This value is close to the values of the correlation coefficients of human and machine ratings obtained when predicting affective ratings, concreteness ratings and other psycholinguistic characteristics of English words (Buechel & Hahn, 2018; Charbonnier & Wartena, 2019; Bochkarev et al., 2021). There are a number of independently obtained English dictionaries with affective and concreteness ratings by different groups of researchers. The comparisons carried out in (Charbonnier & Wartena, 2019) showed that the achieved level of correlation of human and machine ratings is already close to the level of correlation of human ratings presented by different groups.

It is problematic to conduct similar comparisons for the socialness rating because the dictionary presented in (Diveica et al., 2023) is still the only large English dictionary with socialness ratings.

The Pearson`s correlation coefficient between the human ratings presented in (Diveica et al., 2023) and (Binder et al., 2016) is 0.76, but it is calculated only for 258 words that are included in both dictionaries. It is mentioned in (Wang et al., 2023) that the Pearson`s correlation coefficient between the human ratings obtained by translating Chinese words from the dictionary proposed by the authors of this work and the ratings of the dictionary by (Diveica et al., 2023) is 0.724. Thus, the level of correlation between human and machine ratings obtained in our work (see Table 1) significantly exceeds the level of correlation between human ratings obtained by different researchers. We also calculated the Pearson`s and Spearman`s correlation coefficients between the machine ratings we obtained (neural network predictor, fasttext-CommonCrawl vectors) and the ratings of 535 words from the dictionary by (Binder et al., 2016). They were 0.7545 and 0.7944, respectively, which is no lower than the correlation coefficients between the human ratings given in the two dictionaries.

Besides, similarity of the obtained value of the correlation coefficients of human and machine socialness ratings with the correlation coefficients of human and machine ratings for other psycholinguistic parameters suggests that the obtained level of accuracy in predicting socialness ratings is also close to the maximum achievable.

Diachronic Models

The low-dimensional pre-trained vectors available in the public domain were obtained by training on synchronic text corpora. Thus, they are not suitable for obtaining diachronic estimates of word socialness ratings. In contrast, the model that employs explicit word vectors allows one to easily obtain diachronic estimates of word socialness ratings using any diachronic corpus of sufficient size. We a priori expect that the perception of socialness of many words may change over time. Indeed, as soon as we begin to consider specific examples, we immediately reveal cases of such changes. The examples considered show, firstly, that the socialness rating of a word may undergo abrupt changes when the word acquires new meaning, connotation or due to the change of cultural context. A complete classification of cases of abrupt word sociality ratings requires a separate large study; in this paper, we considered only a few examples illustrating various possible directions for further work. Nevertheless, the examples given show that a change in the concreteness rating may be a marker of lexical semantic change.

A large number of works are devoted to the task of lexical semantic change detection (Tang, 2018; Hengchen et al. 2021). In most cases, such works use one or another diachronic vector representation of words. A change in the vector representing the word or a change in the word direct context in the vector space is considered as an indicator of meaning change. An alternative approach is also possible, first described in (Ryzhova et al., 2021), when the statistics of the use of words in the text in one grammatical form or another (grammatical profiles of the word) are considered, and a change in such statistics serves as a marker of lexical semantic change. In the work (Ryzhova et al., 2021), only grammatical features of words were considered, however, for lexical semantic change detection, such features as the use of a word as a proper name or a common noun (Bochkarev et al., 2022), as well as psycholinguistic characteristics of words (Bochkarev et al., 2024a) can also be used. Changes in the socialness rating of words can also serve as additional markers of semantic changes.

Also, in some of the cases considered, we encounter the fact that the meaning of the word does not change, however, its socialness rating changes due to some cultural reasons. Thus, the diachronic model of the socialness ratings of words can be useful in cultural studies.

Rating Transfer

The presence of word embeddings aligned in a single vector space made it easy to transfer socialness ratings from English to 43 other languages. The main problem is how to verify the obtained machine ratings for other languages. A spot check for Russian showed that words that received large positive or large negative machine ratings are usually estimated adequately by the model. A complete manual check of ratings for all languages is extremely labor-intensive and is currently beyond our capabilities. However, for 28 languages we have independent estimates of socialness ratings obtained using two sets of vectors - fasttext-wiki and MuSE. Comparison of the ratings obtained by two independent methods allows us to judge the quality of the resulting dictionaries.

Two factors should be considered while interpreting correlation coefficients presented in Table 2. Initial human ratings were obtained for English, therefore, languages that are more related to English shows better correlation. For example, rating correlation with German and Danish is high and Vietnamese shows the lowest one. Obviously, word social significance is similarly precepted in these languages. The second factor to be considered is that there are more Wikipedia texts used for training written in European languages than in the other ones.

A very important result is an unexpectedly high efficiency of linear predictors in predicting the socialness rating. It was shown in the previous section that the results of linear predictors can be just slightly improved by more complex neural network predictors, which have 5 orders of magnitude more fitting parameters. In this case, estimation of socialness ratings differs sharply from what is observed for other psycholinguistic parameters, such as affective ratings, concreteness ratings and imageability. In all the mentioned cases, except for the socialness rating, linear predictors are very much inferior to neural network predictors in accuracy.

It should also be noted that the linear predictors independently trained on different subsets of words were found to be highly consistent with each other. This proves that, in the space of vectors representing words, there is a distinguished direction responsible for the perception of words as related or not related to the social sphere. Relationships in society play a vital role in human life, which cannot but be reflected in language. Apparently, the significant role of social factors is captured by existing language models, which leads to the appearance of a distinguished direction in the vector space responsible for the degree of perception of a word as related to the social. Thus, the socialness rating of a word in the vector space of vectors representing words can be characterized very simply. The socialness rating grows along the distinguished direction. Accordingly, rating estimates in the first approximation can be obtained as projections of word vectors onto this direction.

The limitations of the present study may be, firstly, related to the features of the dictionary with human ratings used for training the model. As was shown in (Bochkarev et al., 2024b), differences in the composition of the lexicon of affective dictionaries created by the survey method can lead to biases in the obtained machine ratings. It is not yet possible to conduct a similar study for word socialness ratings due to the above mentioned fact that, at the moment, the dictionary by (Diveica et al., 2023) is the only large dictionary of the English language with socialness ratings. The second obvious limitation is related to the fact that the existing models do not provide ratings for different meanings of polysemantic words. Progress in this direction can be achieved by using context-sensitive word embeddings.

CONCLUSION

This paper has solved the problem of compiling a large dictionary with socialness ratings of English words by using proposed computer models. The accuracy of the developed models is high: the best achieved value of the Spearman`s correlation coefficient between human ratings and their machine estimates is 0.8688. The employed models allowed us to extrapolate human ratings to a very wide range of words and we managed to obtain machine ratings for two million words. Therefore, the resulted dictionary of word socialness ratings is several times larger than those created before. Also, ratings for a wide range of words from 43 other languages were obtained by using freely available word embeddings aligned in a single vector space. Besides, a diachronic predictor of socialness rating was constructed using explicit word vectors.

High efficiency of linear predictors in the task of predicting socialness ratings was unexpected. In fact, it is enough to simply find the projection of a vector representing a word onto some selected direction in the vector space, and get a good estimate of the socialness of the word. Such a simple estimate can be further just slightly improved, however, it is a very labour- and time-consuming process. We suppose that as relationships in society play a vital role in human life, the significant impact of social factors is captured by existing language models and leads to the appearance of a distinguished direction in the vector space responsible for the degree of perception of a word as related to the social.

Also, a diachronic predictor of socialness rating is constructed using explicit word vectors. It is shown that using word co-occurrence statistics in a large diachronic corpus, it is possible to detect changes in socialness ratings over time.

The obtained results can be useful for several fields of science. The created dictionary is a good material for psycholinguistic and cultural studies. Moreover, as the analyzed examples of words illustrate that change in socialness rating can be a marker of lexical semantic change, the diachronic model can be used for etymological studies.

There are some directions for further work. The first possible one is to obtain socialness ratings for polysemantic words using context-sensitive word embeddings. Another one is to use context-sensitive embeddings to improve efficiency of transferring ratings to other languages.

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DECLARATION OF COMPETITING INTEREST

None declared.

AUTHOR CONTRIBUTION

Vladimir Bochkarev: conceptualization; methodology; writing – original draft; supervision.

Anna Shevlyakova: conceptualization; writing – original draft, review and editing.

Andrey Achkeev: software, visualization.

REFERENCES

Basile, P., & McGillivray, B. (2018). Exploiting the web for semantic change detection. *Lecture Notes in Computer Science, 11198*, 194-208. https://doi.org/10.1007/978-3-030-01771-2_13

Binder, J.R., Conant, L.L., Humphries, C.J., Fernandino, L., Simons, S.B., Aguilar, M., & Desai, R.H. (2016). Toward a brain-based componential semantic representation. *Cognitive Neuropsychology, 33*(3-4), 130-74. https://doi.org/10.1080/02643294.2016.1147426

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching Word Vectors with Subword Information. *Transactions of the Association for Computational Linguistics, 5*, 135–146. https://doi.org/10.1162/tacl_a_00051

Bochkarev, V. V., Savinkov, A. V., & Shevlyakova, A. V. (2021). Estimation of imageability ratings of English words using neural networks. In I. Batyrshin, A. Gelbukh, & G. Sidorov (Eds.), Advances in Soft Computing. MICAI 2021. L*ecture Notes in Computer Science* (vol. 13068, pp. 59–69). Springer. https://doi.org/10.1007/978-3-030-89820-5_5

Bochkarev, V. V., Khristoforov, S. V., Shevlyakova, A. V., & Solovyev, V. D. (2022). Neural network algorithm for detection of new word meanings denoting named entities. *IEEE Access, 10,* 68499–68512. https://doi.org/10.1109/ACCESS.2022.3186681

Bochkarev, V., Khristoforov, S., Shevlyakova, A., & Solovyev, V. (2024). Diachronic analysis of a word concreteness rating: Impact of semantic change. *Lobachevskii Journal of Mathematics, 45*, 961–971. https://doi.org/10.1134/S1995080224600559

Bochkarev, V., Solovyev, V., Nestik, T., & Shevlyakova, A. (2024). Variations in average word valence of Russian books over a century and social change. *Journal of Mathematical Sciences, 285*, 14–27. https://doi.org/10.1007/s10958-024-07419-z

Buechel, S., & Hahn, U. (2018). Word emotion induction for multiple languages as a deep multi-task learning problem. *Proceedings of NAACL-HLT 2018* (pp. 1907–1918). Association for Computational Linguistics. https://doi.org/10.18653/v1/N18-1173

Bullinaria, J., & Levy, J. (2007). Extracting semantic representations from word co-occurrence statistics: A computational study. *Behavior Research Methods, 39*, 510–526. https://doi.org/10.3758/BF03193020

Bullinaria, J. A., & Levy, J. P. (2012). Extracting semantic representations from word co-occurrence statistics: Stop-lists, stemming, and SVD. *Behavior Research Methods, 44*(3), 890–907. https://doi.org/10.3758/s13428-011-0183-8

Charbonnier, J., & Wartena, C. (2019). Predicting word concreteness and imagery. P*roceedings of the 13th International Conference on Computational Semantics - Long Papers* (pp. 176–187). Association for Computational Linguistics. https://doi.org/10.18653/v1/W19-0415

Conneau, A., Lample, G., Denoyer, L., Ranzato, M. A., & Jégou, H. (2017). *Word translation without parallel data.* arXiv preprint arXiv:1710.04087.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (vol. 1: Long and Short Papers, pp. 4171–4186). Association for Computational Linguistics.

Diveica, V., Pexman, P. M., & Binney, R. J. (2023). Quantifying social semantics: An inclusive definition of socialness and ratings for 8388 English words. Behavior Research Methods, 55, 461–473. https://doi.org/10.3758/s13428-022-01810-x

Firth, J. (1957). A synopsis of linguistic theory, 1930-55. *Studies in linguistic analysis* (Special Volume of the Philological Society, pp. 1-31). Blackwell.

Grave, E., Bojanowski, P., Gupta, P., Joulin, A., & Mikolov, T. (2018). Learning word vectors for 157 languages. *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).* ELRA.

Gulordava, K., & Baroni, M. (2011). A distributional similarity approach to the detection of semantic change in the Google Books Ngram corpus. *Proceedings of the GEMS 2011 Workshop on Geometrical Models of Natural Language Semantics* (pp. 67–71). Association for Computational Linguistics.

Harris, Z. (1970). *Papers in structural and transformational linguistics.* Reidel.

Hengchen, S., Tahmasebi, N., Schlechtweg, D., & Dubossarsky, H. (2021). Challenges for computational lexical semantic change. In N. Tahmasebi, L. Borin, A. Jatowt, Y. Xu, & S. Hengchen (Eds.), *Computational approaches to semantic change* (pp. 341–372). Language Science Press.

Joulin, A., Bojanowski, P., Mikolov, T., Jégou, H., & Grave, E. (2018). Loss in translation: Learning bilingual word mapping with a retrieval criterion. *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing* (pp. 2979–2984). Association for Computational Linguistics.

Khristoforov, S., Bochkarev, V., & Shevlyakova, A. (2020). Recognition of parts of speech using the vector of bigram frequencies. In W. van der Aalst et al. (Eds.), Analysis of images, social networks and texts. *AIST 2019, Communications in Computer and Information Science* (vol. 1086, pp. 132–142). Springer. https://doi.org/10.1007/978-3-030-39575-9_13

Koper, M., & Schulte im Walde, S. (2016). Automatically generated affective norms of abstractness, arousal, imageability and valence for 350,000 German lemmas. *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)* (pp. 2595–2598). ELRA.

Lin, Y., Michel, J.-B., Aiden, E. L., Orwant, J., Brockman, W., & Petrov, S. (2012). Syntactic annotations for the Google Books Ngram Corpus. In H. Li, C.-Y. Lin, M. Osborne, G. G. Lee, & J. C. Park (Eds.), *50th Annual Meeting of the Association for Computational Linguistics 2012: Proceedings of the Conference* (vol. 2, pp. 238–242). Association for Computational Linguistics.

Linzmayer, O. (2004). *Apple confidential 2.0: The definitive history of the world's most colorful company* (2nd ed.). No Starch Press.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in neural information processing systems* (vol. 26, pp. 3111–3119). Curran Associates, Inc.

Mohammad, S., Kiritchenko, S., & Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. *Second Joint Conference on Lexical and Computational Semantics (*SEM) (vol. 2: Proceedings of the Seventh International Workshop on Semantic Evaluation, pp. 321–327). Association for Computational Linguistics.

Pantel, P. (2005). Inducing ontological co-occurrence vectors. *Proceedings of the 43rd Conference of the Association for Computational Linguistics* (pp. 125–132). Association for Computational Linguistics. https://doi.org/10.3115/1219840.1219856

Pennington, J., Socher, R., & Manning, C. (2014). GloVe: Global vectors for word representation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 1532–1543). Association for Computational Linguistics. https://doi.org/10.3115/v1/D14-1162

Peters, M., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (vol. 1: Long Papers, pp. 2227–2237). Association for Computational Linguistics. https://doi.org/10.18653/v1/N18-1202

Pexman, P. M., Diveica, V., & Binney, R. J. (2022). Social semantics: The organization and grounding of abstract concepts. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 378(1870), 20210363. https://doi.org/10.1098/rstb.2021.0363

Pilehvar, M. T., & Camacho-Collados, J. (2020). *Embeddings in natural language processing: Theory and advances in vector representations of meaning.* Morgan & Claypool Publishers.

Rubenstein, H., & Goodenough, J. (1965). Contextual correlates of synonymy. *Communications of the ACM, 8*(10), 627–633. https://doi.org/10.1145/365628.365657

Ryzhova, A., Ryzhova, D., & Sochenkov, I. (2021). Detection of semantic changes in Russian nouns with distributional models and grammatical features. *Komp'juternaja Lingvistika i Intellektual'nye Tehnologii, 20*, 597–606.

Schweizer, P., & Schweizer, R. (2004). *The Bushes: Portrait of a dynasty* (1st ed.). Doubleday.

Tang, X. (2018). A state-of-the-art of semantic change computation. *Natural Language Engineering, 24*(5), 649–676. https://doi.org/10.1017/S1351324918000220

Turney, P. D., & Pantel, P. (2010). From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research, 37*(1), 141–188. https://doi.org/10.1613/jair.2934

Wang, S., Zhang, Y., Shi, W., et al. (2023). A large dataset of semantic ratings and its computational extension. *Scientific Data, 10*, 106. https://doi.org/10.1038/s41597-023-01995-6

Weeds, J., Weir, D., & McCarthy, D. (2004). Characterising measures of lexical distributional similarity. *Proceedings of the 20th International Conference on Computational Linguistics* (pp. 1015–1021). COLING.

Worth, P. (2023). Word embeddings and semantic spaces in natural language processing. *International Journal of Intelligence Science, 13*, 1–21. https://doi.org/10.4236/ijis.2023.131001

Xu, Y., & Kemp, C. (2015). A computational evaluation of two laws of semantic change. *Proceedings of the 37th Annual Meeting of the Cognitive Science Society (CogSci 2015)*. Association for Computational Linguistics.