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# Evaluating Semantic Changes in the Concept of Happiness with Diachronic Word Embeddings

*Keywords: diachronic word embedding, semantic change, happiness study, social psychology, computational linguistics*

## Extended Abstract

**Introduction and Problem Statement:** Oishi and colleagues found American concept of happiness experienced two types of semantic changes [3]. First, by analyzing dictionary definitions and State of the Union addresses, they found, while *happiness* is now defined as *favorable internal feelings*, it had been used as *good luck; good fortune* until around 1920. Secondly, with the analysis of State of the Union addresses and Google Ngram Viewer [1], they found *happiness* had been used to refer to the collective (e.g., nation) until around 1920 while it is now used to refer to the individual (e.g., person). These results show the concepts of happiness are inherently dynamic.

However, the prior study has several limitations. First, the data was not domain-balanced and large enough as they mainly analyzed the dictionary and the State of the Union addresses. Second, in their analysis of the State of the Union Address, two coders rated if *happiness* is used as good luck or fortune. However, it is difficult to ensure validity as coding relies on coders' skills and knowledge. In fact, one of two coders gave significantly higher ratings on average in their study. Finally, manual coding takes cost and time as coders need to be employed and the speed of analysis is limited by the pace of human reading. The problem of cost and time makes it difficult to apply the method on a much larger scale.

The present research aims to remedy these problems by using diachronic embedding models trained on the large domain-balanced corpus. I re-examine two research questions. Research Question 1: Is *happiness* less associated with the concept of luck over time? Research Question 2: Is *happiness* less associated with *nation* and more associated with *person* over time?

**Data and Methodology:** I utilize diachronic word embeddings trained with a genre-balanced American English corpus [2]. Word embeddings are available between 1810 and 2009 and trained for each decade. I compute the cosine similarity between happiness and other words as it measures how semantically close a pair of words is. By computing the cosine similarity across decades, one can evaluate the semantic change in *happiness*. To examine RQ1 and RQ2, cosine similarities were calculated for the following word pairs. RQ1: cos-sim(*happiness*, *luck*), cos-sim(*happiness*, *fortune*), RQ2: cos-sim(*happiness*, *nation*), cos-sim(*happiness*, *person*). The words are selected based on the previous study [3]. As the average cosine similarity for each decade increases over time, cosine similarities were normalized within each decade. Please note that the cosine similarities reporeted below are normalized.

**Result:** RQ1: Although it was expected that similarities between both word pairs become smaller over time, it showed mixed results. The similarity between *happiness* and *fortune*

[1] https://books.google.com/ngrams/

becomes smaller over time, whereas the similarity between *happiness* and *luck* becomes larger over time (Figure 1). Both similarity changes were statistically significant (Table 1).

RQ2: As expected, the similarity between *happiness* and *person* becomes larger over time, while the similarity between *happiness* and *nation* becomes smaller over time (Figure 2). Both changes in similarity were statistically significant (Table 2 ).

**Discussion:** RQ1: Why did *luck* show the opposite result from the previous study? Here, I discuss three possibilities. 1. As semantic change is interdependent, not only *happiness* but *luck* could also experience semantic change. According to the law of conformity, infrequent words tend to change at a faster rate [2]. As the frequency of *luck* was smaller until the beginning of the 1900s (Figure 3), It is possible that cosine similarities between *happiness* and *luck* were inaccurate because the meaning of *luck* was unstable. 2. Another possibility is the instability of the embedding models. It is known that cosine similarities computed with word embeddings can be unstable for various reasons such as the presence of specific documents, the size of the corpus, to name a few [1]. Future research can aim for more fine-grained analyses by averaging cosine similarities over bootstrap samples or comparing results from multiple embedding models trained on different corpora. 3. Finally, the dictionary definition of happiness might not be corresponding to the daily use of it. Although the previous study also analyzed the State of the Union addresses, it is an official and political document. In contrast, the corpus used for training the word embeddings is large enough and representative of the American English at each time [2]. Although it is unlikely, *luck* might have been used differently from the dictionary definition or the State of the Union addresses.

RQ2: For both similarities, significant changes happen between 1920 and 1930. Interestingly, with the frequency analysis using Google Ngram Viewer, the prior study concluded that 1920 was the turning point when *happiness* started to be used to refer to the individual [3]. It is worthwhile to note that, although I used the different methodology and corpus, both analyses demonstrate similar results.

**Theoretical Contribution:** With the availability of culturally rich corpora, it is becoming increasingly common to apply diachronic word embeddings for analyzing semantic change. While diachronic word embedding is a promising tool, limitations of this methodology are not fully explored. The study offers a brief insight into the strength and weaknesses of diachronic word embeddings.

# References

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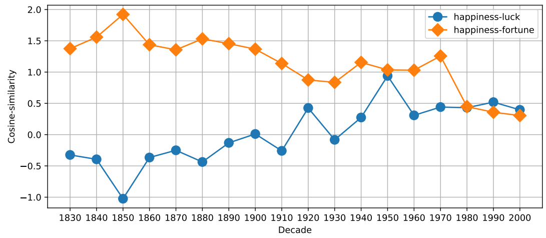


Figure 1: Cosine-similarities across decades between *happiness* and *luck*, *happiness* and *fortune*.

| | Spearman correlation | $p$ |
|---|---|---|
| happiness-luck | 0.86 | $< .001$ |
| happiness-fortune | $-0.86$ | $< .001$ |

Table 1: Spearman correlations against time and statistical significance for each word pair

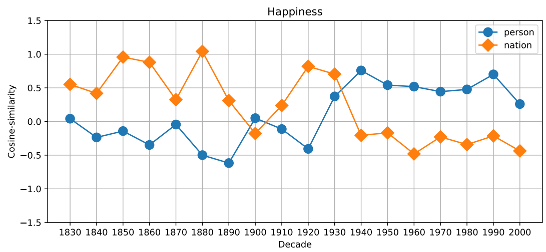


Figure 2: Cosine-similarities across decades between *happiness* and *nation*, *happiness* and *person*

| | Spearman correlation | $p$ |
|---|---|---|
| happiness-person | 0.73 | $< .001$ |
| happiness-nation | $-0.78$ | $< .001$ |

Table 2: Spearman correlations against time and statistical significance for each word pair

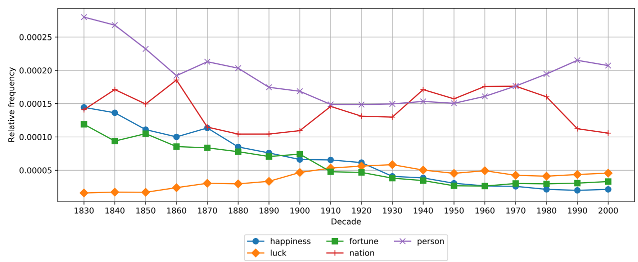


Figure 3: Relative frequency for each target word across decades