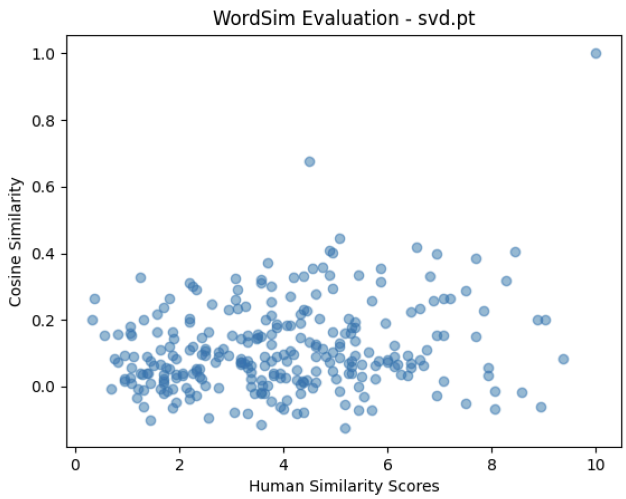
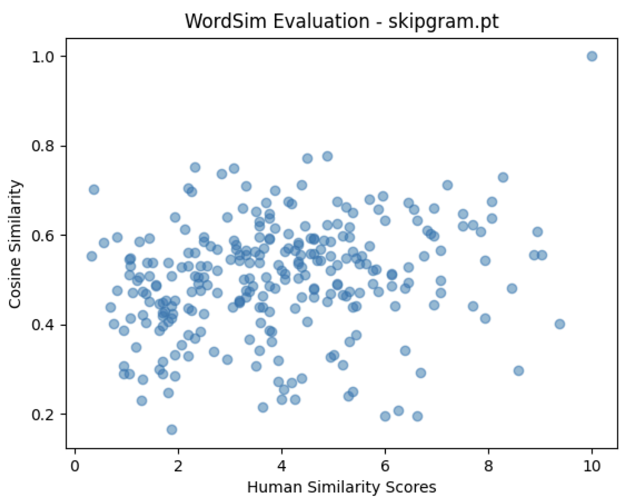
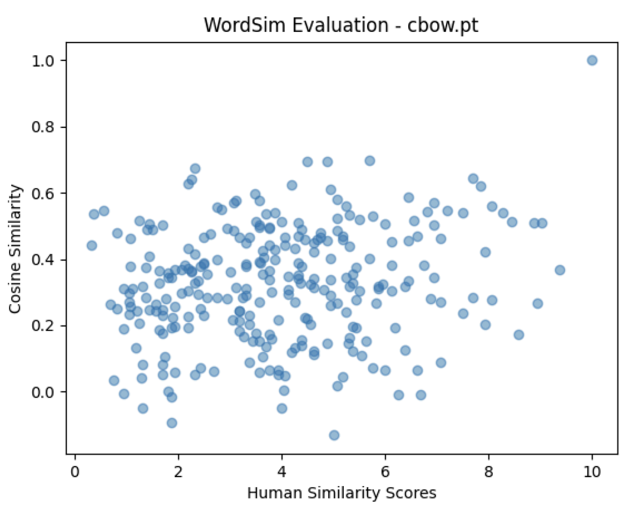
iNLP Assignment 3 Report - Ishaan Romil (2023114011)

Graphs







Spearman Rank Coefficients:

SVD	CBOW	Skipgram
0.1659	0.2053	0.2403

Hyperparameters

SVD Model (svd.py):
- EMBEDDING_DIM = 300
- WINDOW_SIZE = 5
- MIN_COUNT = 5

Skip-gram Model (skipgram.py):
- EMBEDDING_DIM = 100
- WINDOW_SIZE = 2
- MIN_COUNT = 5
- NEGATIVE_SAMPLES = 5
- EPOCHS = 5
- BATCH_SIZE = 512
- LEARNING_RATE = 0.002

CBOW Model (cbow.py):

- EMBEDDING_DIM = 300
- WINDOW_SIZE = 3
- MIN_COUNT = 5
- NEGATIVE_SAMPLES = 5
- EPOCHS = 5
- BATCH_SIZE = 128
- LEARNING_RATE = 0.001

Analysis

SVD Model

The SVD model is computationally efficient and works well for small to medium-sized corpora. It captures global word associations effectively, which makes it useful for tasks where general word co-occurrence patterns are important. However, as shown in the graph, the model struggles with capturing finer semantic relationships, particularly for higher similarity values. The points in the scatter plot are widely spread across the graph, with no clear upward trend, indicating that SVD does not align well with human similarity judgments for word pairs that have high semantic similarity. This weak correlation suggests that SVD is more suited to tasks where global relationships are key, but not for nuanced word similarity evaluation.

In comparison to prediction-based models like CBOW and Skip-gram, SVD falls short in capturing the contextual subtleties of word meaning. The graph clearly shows that while SVD can represent broad word associations, it is unable to predict fine-grained semantic similarities as effectively as these models. CBOW and Skip-gram are designed to learn word representations by considering the context in which words appear, allowing them to better reflect human similarity scores. This is evident in the scatter plots for CBOW and Skip-gram, where the points exhibit more structured and defined correlations with human similarity ratings.

CBOW Model

The CBOW (Continuous Bag of Words) model is effective in capturing word meanings by using the surrounding context of a target word, which allows it to better reflect semantic similarity than SVD. By averaging the surrounding context words to predict the target word, CBOW is able to represent word relationships more accurately, especially in larger corpora. The graph shows a more structured distribution compared to SVD, suggesting that CBOW is better at capturing broader semantic relationships across the vocabulary. Its ability to handle large datasets makes it a strong choice for general word similarity tasks.

However, CBOW does face some limitations when it comes to rare words, as averaging context words can dilute the meaning of less frequent terms. This is reflected in the graph, where CBOW does not align as well with human similarity ratings for word pairs with high similarity values compared to Skip-gram. Despite having a more defined correlation than SVD, CBOW lacks the precision seen in Skip-gram for capturing higher similarity scores, indicating that it may not capture the most subtle or nuanced semantic relationships.

Skip-gram Model

The Skip-gram model excels at capturing detailed semantic relationships, particularly for rare words, which makes it more effective than both SVD and CBOW in the WordSim task. By focusing on context prediction, Skip-gram captures subtle semantic nuances and aligns more closely with human similarity judgments, particularly for word pairs with higher similarity scores.

However, Skip-gram is computationally more expensive than CBOW, as it requires more resources due to its target-word-based prediction strategy. Despite this, Skip-gram remains the best model for capturing semantic similarity in tasks that require detailed analysis of word meanings. Skip-gram performs the best because it shows a clear upward trend in the graph, indicating a strong correlation between cosine similarity and human similarity scores. This suggests that Skip-gram captures semantic relationships more accurately, especially for higher similarity values. Unlike SVD and CBOW, which have more scattered and less defined correlations, Skip-gram aligns more closely with human judgments of word similarity.

Conclusion

In conclusion, the Skip-gram model outperforms both SVD and CBOW in the WordSim task, providing the most accurate representation of word similarity as judged by human similarity scores. Skip-gram effectively captures nuanced semantic relationships, especially for rare words, making it the best choice for tasks that require detailed semantic understanding. On the other hand, CBOW offers a good balance between performance and computational efficiency, making it a solid choice for general word similarity tasks. SVD, while efficient for global word co-occurrence analysis, falls short when it comes to capturing fine-grained semantic similarities and should not be relied upon for tasks requiring detailed understanding of word meanings.