

Exploring Word Embeddings and Word Analogies

NLP Assignment 1



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**Analogy Test Results**

1. Semantic Analogy Tests :

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Test # | Test | Expected Answer | GloVe Result | Word2Vec Result |
| 1 | milk:cow :: honey:? | bee | mad | bee |
| 2 | light:dark :: day:? | night | days | night |
| 3 | mountain:hill :: ocean:? | sea | waters | sea |
| 4 | book:author :: song:? | singer | singer | songs |
| 5 | compass:direction :: clock:? | time | time | tackled\_inbounds |
| 6 | oxygen:breathe :: food:? | eat | eat | eat |
| 7 | programming:it :: medicine:? | pharmacy | medical | medicines |
| 8 | glasses:eyes :: headphones:? | ears | ears | earphones |
| 9 | coffee:caffeine :: beer:? | alcohol | alcohol | caffeinated\_drinks |
| 10 | doctor:hospital :: teacher:? | school | school | elementary |

1. *Syntactic Analogy Tests*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Test # | Test | Expected Answer | GloVe Result | Word2Vec Result |
| 1 | jump:jumped :: sing:? | sang | sang | sang |
| 2 | bright:brightness :: happy:? | happiness | amplitude | luminance |
| 3 | break:broken :: go:? | gone | gone | gone |
| 4 | educate:education :: communicate:? | communication | communication | communication |
| 5 | test:tested :: train:? | trained | trains | trains |
| 6 | try:tries :: cry:? | cries | cries | cries |
| 7 | teach:teacher :: build:? | builder | building | builder |
| 8 | easy:easier :: hard:? | harder | harder | harder |
| 9 | boy:boys :: girl:? | girls | girls | girls |
| 10 | honest:honestly :: calm:? | calmly | calmness | calmed |

1. Accuracy Summary :

|  |  |  |
| --- | --- | --- |
| Analogy Type | GloVe Accuracy | Word2Vec Accuracy |
| Semantic | 60% | 40% |
| Syntactic | 60% | 70% |

**1. Compare the accuracy obtained from the Word2Vec and GloVe models for both semantic and syntactic analogy tests.**

The accuracy scores obtained from the analogy evaluations show that the two models perform differently depending on the type of analogy:

**Semantic analogies:** Word2Vec: 40% GloVe: 60%

**Syntactic analogies:** Word2Vec: 70% GloVe: 60%

These results clearly indicate that GloVe outperforms Word2Vec in semantic tasks, while Word2Vec has the edge in syntactic tasks.

For example: In the semantic analogy doctor:hospital :: teacher:?, GloVe predicted “school” which is correct, while Word2Vec predicted “elementary”, which is related but less precise.

On the syntactic side, in the analogy teach:teacher :: build:?, Word2Vec predicted “builder” (correct), while GloVe predicted “building”, which is a different grammatical form.

This comparison highlights that the choice of model should depend on the nature of the task: whether it focuses on meaning or grammar.

**2. Provide a detailed explanation for the observed differences or similarities.**

The differences arise from how each model is trained and what linguistic information it prioritizes:

a) **Word2Vec:**

Trained using either Skip-gram or CBOW models, both of which rely on local context windows (i.e., nearby words).

This makes Word2Vec especially good at learning syntactic relationships, such as verb tense changes (go:went), adjective forms (happy:happier), or pluralization (boy:boys).

Since syntax often depends on the order and closeness of words in sentences, Word2Vec’s architecture captures these patterns effectively.

b) **GloVe:**

Instead of relying on local contexts, GloVe uses global co-occurrence statistics from the entire corpus.

It builds a co-occurrence matrix and factorizes it to find statistical relationships between words, which helps capture conceptual or semantic similarities.

For example, GloVe understands that "doctor" and "hospital" frequently occur together, and so does "teacher" and "school", which is why it excels in such analogies.

3**. Discuss any differences in accuracy between the two models and hypothesize why these differences might occur.**

The accuracy differences—especially the contrast between higher syntactic accuracy in Word2Vec and higher semantic accuracy in GloVe—can be understood in terms of training objectives and data usage.

Hypothesis for the difference:

Word2Vec use of sliding windows encourages the model to memorize word forms and grammatical patterns based on word order and proximity. This makes it ideal for syntax-sensitive tasks like forming past tenses, comparatives, or derivational forms (teach → teacher, easy → easier).

GloVe, on the other hand, does not take word order into account directly, but it builds word meaning based on how often words appear together globally. This broadens its view of language, making it better at capturing thematic or conceptual associations (e.g., coffee:caffeine :: beer:alcohol). Additionally, GloVe may perform slightly worse in syntactic tasks because it does not capture functional usage or grammar patterns as explicitly as Word2Vec does. Conversely, Word2Vec might miss some subtle semantic relations because it’s trained to predict context within a limited window.