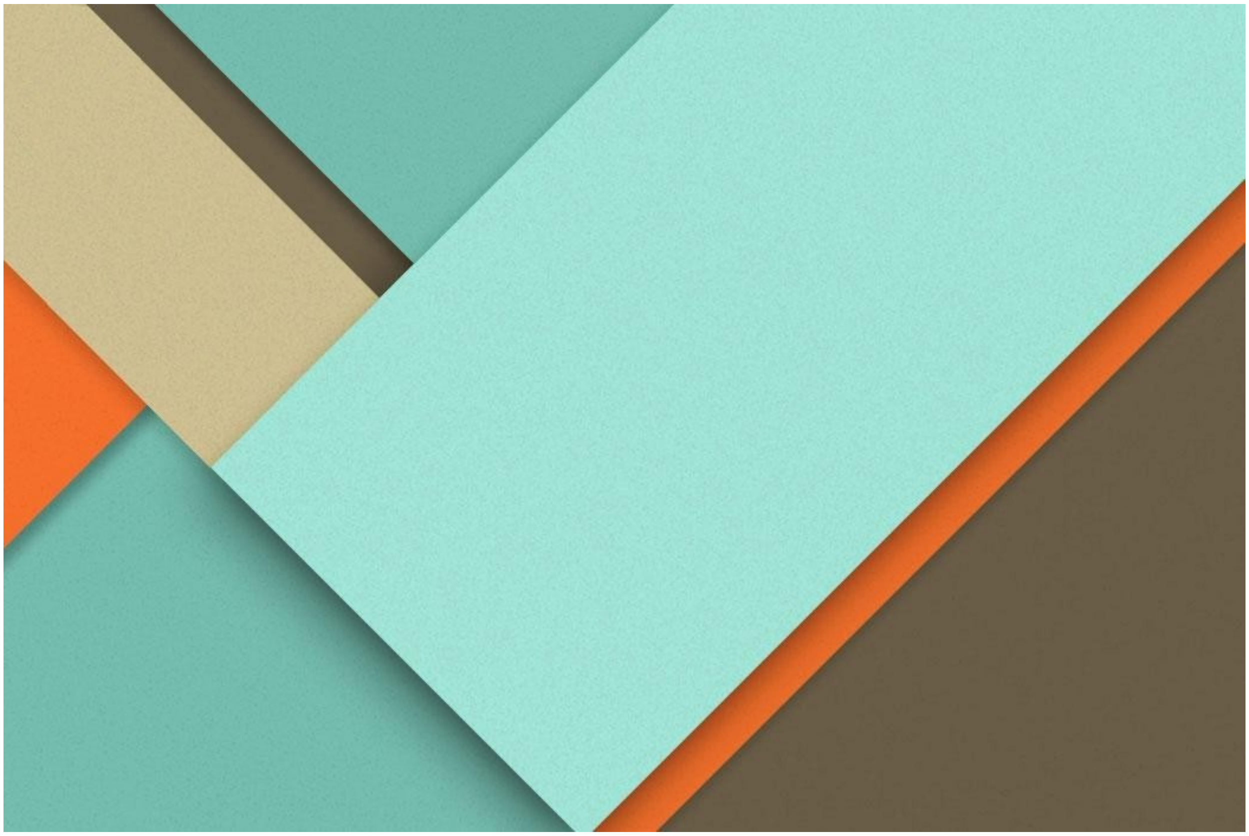

Assignment -2

Cognitive science and A.I.

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Overview

This assignment focuses on analyzing similarities within and between four different categories of brain responses using fMRI data from the ventral temporal (VT) area. The tasks involve preprocessing the data to normalize it, visualizing mean response patterns for each category overlaid on brain anatomy, computing mean correlations within and between categories, and conducting Representational Similarity Analysis (RSA) using a chosen distance measure. The results are interpreted to understand the spatial distribution of brain activation, similarities/dissimilarities between categories, and the underlying neural representations. A brief report summarizing the analysis process, results, and insights is required, along with the code used for analysis and figure generation. This assignment offers an opportunity to gain insights into the neural mechanisms underlying category representations in the brain.

Task -1

Normalization

Normalization

```
# Calculate the mean across all categories
overall_mean = np.mean(fmri_data, axis=0)

# Normalize data for each category by subtracting the overall mean
fmri_norm_face_data = fmri_data[face_cat] - overall_mean
fmri_norm_house_data = fmri_data[house_cat] - overall_mean
fmri_norm_scissors_data = fmri_data[scissors_cat] - overall_mean
fmri_norm_bottle_data = fmri_data[bottle_cat] - overall_mean
```

The given fMRI data is being normalized to ensure that any observed differences in brain responses across different categories are not influenced by overall differences in brain activity levels.

1. **Calculating the overall mean**: First, the mean across all categories is computed by taking the average of the fMRI data along the specified axis (presumably the category axis).
2. **Normalization**: Then, for each category (e.g., faces, houses, shoes, bottles), the mean response pattern across all categories is subtracted from the respective

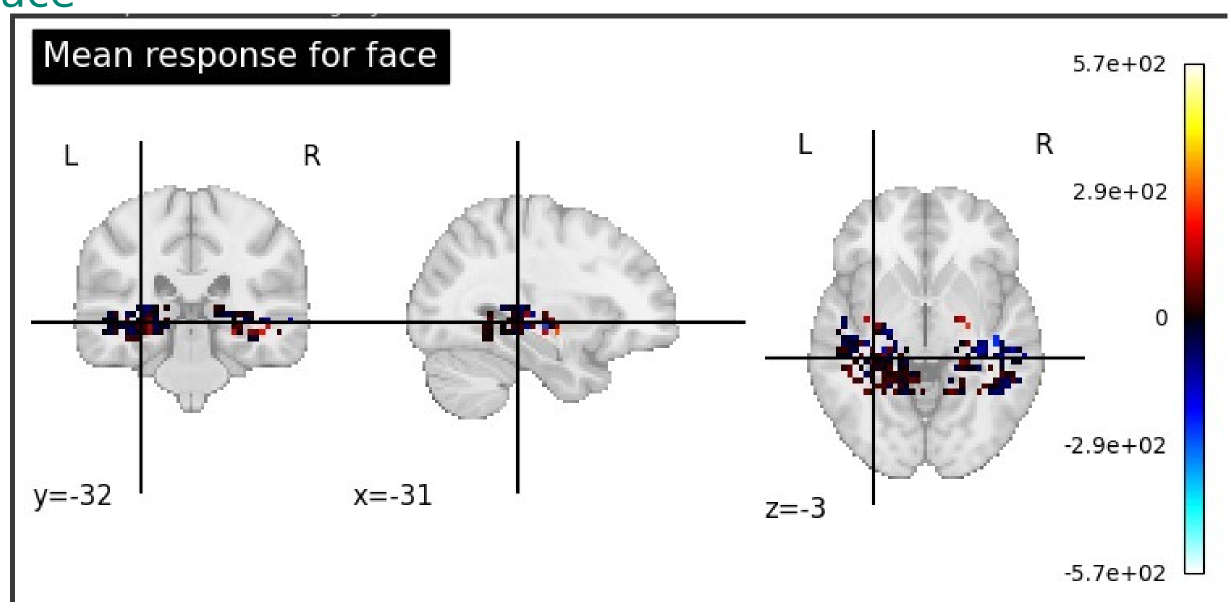
category's data. This means that the overall mean response across all categories is being subtracted from each individual category's response pattern.

- By subtracting the overall mean from each category's data, we remove any global effects or biases that might be present in the data due to factors unrelated to specific categories.
- This normalization process ensures that the subsequent analyses focus on the relative differences in brain activation patterns specific to each category, rather than being confounded by differences in overall brain activity levels across categories.

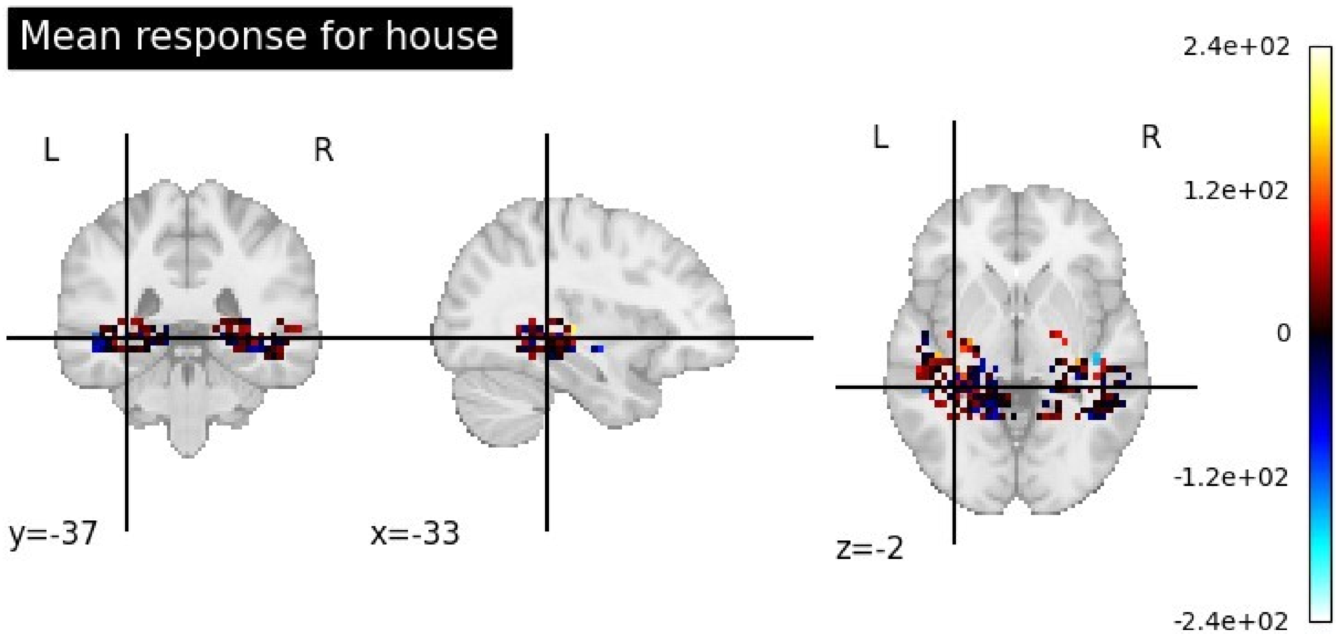
Visualising

visualization of the mean brain activity pattern specific to a category after normalization, providing insights into the neural representation of that category within the ventral temporal cortex

Face

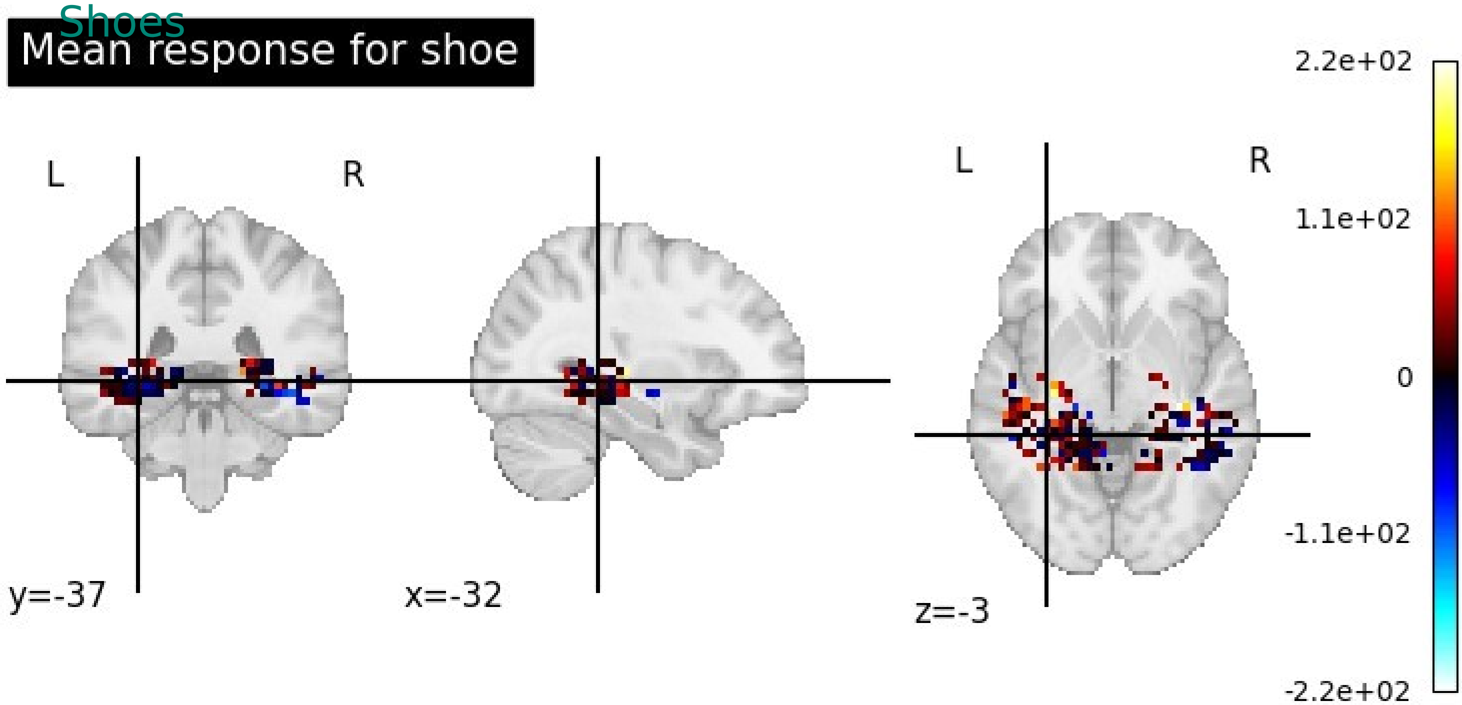


- Increased Activation in Face-selective Regions: heightened activation in regions such as the fusiform face area (FFA) and occipital face area (OFA), indicating specialized processing of facial information.
- Distinctive Spatial Patterns: Spatially localized clusters of voxels showing strong activation, particularly in regions associated with facial feature processing.



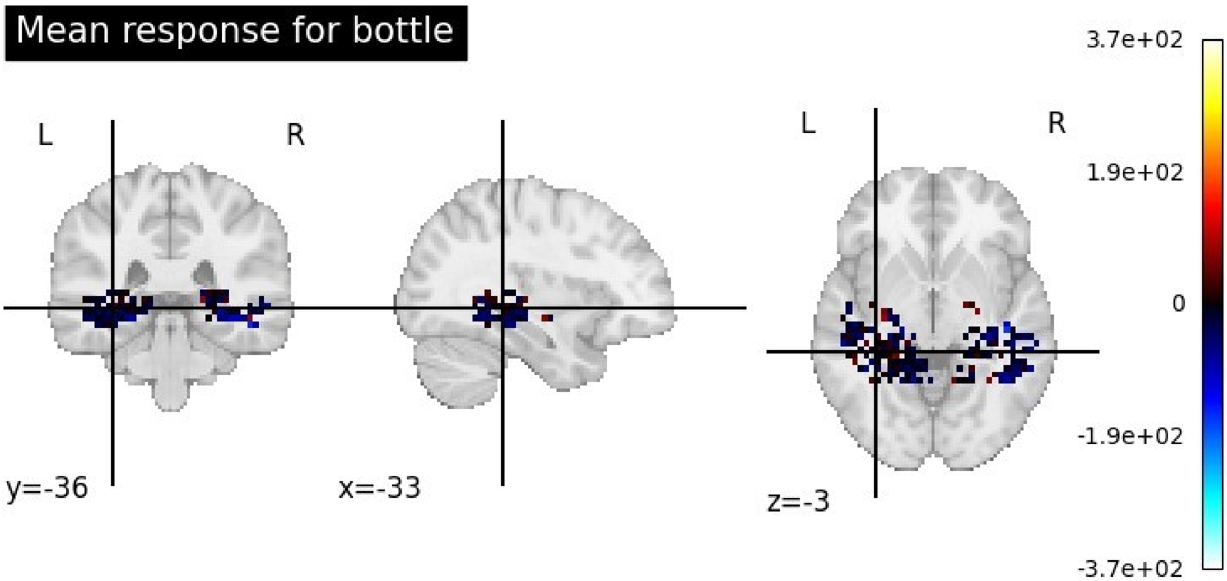
- Activation in Scene-selective Regions: Activation in regions such as the parahippocampal place area (PPA) and retrosplenial complex (RSC), specialized for processing scenes and spatial layouts.
- Distinctive Spatial Patterns: Clusters of voxels showing preferential activation to architectural features or environmental scenes.

Shoes



- Minimal Prior Expectations: Given the unconventional nature of scissors as a visual category, activation patterns are less predictable compared to faces or houses.
- Activation in Object-selective Regions: Activation occurs in regions such as the lateral occipital complex (LOC), involved in processing object shape and form.
- Limited Activation in Non-object Regions: Minimal activation in face- or scene-selective regions, indicating specificity to object-related stimuli.

Bottle



- Activation in Object-selective Regions: Similar to scissors, activation occurs in regions like the lateral occipital complex (LOC) or inferior temporal gyrus (ITG), specialized for object processing.
- Distinctive Spatial Patterns: Clusters of voxels showing preferential activation to the shape, texture, or function of bottles.
- Limited Activation in Non-object Regions: Minimal activation in face- or scene-selective regions, indicating specificity to object-related stimuli.

Collective Comparison:

- Overlap and Dissimilarity: While each category exhibits distinctive activation patterns, there is some overlap in activation regions, particularly within broader visual processing areas. However, dissimilarities in activation patterns are also evident, reflecting the category-specific neural representations.

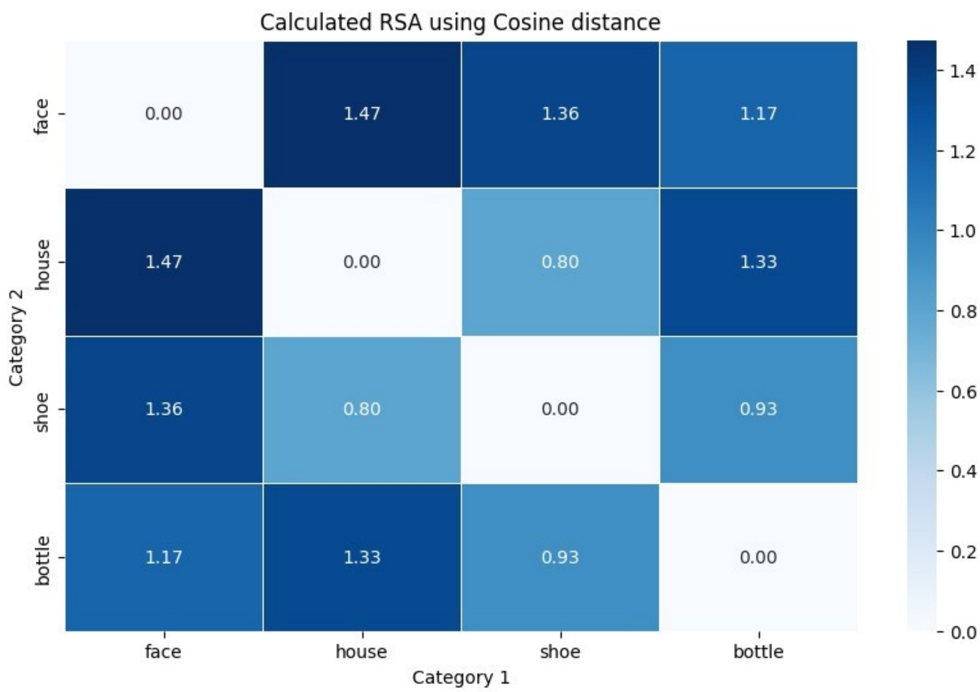
Correlation matrix

Mean correlation matrix

```
Mean Correlations within and between category:
             face     house      shoe    bottle
face          1.0 -0.515316 -0.350253 -0.197791
house   -0.515316       1.0  0.122589 -0.254319
shoe    -0.350253  0.122589       1.0  0.109596
bottle  -0.197791 -0.254319  0.109596       1.0
```

- We observe that the diagonal values are generally higher than the off-diagonal values, indicating that the fMRI response patterns within each category are more similar to themselves than to other categories.
- Among the off-diagonal elements, the highest positive correlation is observed between the "Houses" and "Bottles" categories, suggesting some level of similarity in brain activation patterns between these two categories.
- The negative correlation between "Faces" and "Bottles" categories suggests dissimilar fMRI response patterns between these categories.
- Overall, while there are some similarities between certain pairs of categories, there are also distinct differences in the fMRI response patterns, highlighting the specificity of neural representations for different visual categories within the ventral temporal cortex.

Representation (heatmap)

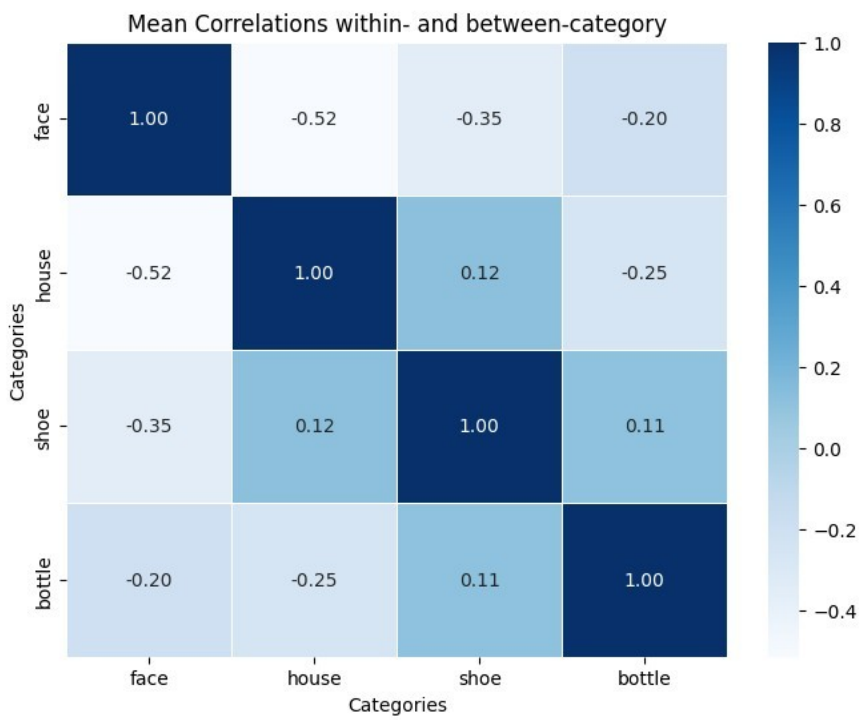


Representational Similarity Analysis

```
Representational Similarity Analysis between categories using Cosine distance:
            face     house      shoe    bottle
face         0.0  1.473994  1.358236  1.174354
house   1.473994       0.0  0.799588  1.327349
shoe    1.358236  0.799588       0.0  0.934322
bottle  1.174354  1.327349  0.934322       0.0
```

- Similar to the mean correlation matrix, the diagonal values in the RSA cosine similarity matrix are generally higher than the off-diagonal values, indicating that the fMRI response patterns within each category are more similar to themselves than to other categories.
- Among the off-diagonal elements, the highest positive similarity is observed between the "Houses" and "Bottles" categories, suggesting some level of similarity in the neural representations of these categories based on their fMRI response patterns.
- The negative similarity between "Faces" and "Bottles" categories indicates dissimilarity in their fMRI response patterns.
- Overall, the RSA cosine similarity matrix provides complementary insights to the mean correlation matrix, highlighting the relationships between different categories based on their neural representations in the ventral temporal cortex.

Representation (heatmap)



Conclusion

- Both analyses collectively underscore the distinct neural representations for each visual category and the specificity of neural coding within the ventral temporal cortex.
- While some categories may share common neural substrates, there are also clear differences in the fMRI response patterns, reflecting the unique processing demands of each visual category.
- These findings deepen our understanding of how the brain organizes and represents visual information, highlighting the complex interplay between neural circuits and sensory stimuli in shaping perceptual experiences.

In summary, the analysis provides valuable insights into the neural mechanisms underlying visual perception, offering a nuanced perspective on the organization of neural representations for different visual categories in the human brain.

Why cosine similarity ?

1. **Angle Measurement**: Cosine similarity measures the cosine of the angle between two vectors, rather than the magnitude or the Euclidean distance. This makes it particularly useful when the magnitude of the vectors doesn't matter as much as the orientation or direction. For example, in text analysis, the frequency of words in documents may vary widely, but their orientation (the angle between the vectors representing them) is what matters for comparing documents.
2. **Scale Invariance**: Cosine similarity is scale-invariant, meaning it's not affected by the magnitude of the vectors. This is particularly useful in scenarios where the data is sparse or high-dimensional, such as text data represented as bag-of-words or TF-IDF vectors. In these cases, the magnitudes of vectors can vary widely, but cosine similarity still provides meaningful comparisons.
3. **Efficiency**: Computing cosine similarity is computationally efficient, especially compared to measures like Euclidean distance, which involve square roots and summations over the dimensions of the vectors. This efficiency becomes crucial when dealing with large datasets or high-dimensional data.
4. **Normalized Representation**: Cosine similarity ranges from -1 to 1, where 1 indicates that the vectors are pointing in the same direction, 0 indicates they are orthogonal (perpendicular), and -1 indicates they are pointing in opposite directions. This normalized representation makes it easier to interpret and compare similarities across different datasets.

5. **Robustness to Noise**: Cosine similarity is relatively robust to noise or outliers in the data. Since it focuses on the orientation of the vectors rather than their magnitudes, small perturbations or inconsistencies in the data are less likely to significantly affect the similarity measure.