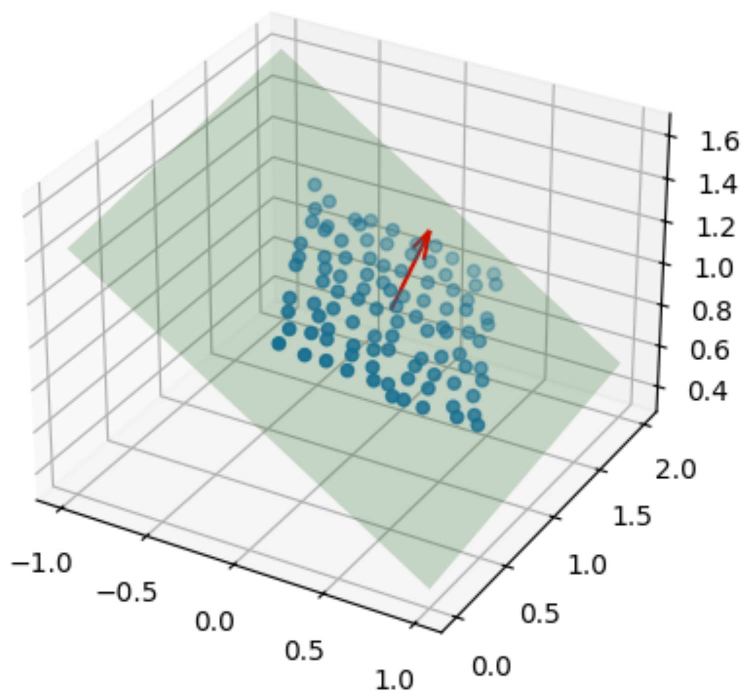
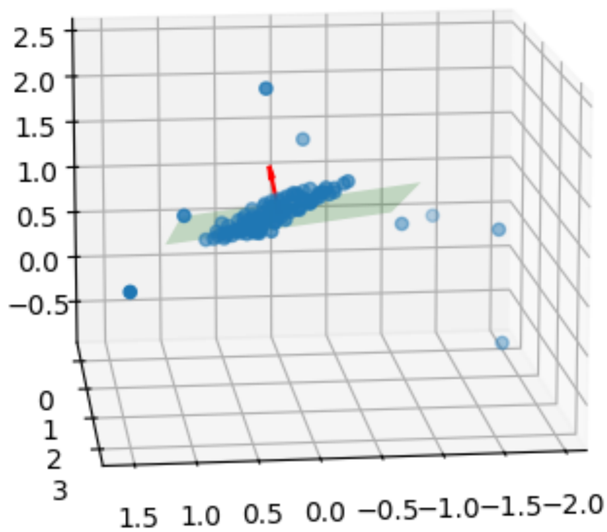
CS 5335 : Robotic Science and Systems
HW 4: Point cloud Analysis

By - Sujai Rajan

Q_1_a)

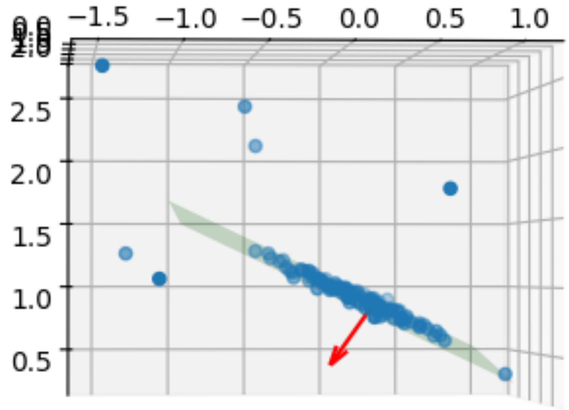


Q_1_b)



Outliers can profoundly influence the calculation of the sample mean and covariance matrix, leading to erroneous plane fitting. These outlier points, which significantly differ from the bulk of the data, can distort the mean and covariance computations, thus misguiding the plane fitting process away from an accurate representation of the primary data distribution.

Q_1_c)



RANSAC-Based Approach:
Advantages:

- **Resilience to Outliers:** RANSAC excels in environments cluttered with outliers, providing reliable plane parameter estimation even in challenging conditions.
- **Self-Sufficiency:** The algorithm's need for minimal parameter specification streamlines its application, enhancing its user-friendliness and automation.

Limitations:

- **Resource Intensity:** The iterative nature of RANSAC, coupled with the necessity for multiple model fittings, demands significant computational resources, particularly for extensive datasets.
- **Inherent Variability:** The stochastic foundation of RANSAC, rooted in random subset selection, introduces an element of unpredictability to the results, which may vary slightly across different executions.

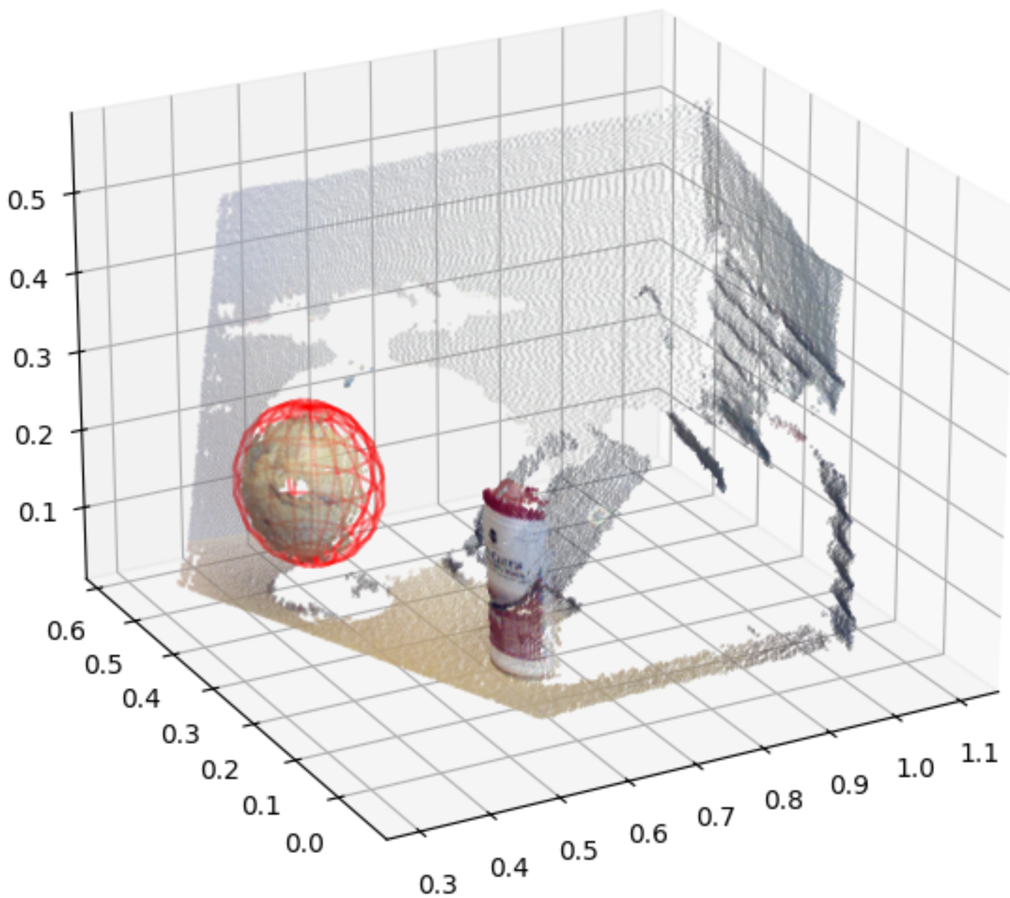
Sample Mean and Covariance-Based Approach:
Strengths:

- **Simplicity in Execution:** This method is distinguished by its straightforwardness, offering an uncomplicated solution that is readily implementable.
- **Computational Efficiency:** It stands out for its rapid processing capability, making it particularly suitable for smaller datasets where it efficiently delivers accurate plane parameter estimations.

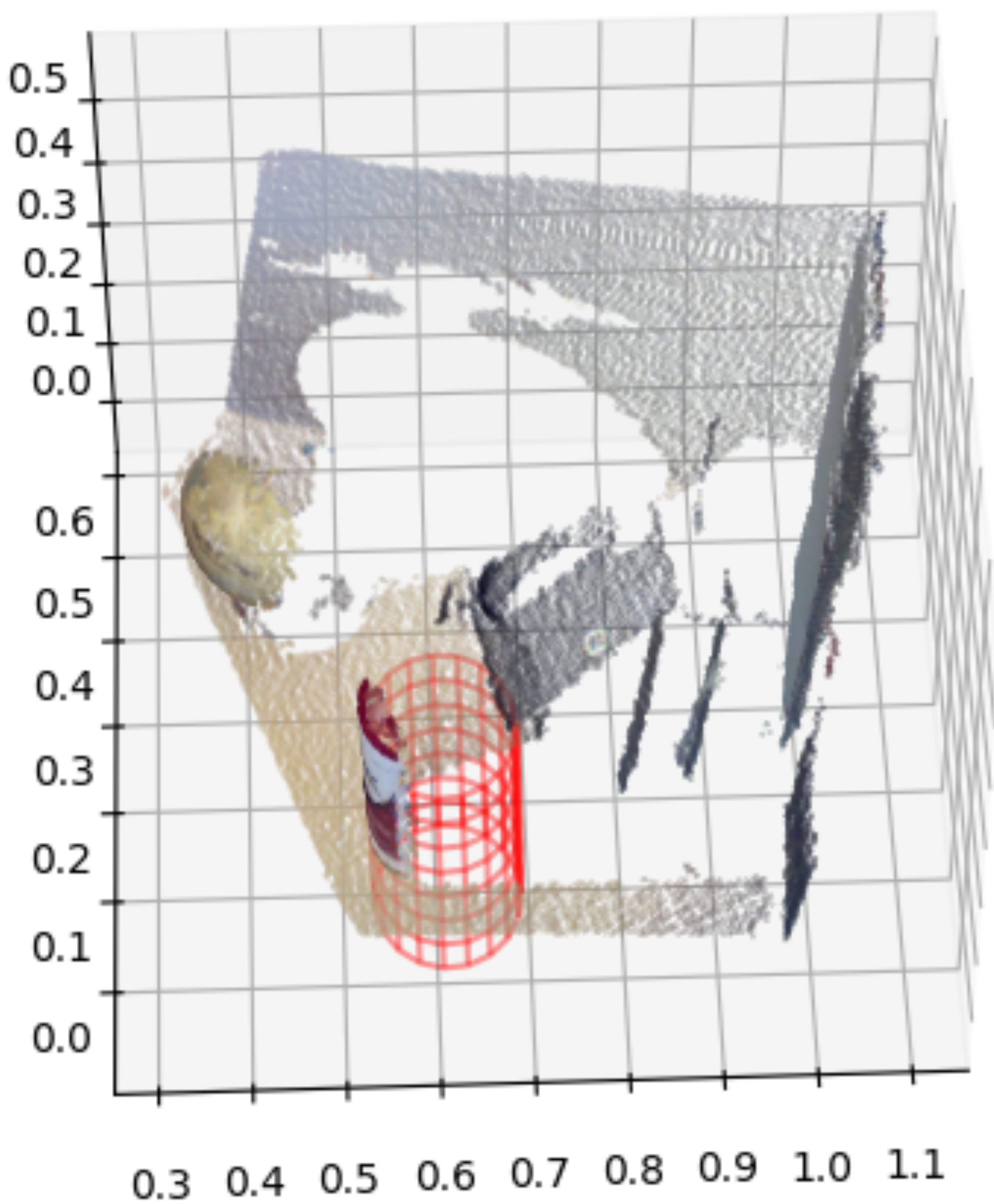
Weaknesses:

- **Vulnerability to Outliers:** Its major drawback is its susceptibility to outliers, which can significantly skew the estimated plane parameters, leading to erroneous results.
- **Necessity for Manual Input:** The requirement for manually determining the extent of data inclusion for covariance matrix computation introduces a layer of subjectivity, potentially impacting the precision of the estimated parameters.

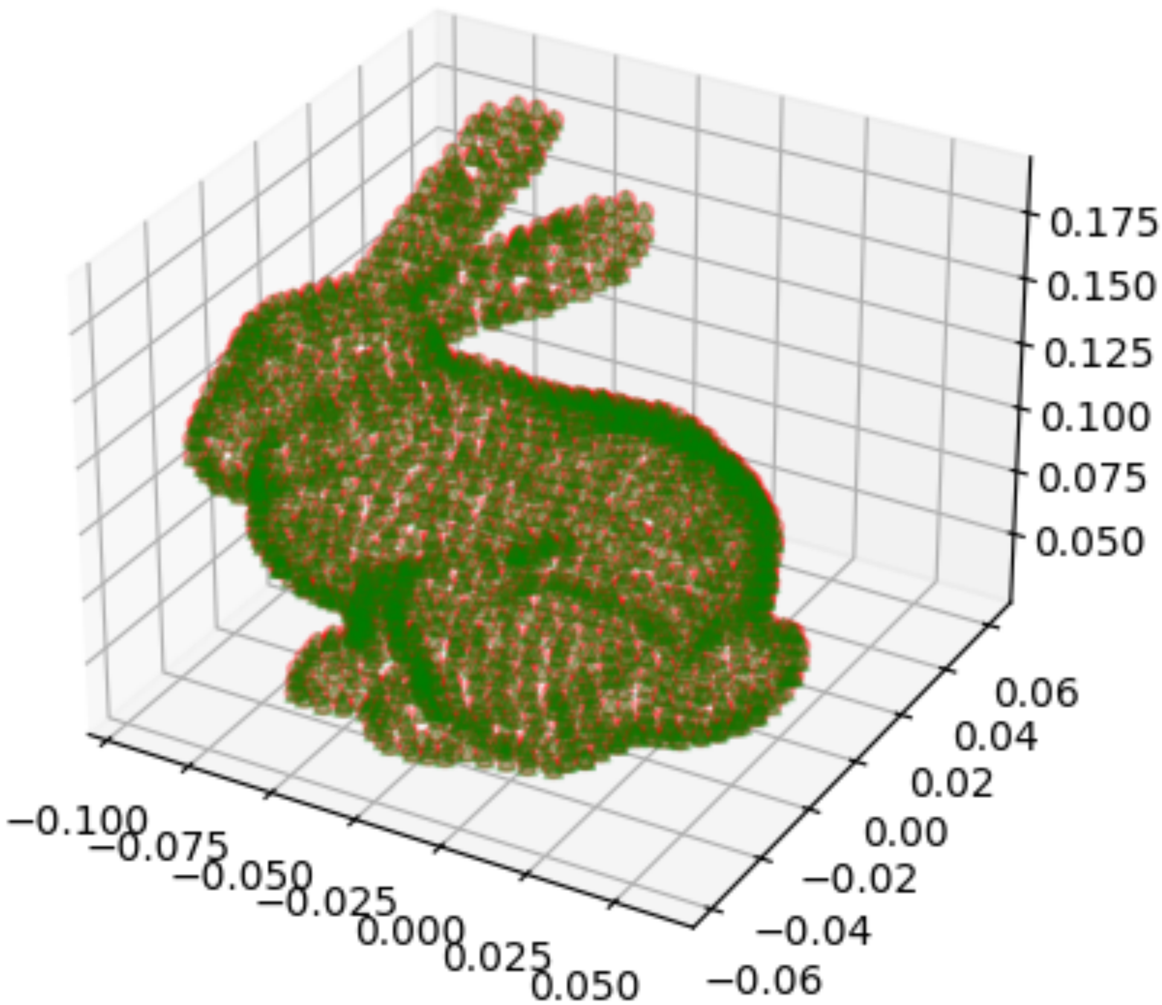
Q_2)



Q_3)



Q_4_a)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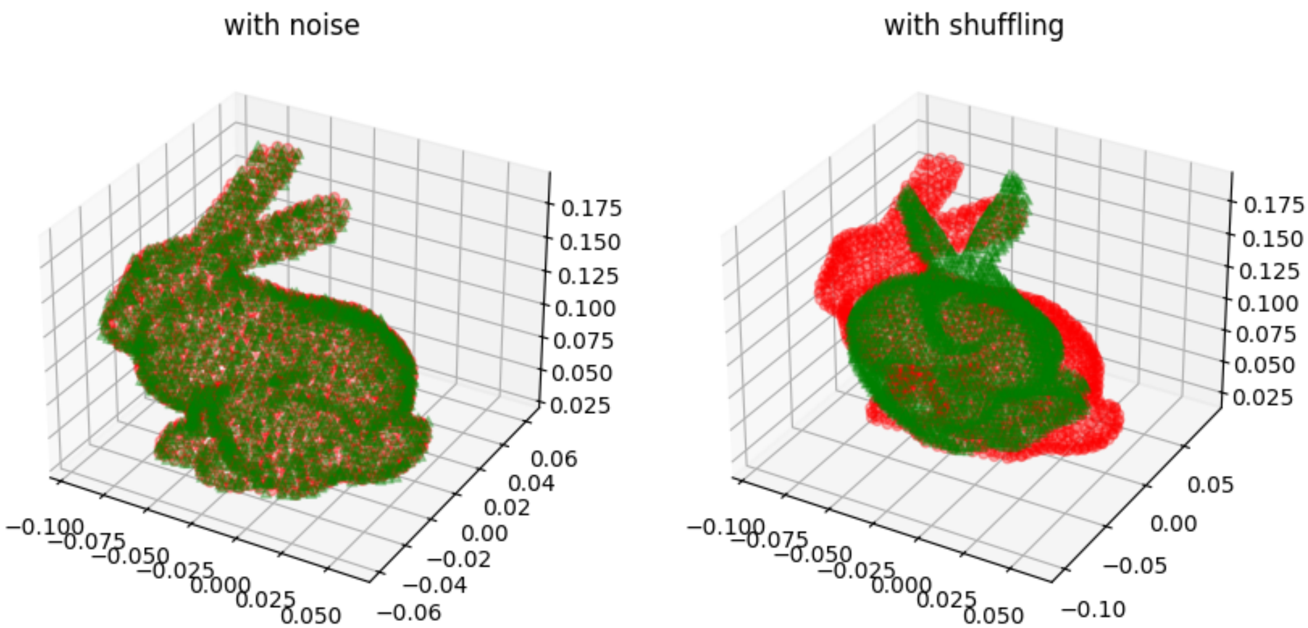
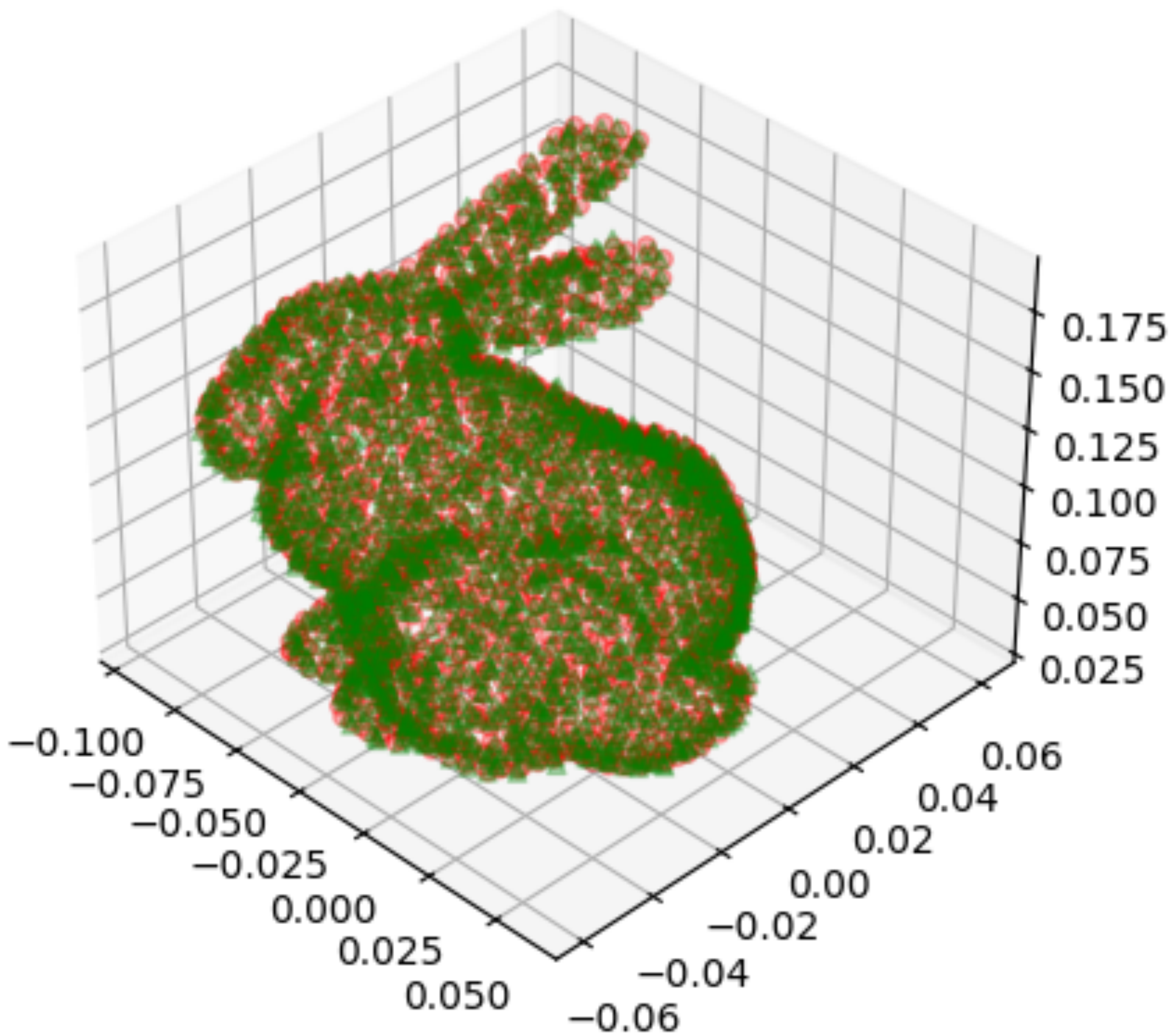
Q_4_b)



Under the assumption of point correspondence between two sets, the algorithm determines the optimal rotation and translation to align these sets. This process commences by centering the points, negating any initial translation, followed by the utilization of Singular Value Decomposition (SVD) to ascertain the precise rotation and translation for the alignment of the centered points. The algorithm's performance remains stable in the presence of Gaussian noise, attributed to the centering step which counteracts translation effects and the inherent zero-mean characteristic of the noise, ensuring the reliability of the SVD outcomes. Contrarily, altering the order of points disrupts the foundational correspondence assumption, rendering the alignment process ineffective. Consequently, the resulting transformation matrix, predicated on mismatched point pairs, may fail to accurately align the two sets.

Q_4_c)



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