

# Geometric and Computational Aspects of Data Depth

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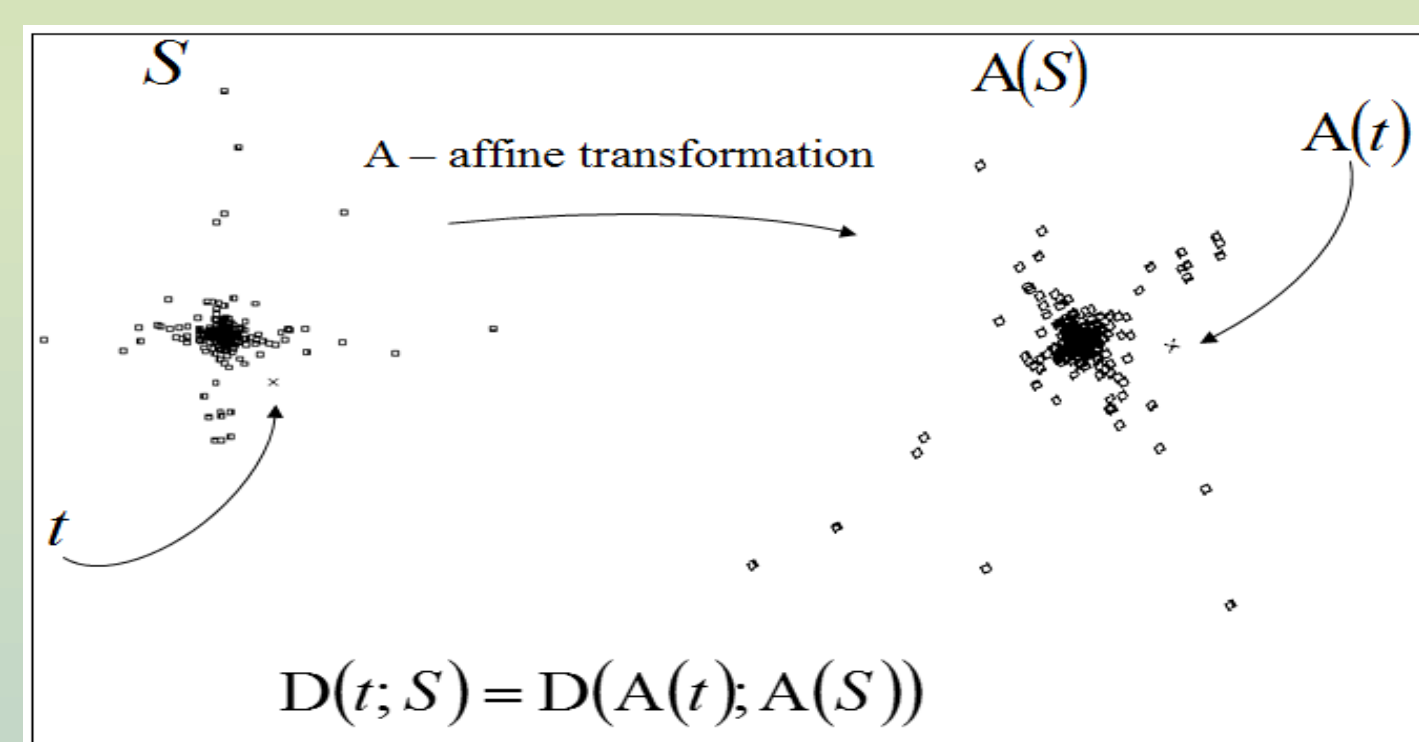
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## Introduction

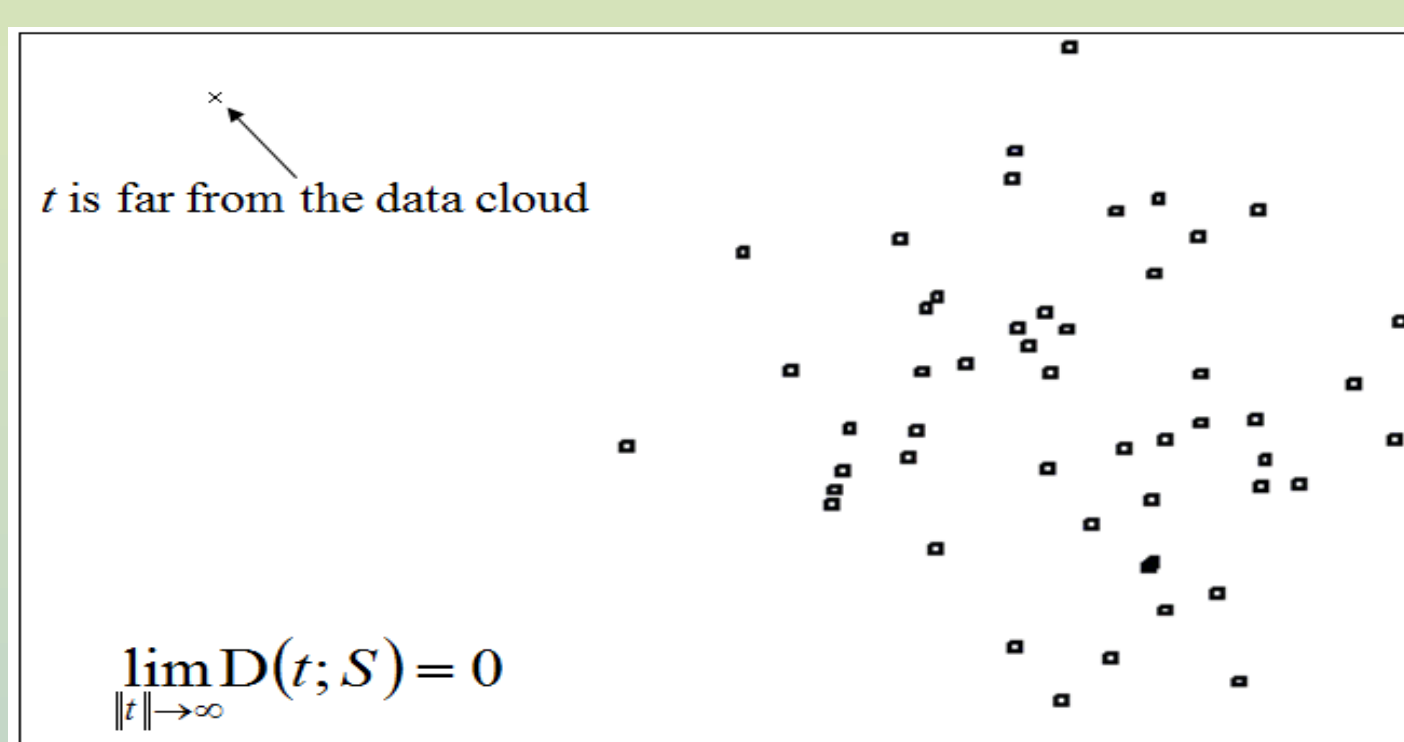
- Rank statistic tests play an important role in univariate nonparametric statistics. If one attempts to generalize rank tests to the multivariate case, the problem of defining a multivariate order statistic will occur. This problem can be attributed to the absence of a natural linear order on  $\mathbb{R}^d$ . Thus is not clear how to define a multivariate order or rank statistic in a meaningful way.
- One approach to overcome this problem is to use the notion of data depth. Data depth measures the ‘centrality’ of a point in a given data cloud in non-parametric multivariate data analysis. In other words, it indicates, in some sense, how deep a point is located with respect to the data cloud. Using data depth, a multivariate order statistic can be defined by ordering the data points according to their depth in a suitable data cloud.

## Framework of Data Depth

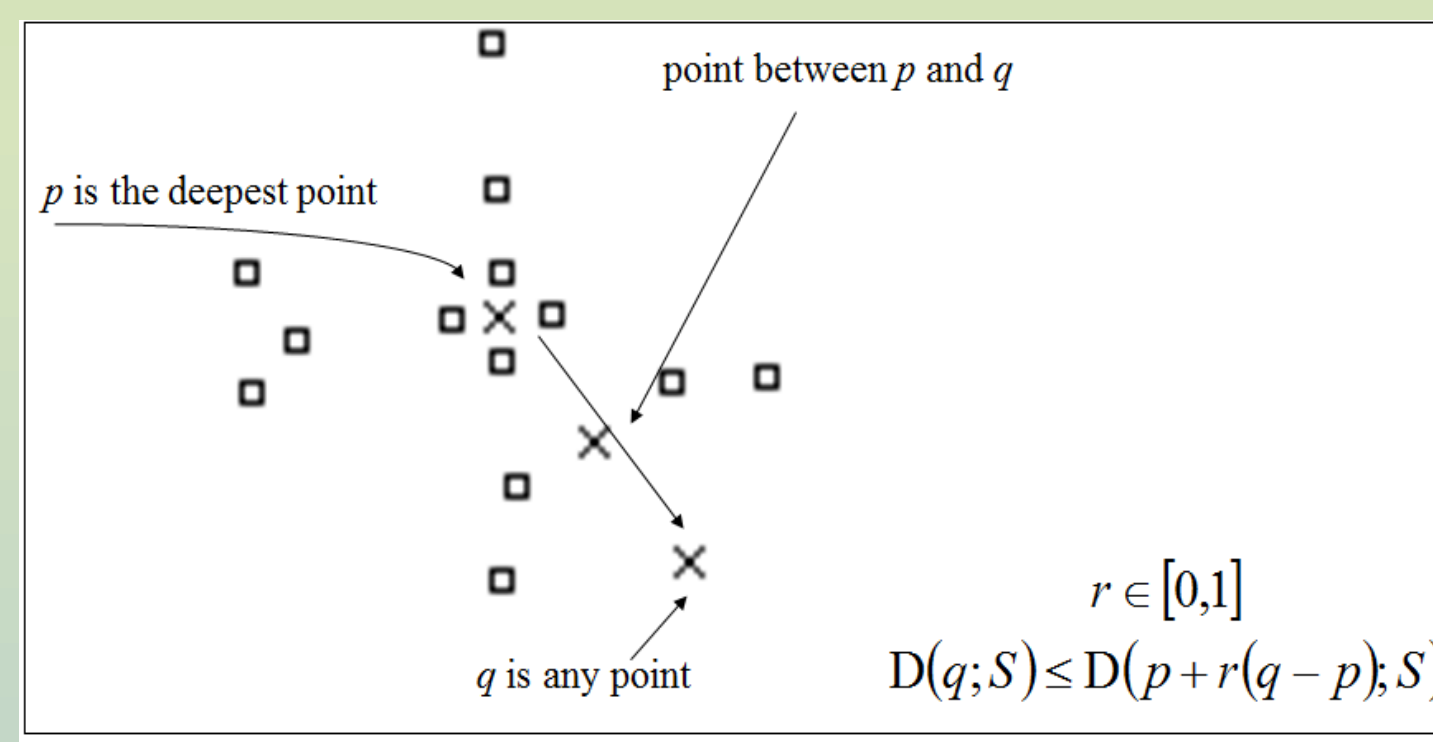
### 1. Affine invariance



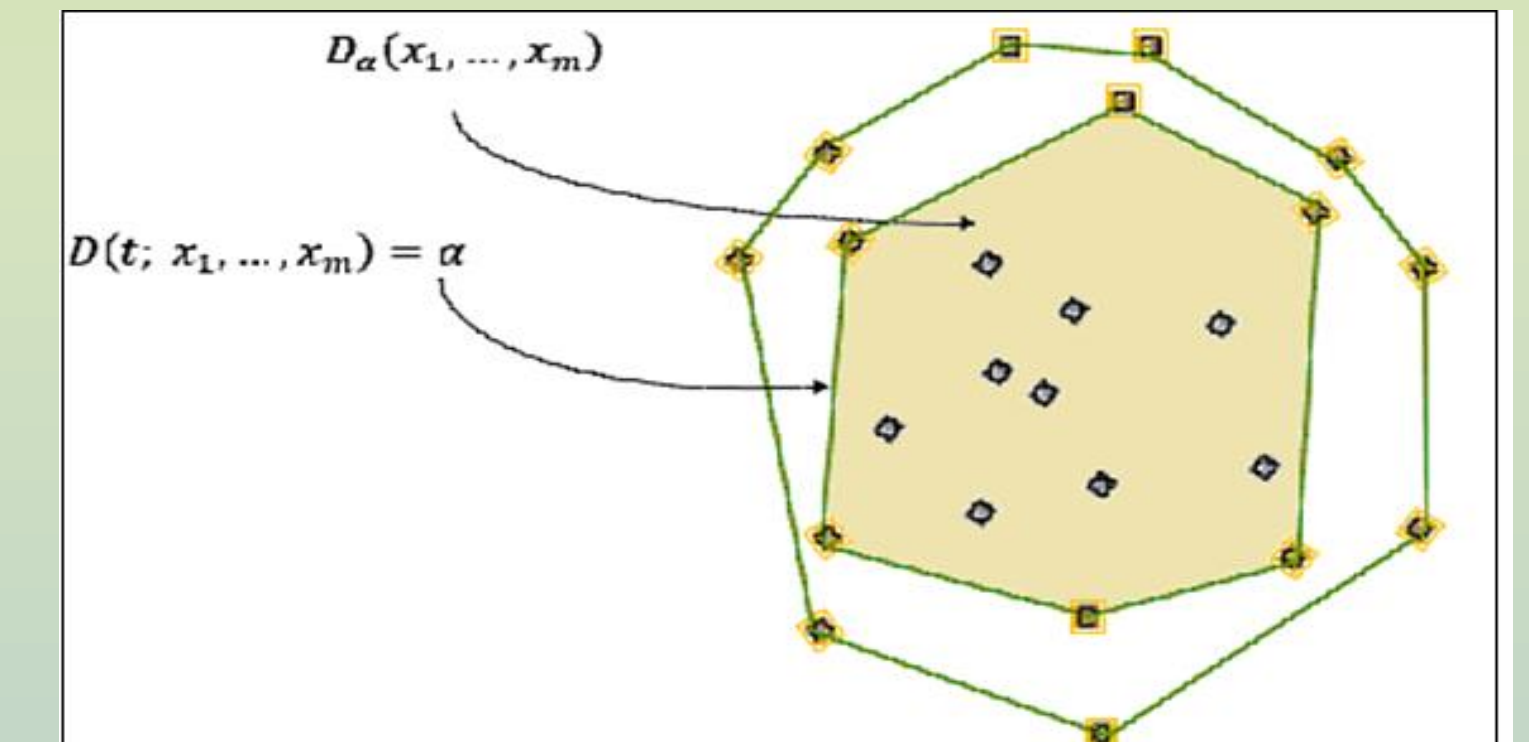
### 2. Vanishing at infinity



### 3. Monotone on rays



### 4. Upper semi-continuity



**Different Notions of Data Depth :** Among many different data depths, our research is mostly focused on the following data depths

1. **Halfspace depth:**  $HD(t; S) = \inf \{P(S \cap H); \forall H \text{ containing } t\} \rightarrow \text{Figure 1}$

2. **Oja depth:**  $OjD(t; S) = \frac{1}{\binom{n}{d}} \sum_{(x_1, \dots, x_d) \in \binom{S}{d}} Vol_d(\text{conv}\{t, x_1, \dots, x_d\}) \rightarrow \text{Figure 2}$

3. **Simplicial depth:**  $SD(t; S) = \frac{1}{\binom{n}{d+1}} \sum I(t \in S[x_1, \dots, x_{d+1}]) \rightarrow \text{Figure 3}$

4. **Majority depth:**  $MjD(t; S) = \frac{1}{\binom{n}{d}} \sum I(t \in MjS(x_1, \dots, x_d)) \rightarrow \text{Figure 4}$

5. **Lens depth:**  $LD(t; S) = \frac{1}{\binom{n}{2}} \sum_{i < j} I(t \in L(x_i, x_j)) \rightarrow \text{Figure 5}$

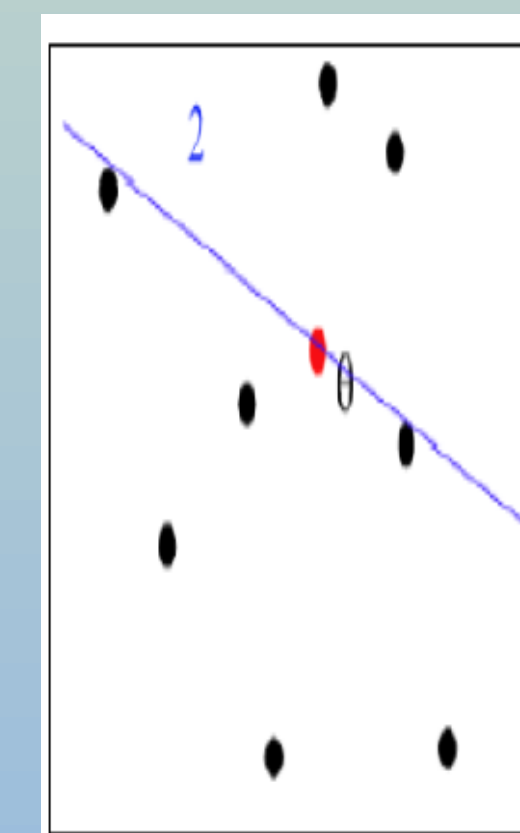


Figure1

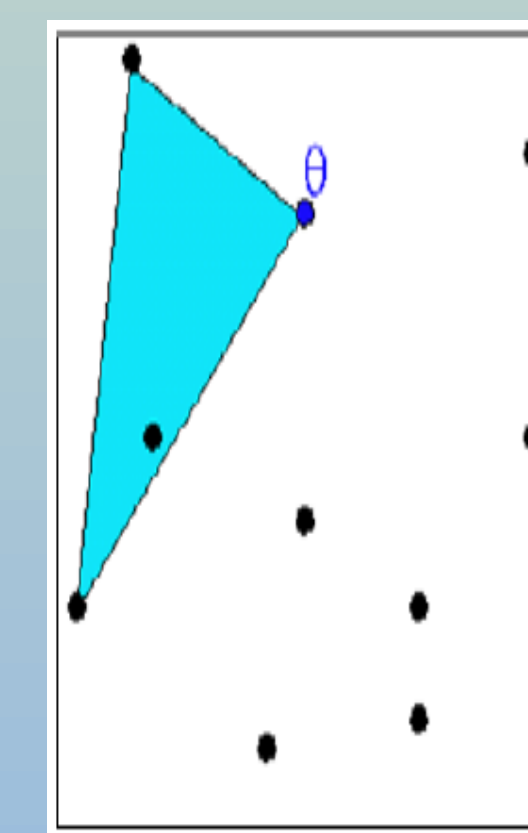


Figure2

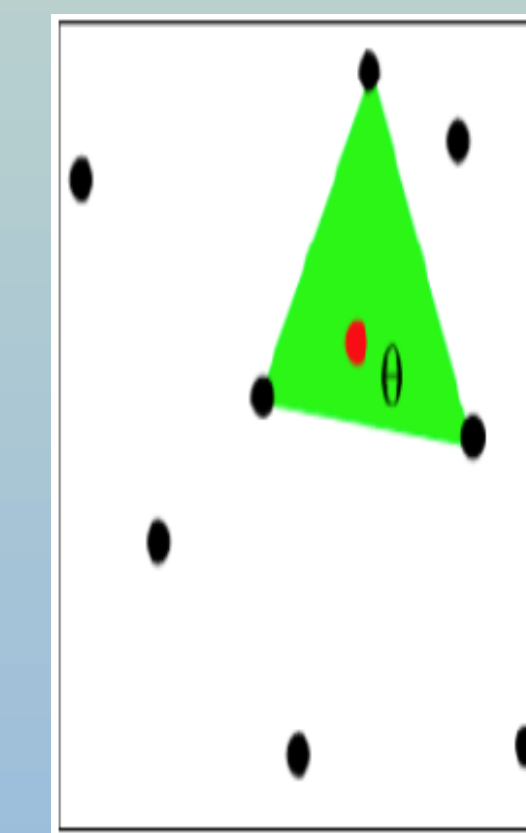


Figure3

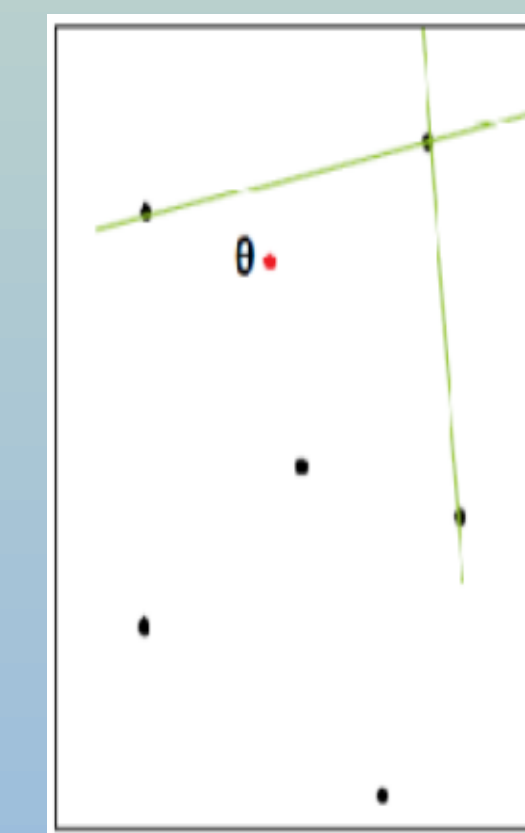


Figure4

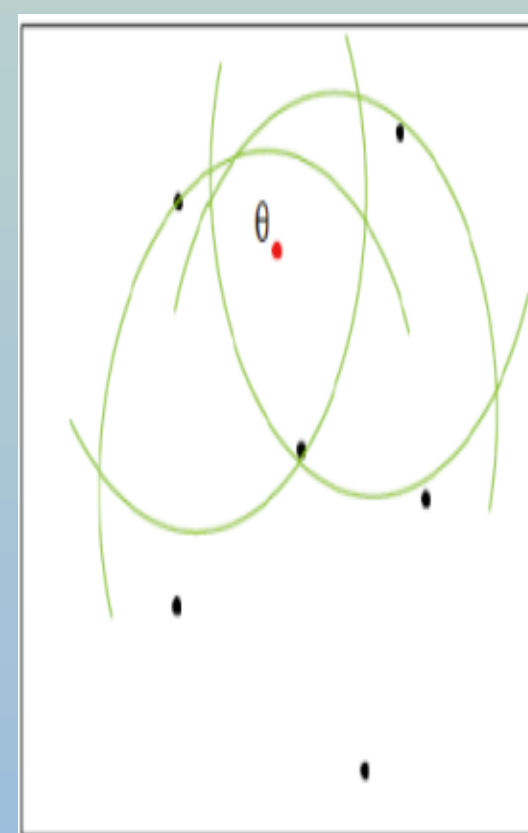


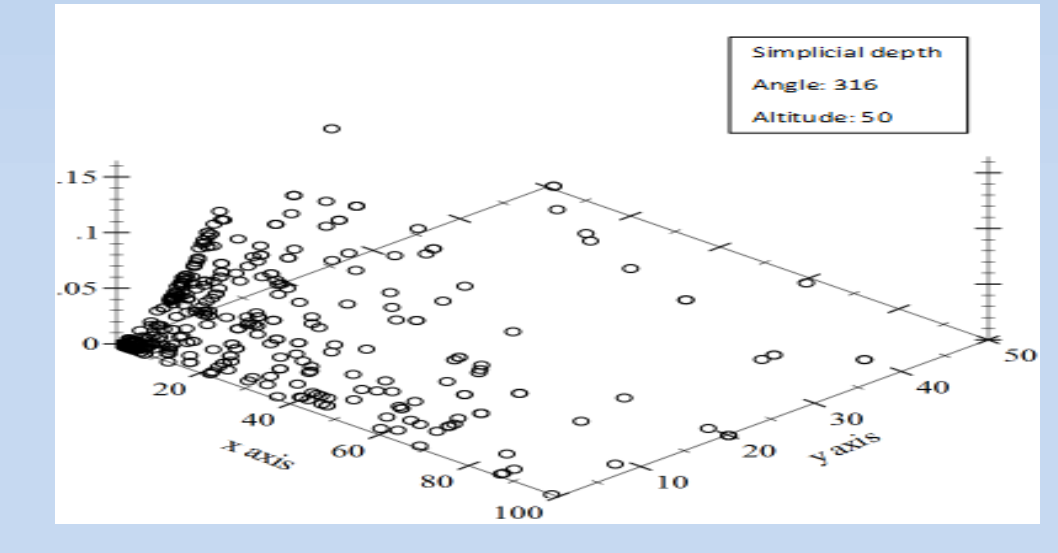
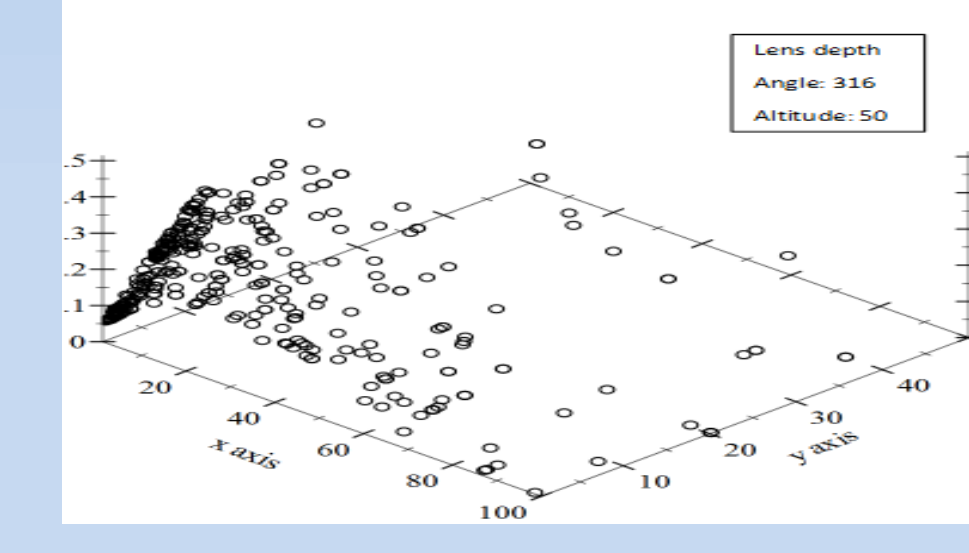
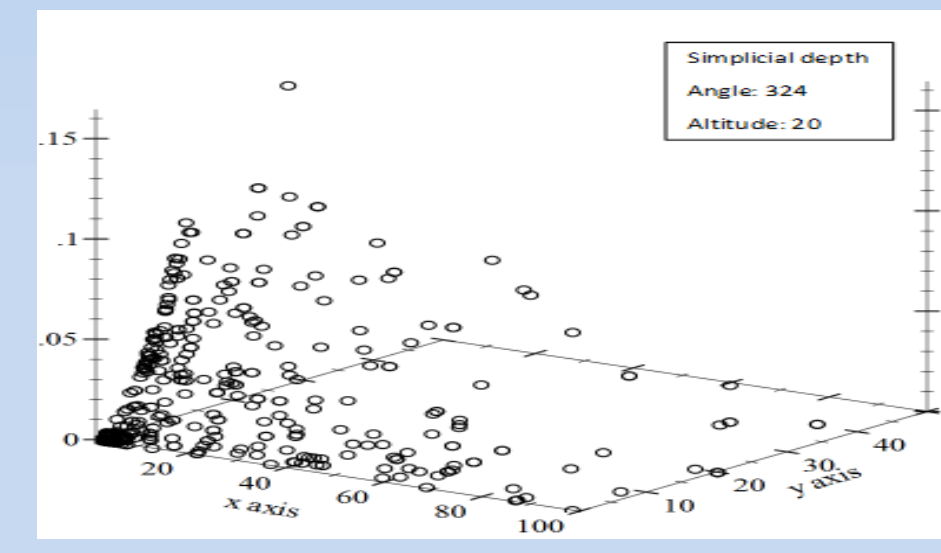
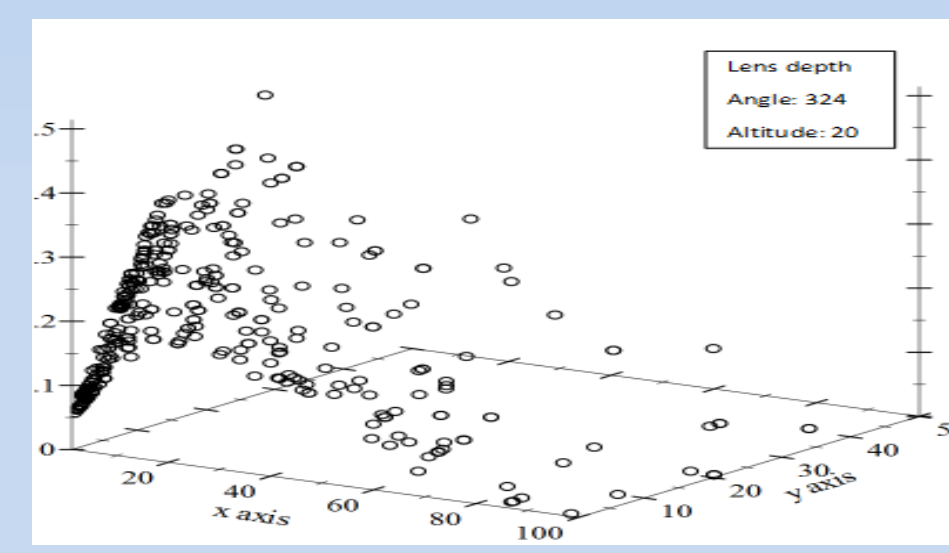
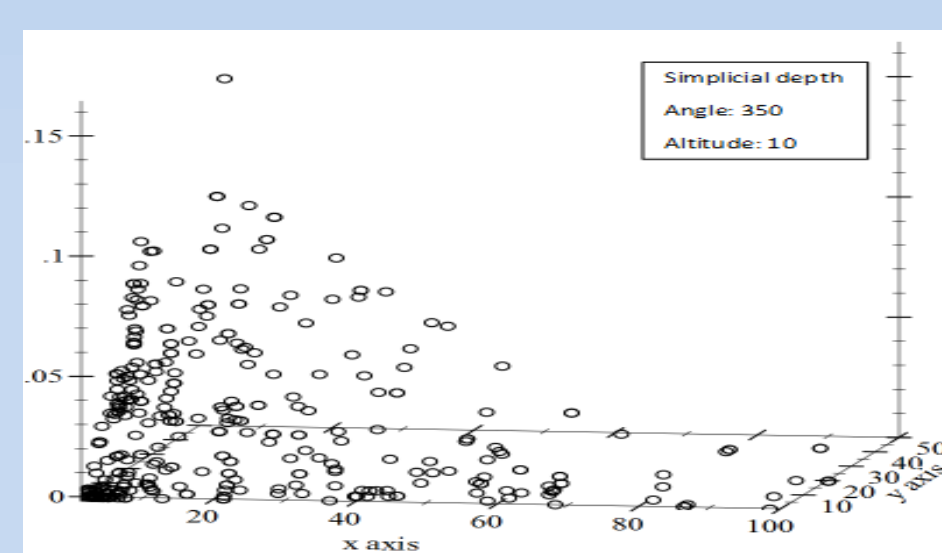
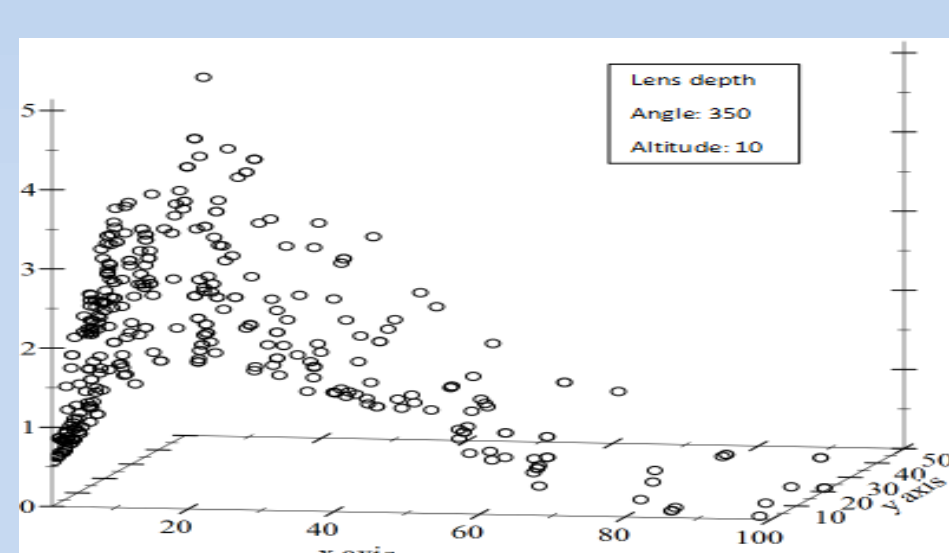
Figure5

## Time Complexity

Depth Function	Depth Time Complexity	Bivariate Median Time Complexity
Halfspace depth	$O(m^{d-1} \log m)$	$O(m \log^3 m)$
Oja	$O(m^d)$	$O(m^3 \log m)$
Majority		$O((n+m) \log n)$ (Brodal–Jacod model), $O((n+m) \log n / \log(\log n))$ (RAM model)
Simplicial	$O(m^{d+1})$	$O(m^4)$
Lens	$O(m^2 d)$	$O(m^2)$

## Implementation

We implemented the Lens, Simplicial and Oja depth for a set of bivariate points Theta with respect to a given dataset S in order to compare different data depths. Following are the visualization of the output for random some data.



## Future Work

Our research is currently focused on the following areas.

- 1- Understanding the geometrical aspects of the data depths.
- 2- Investigating some bounds and improving time complexity for computing data depths

