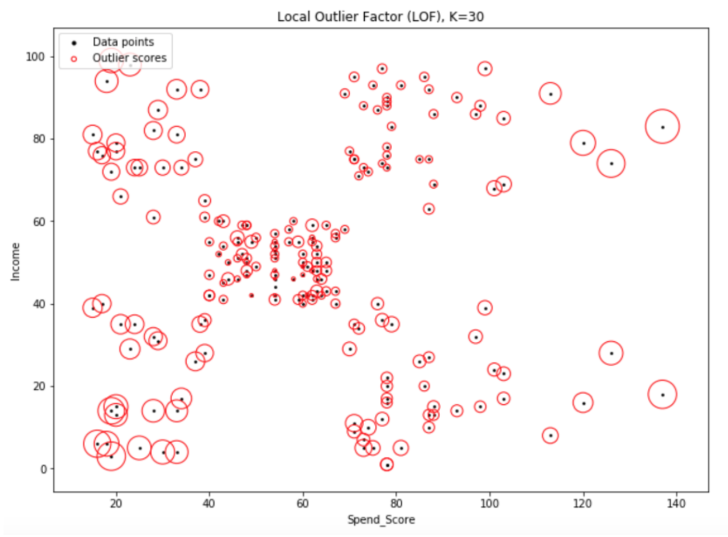
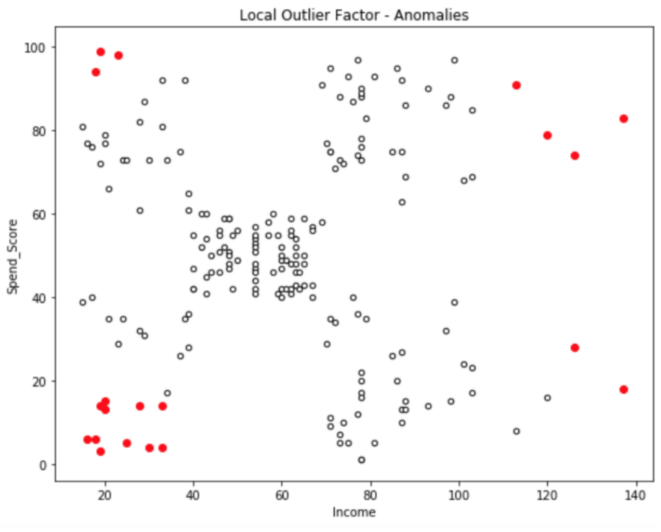



# Anomaly Detection: Local Outlier Factor (LOF)

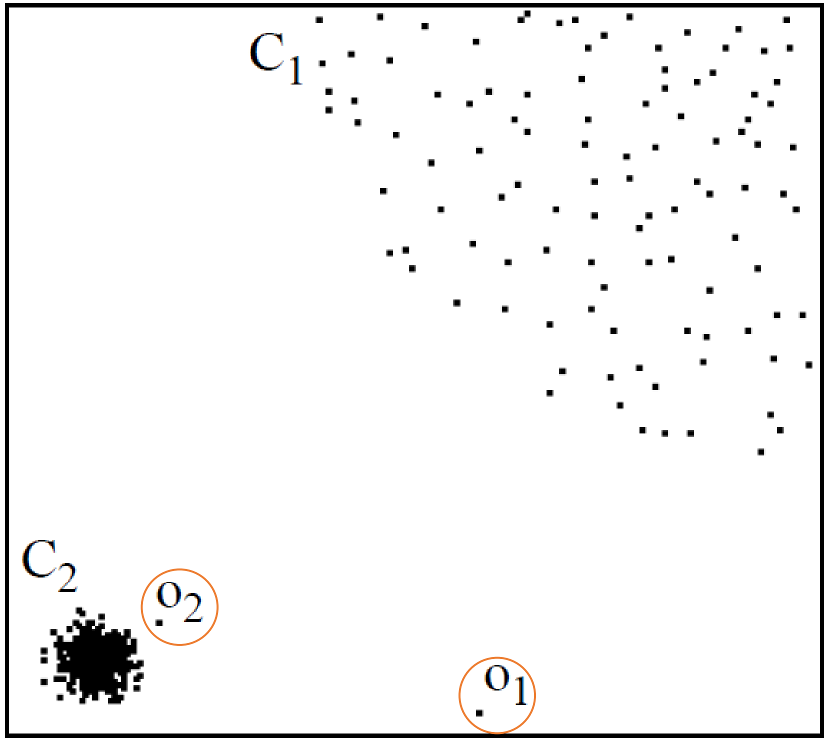
Pilsung Kang

School of Industrial Management Engineering

Korea University

# Local Outlier Factors (LOF)

- Motivation
  - ✓ Compute the novelty score of an instance by considering local density around it



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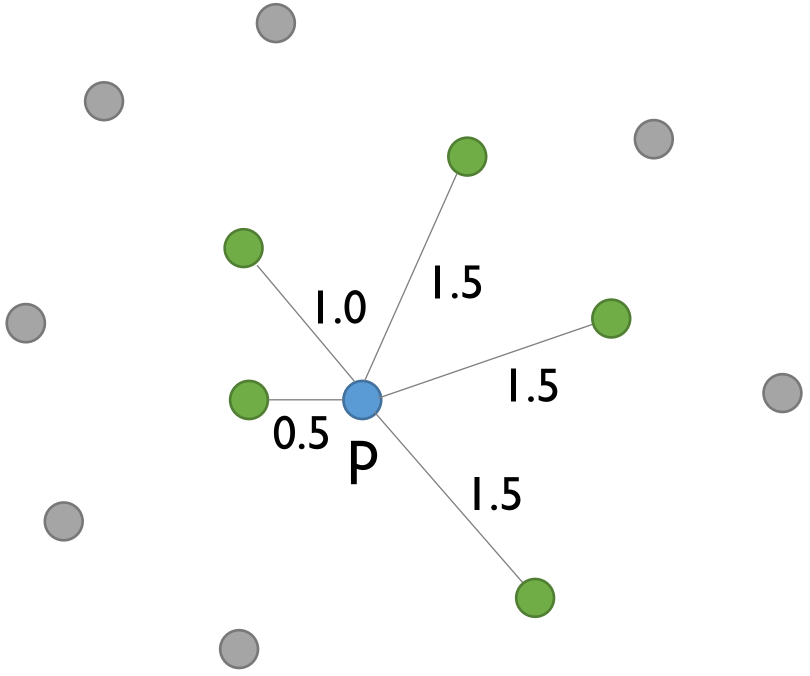
DSBA Data Science & Business Analytics

# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 1: k-distance of an object p
    - For any positive integer k, the k-distance of object p, denoted as k-distance(p), is defined as the distance d(p,o) between p and an object o in D such that
    - for at least k objects o' in D\{p} it holds that $d(p, o') \leq d(p, o)$
    - for at most k-1 objects o' in D\{p} it holds that $d(p, o') < d(p, o)$
    - Simply it is the distance to the k-th nearest neighbor considering ties.

# Local Outlier Factors (LOF)

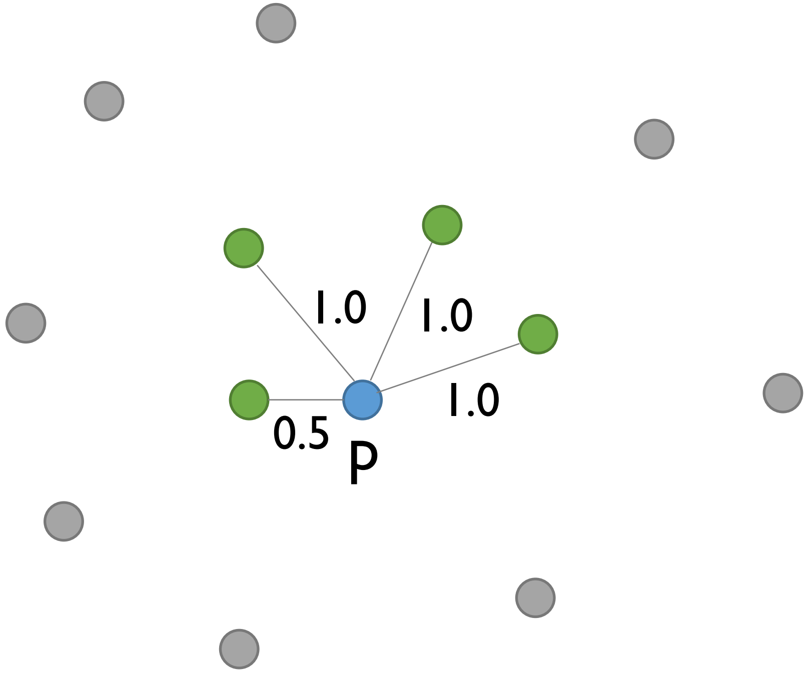
- Local Outlier Factors (LOF)
  - ✓ Definition 1: k-distance of an object p




3-distance of p = 1.5

# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 1: k-distance of an object p




3-distance of p = 1.0

# Local Outlier Factors (LOF)

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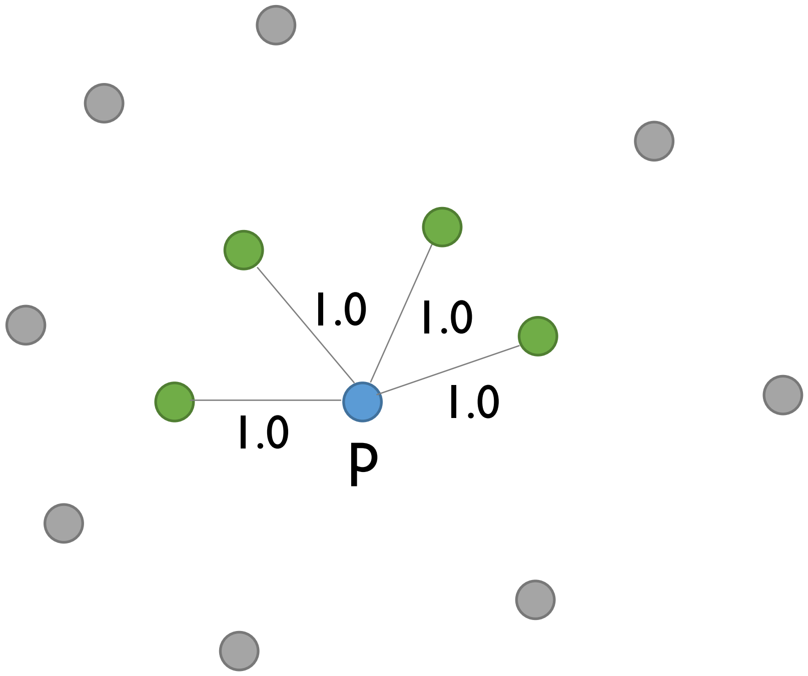
  - ✓ Definition 1: k-distance of an object p




3-distance of p = 1.0

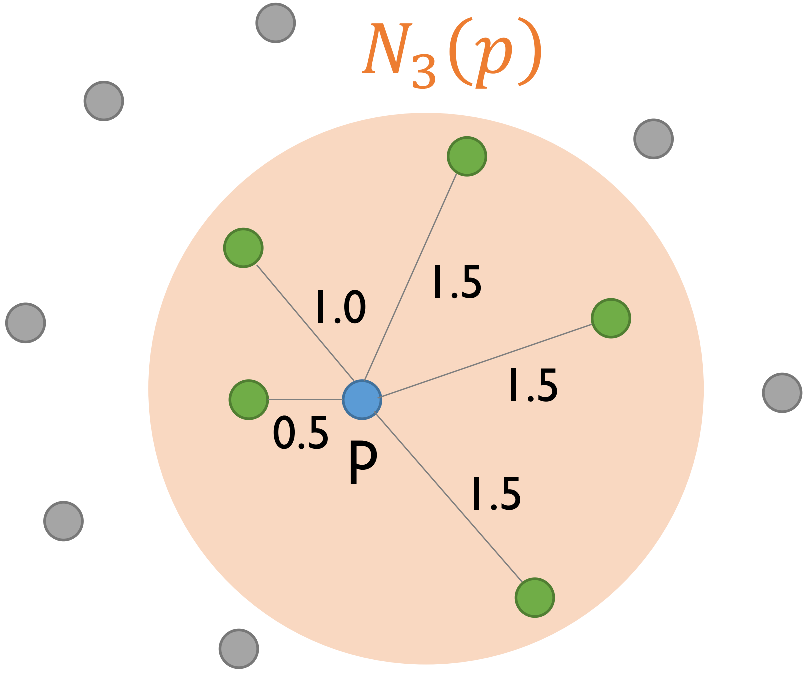
# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 2: k-distance neighborhood of an object p
    - Given the k-distance of p, the k-distance neighborhood of p contains every object whose distance from p is not grater than the k-distance

$$N_k(p) = \{q \in D \backslash \{p\} \mid d(p, q) \leq k - distance(p)\}$$

# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 2: k-distance neighborhood of an object p




3-distance of p = 1.5

# Local Outlier Factors (LOF)

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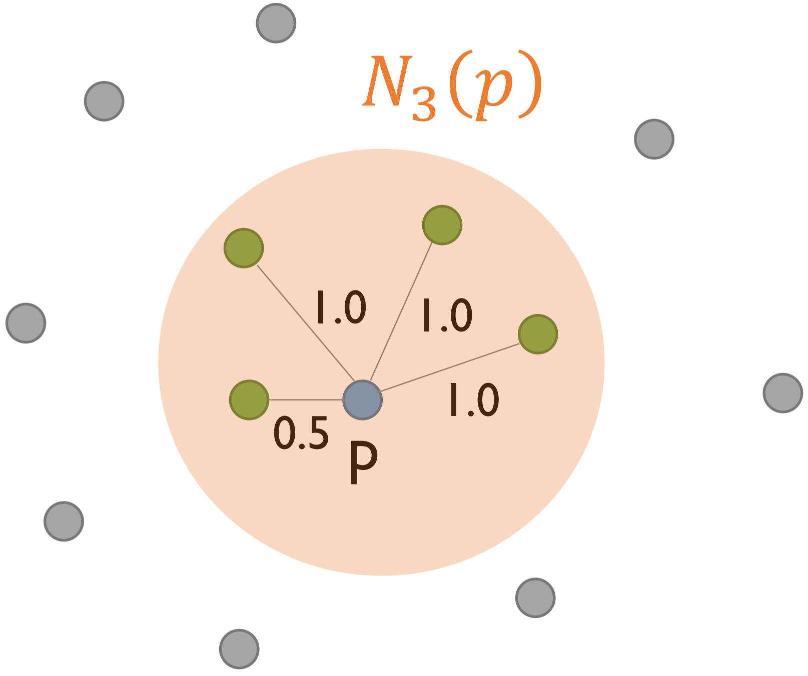
    - ✓ Definition 2: k-distance neighborhood of an object p




3-distance of p = 1.0

# Local Outlier Factors (LOF)

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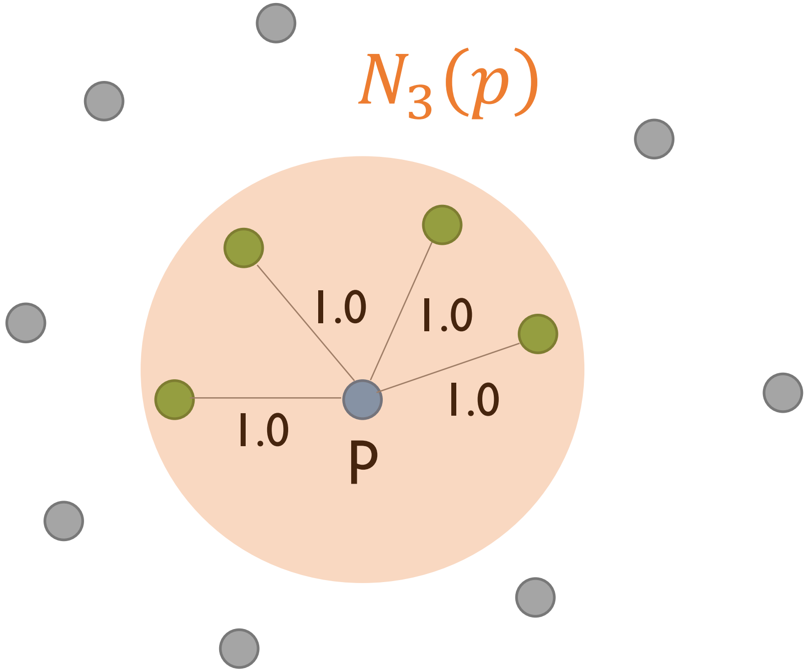
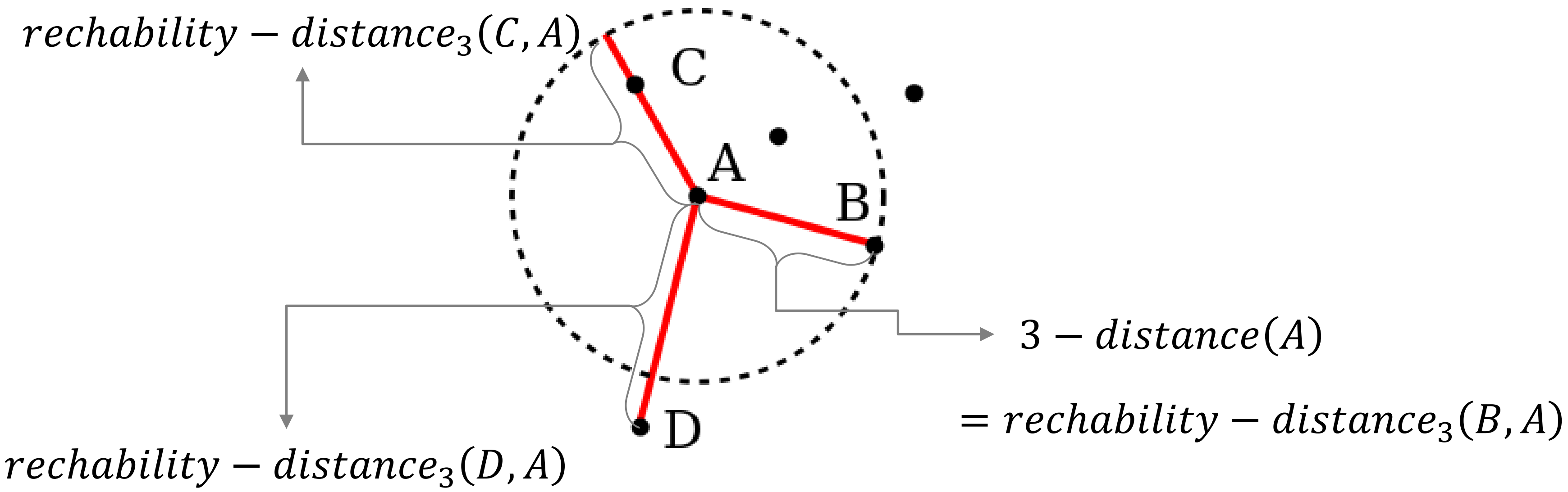
  - ✓ Definition 2: k-distance neighborhood of an object p




3-distance of p = 1.0

# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 3: reachability distance
    - $rechability - distance_k(p, o) = \max\{k - distance(o), d(p, o)\}$
    - Examples



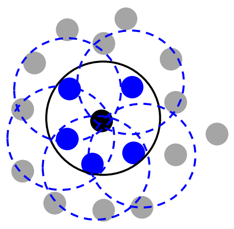
# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 4: local reachability density of an object p

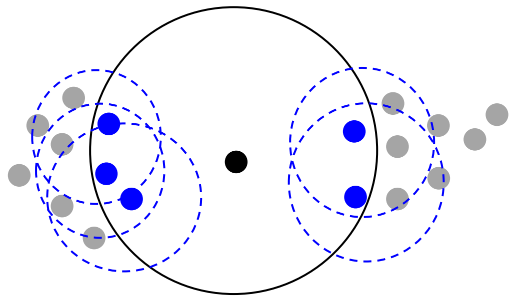
$$lrd_k(p) = \frac{|N_k(p)|}{\sum_{o \in N_k(p)} reachability - distance_k(p, o)}$$

- Case 1: p is located in the middle of a denser area: the denominator of $lrd_k(p)$ becomes small, which results in a large $lrd_k(p)$
- Case 2: p is located in a spare are between two dense data clusters: the denominator of $lrd_k(p)$ becomes large, which results in a small $lrd_k(p)$

Case 1



Case 2

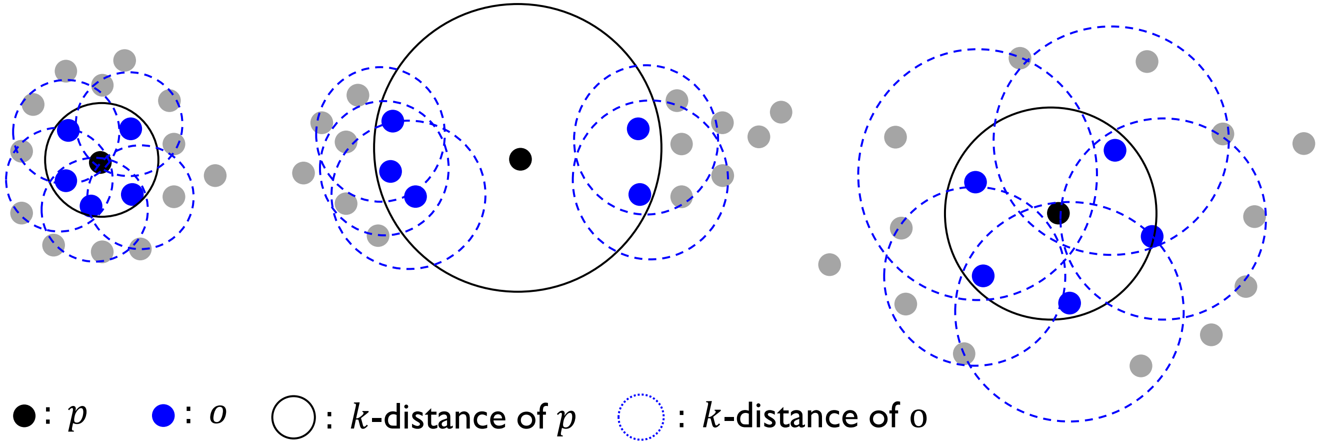


# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ Definition 5: local outlier factor of an object p

$$LOF_k(p) = \frac{\sum_{o \in N_k(p)} \frac{lrd_k(o)}{lrd_k(p)}}{|N_k(p)|} = \frac{\frac{1}{lrd_k(p)} \sum_{o \in N_k(p)} lrd_k(o)}{|N_k(p)|}$$

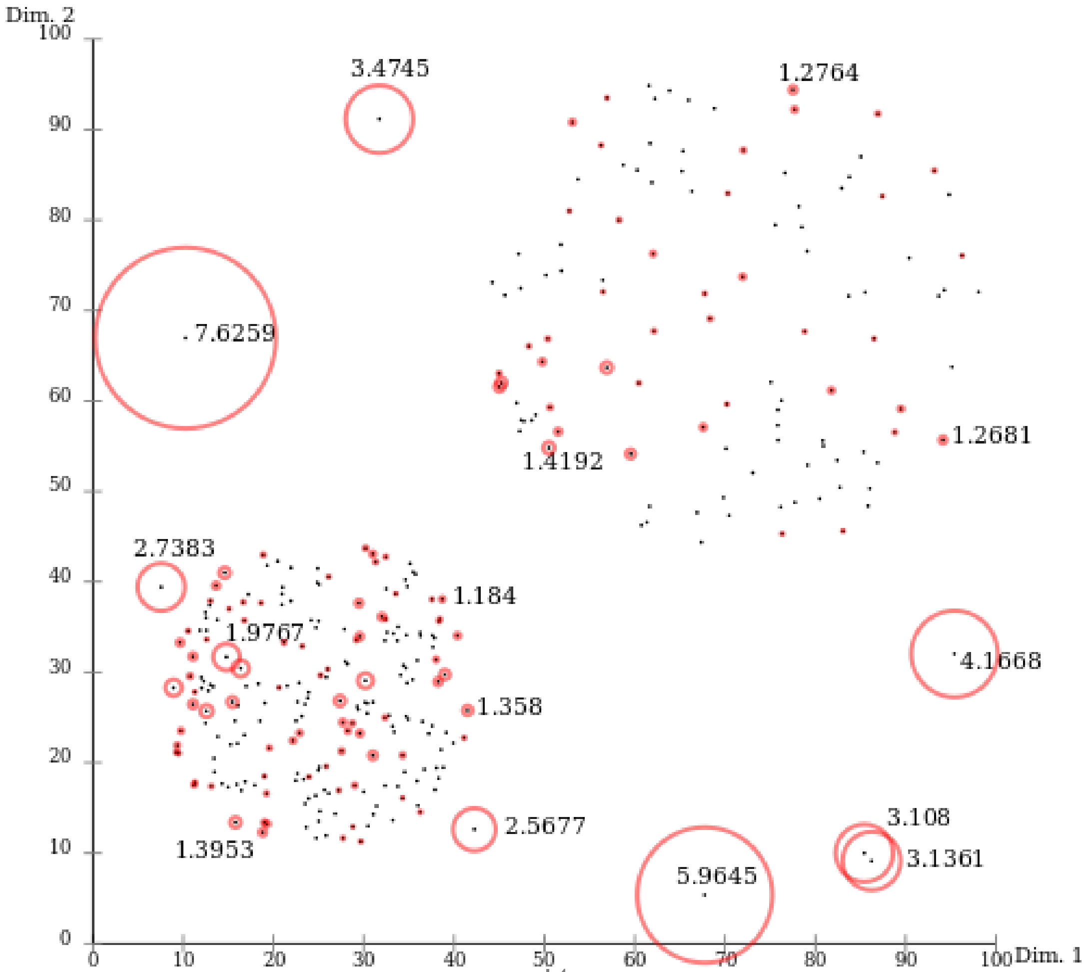
Case 1 Case 2 Case 3




| Case | $lrd_k(p)$ | $lrd_k(o)$ | $LOF_k(p)$ |
|---|---|---|---|
| Case 1 | Large | Large | Small |
| Case 2 | Small | Large | Large |
| Case 3 | Small | Small | Small |

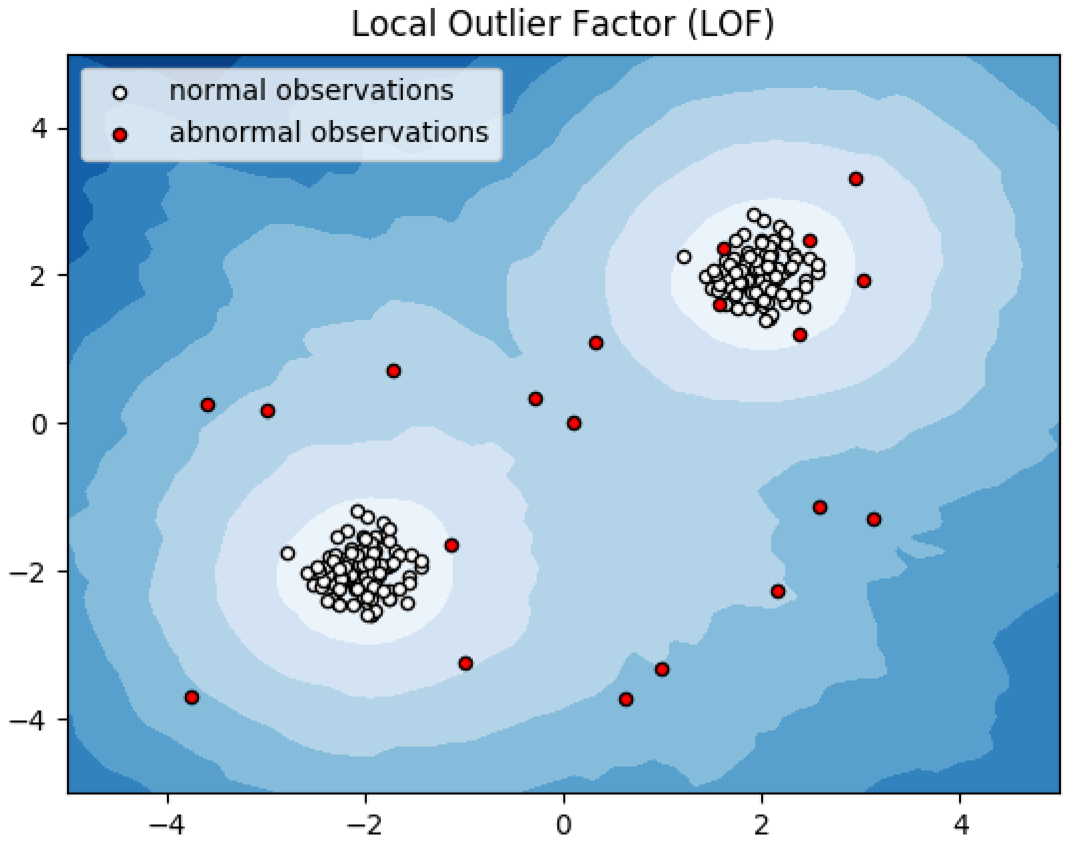
# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ For each point, compute the density of its local neighborhood



# Local Outlier Factors (LOF)

- Local Outlier Factors (LOF)
  - ✓ LOF contour plot




http://scikit-learn.org/stable/auto_examples/neighbors/plot_lof.html


Q & A

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Other materials

- Pages 28-33 & 36: http://research.cs.tamu.edu/prism/lectures/pr/pr_l7.pdf
- Figures in Auto-encoder section: https://dl.dropboxusercontent.com/u/19557502/6_01_definition.pdf
- Gramfort, A. (2016). Anomaly/Novelty detection with scikit-learn: https://www.slideshare.net/agramfort/anomalynovelty-detection-with-scikitlearn