ROCF Process

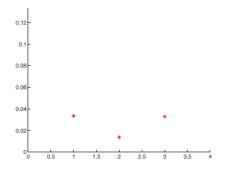
- 먼저 MkNN을 수행해 clustering과 scatter outlier detection을 하고, transition level(*TL*)와 *ROCF*를 정의하고 각 cluste에 대해 *ROCF*를 계산한다.
- Cluster들을 크기 기준 오름차순으로 정렬한 후, b번째 cluster의 ROCF 값이 0.1 보다 크면, 1부터 b번째까지의 cluster는 outlier cluster로 판단한다.
- 0.1보다 큰 ROCF를 가지는 cluster가 없으면, MkNN으로 감지한 scatter outlier만을 outlier로 판단한다.

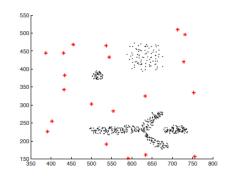
$$TL(C_i) = \frac{|C_{i+1}|}{|C_i|}, i = 1, 2, ..., n-1$$

$$ROCF(C_i) = 1 - e^{-\frac{\pi_i(C_i)}{|C_i|}} = 1 - e^{-\frac{|C_{i+1}|}{|C_i|^2}}, \quad i = 1, 2, \dots, n-1$$

$$|C_1| \leq |C_2| \leq \ldots \leq |C_n|$$

$$max{ROCF(C_i)}$$
 and $ROCF(C_b) > 0.1$, then $C_1, C_2, ..., C_b$

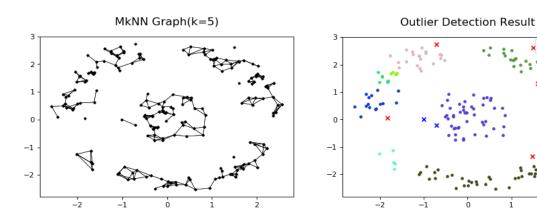




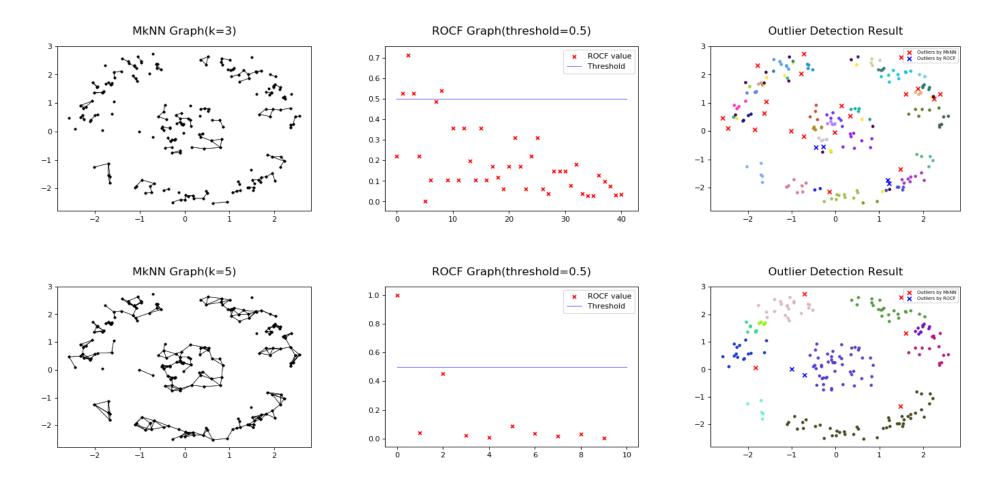
MkNN(Mutual *k*-Nearest Neighbors)

- 기존에 구현을 계획한 Hu, Zhen. (2012)의 MkNN 방법론은 구현의 어려움과 함께 일반적인 outlier detection에 적용되기 어렵다는 한계가 있다.
- 보다 널리 이용되며 일반화하기 용이한 Maier et al. (2009)의 MkNN 방법론에 기초해, ROCF를 적용하기 전 rough clustering 및 scatter outlier detection 을 진행했다.
- 두 data point에 있어, data j가 data i의 k-distance 범위에 있고 data i 또한 data j의 k-distance 범위에 있으면, 두 data point가 연결된 것으로 정의한다. 각 data point의 neighbors는 k 개로 제한된다.
- 각 data point는 mutual한 관계를 가지고 연결되므로, clustering 결과는 그래프로도 표현될 수 있다.

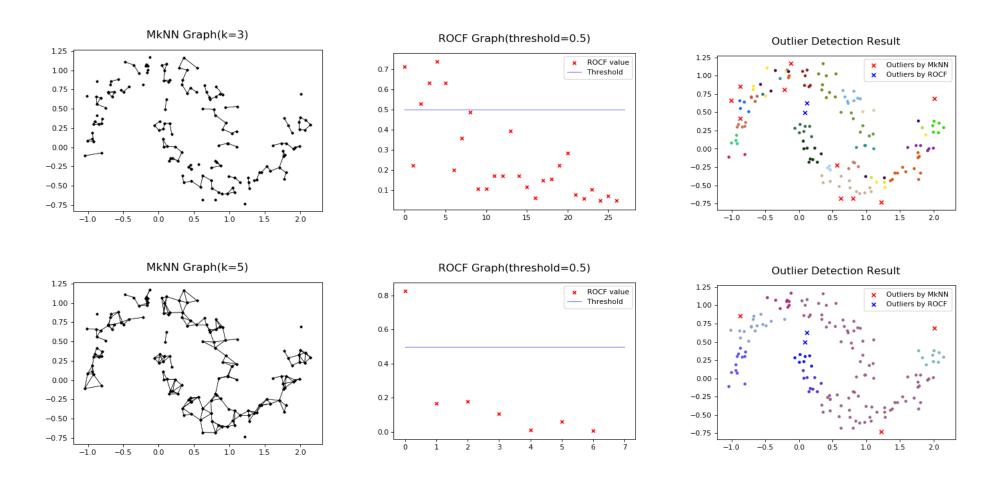
• mutual k-nearest-neighbor graph $G_{\text{mut}}(n, k)$: X_i and X_j are connected if $X_i \in \text{kNN}(X_j)$ and $X_j \in \text{kNN}(X_i)$.



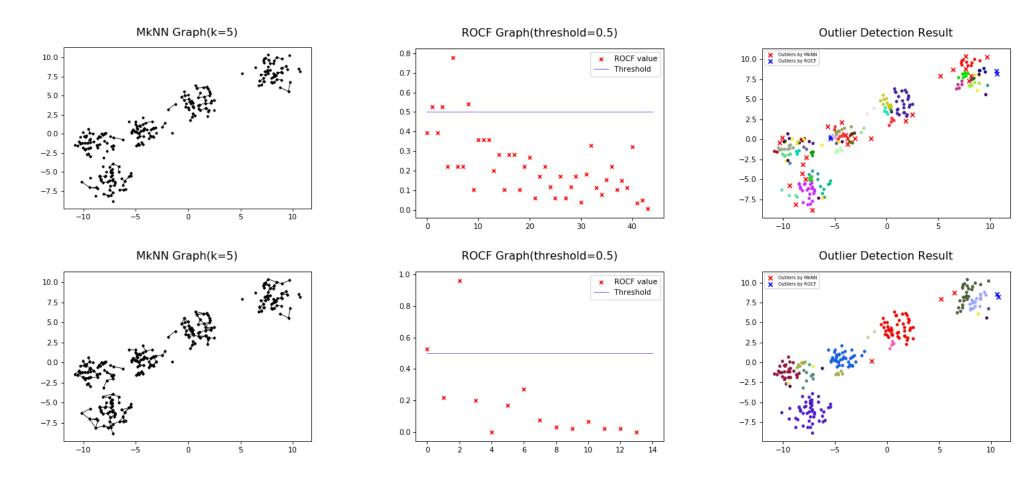
Ring dataset



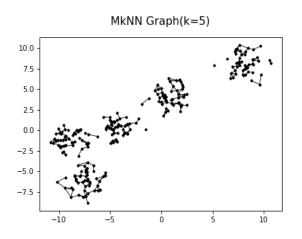
Moon dataset(n_samples= 150, noise= 0.1)

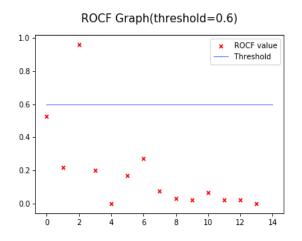


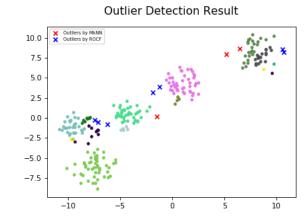
Blobs dataset(n_samples=250, centers=5, n_features=2, random_state=3)



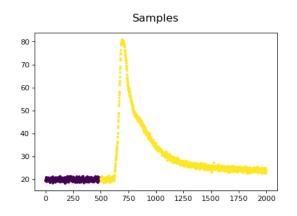
Blobs dataset(n_samples=250, centers=5, n_features=2, random_state=3)

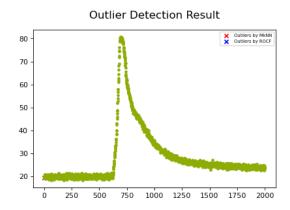






- Fire dataset
- Outliers are not detected.



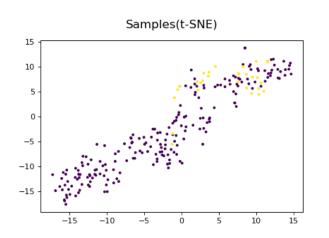


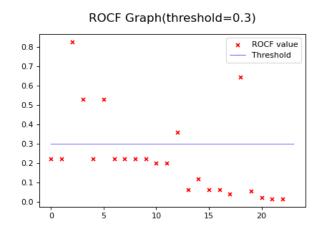
Vertebral dataset(240 data points, 5 features, 30 outliers)

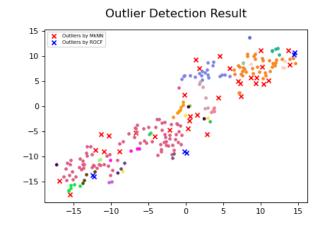
■ k= 4, ROCF threshold= 0.3

Precision: 0.23

Recall: 0.18





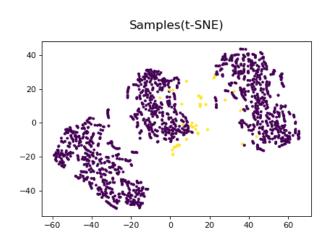


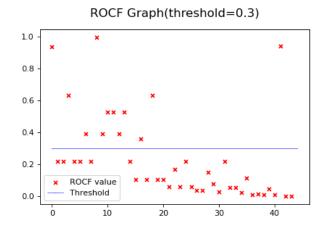
Vowels dataset(1456 data points, 12 features, 50 outliers)

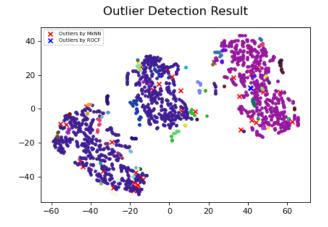
■ k= 4, ROCF threshold= 0.3

■ Precision: 0.2

Recall: 0.28







References

- Maier, Hein, Luxburg. (2009). Optimal construction of k-nearest-neighbor graphs for identifying noisy clusters. Theoretical Computer Science, Volume 410, Issue 19, pp1749-1764.
- Huang et al. (2017). A novel outlier cluster detection algorithm without top-n parameter. Knowledge-Based Systems, Vol.121. pp32-40.