SE ZG522: Big Data Systems

15 Stream Data Procsessing

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May 14, 2022 ONLINE (WILP @ BITS-Pilani Jan-May 2022)

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Frequent pattern mining over data streams

- Applications involves retail market data analysis, network monitoring, web usage mining, and stock market prediction.
- Using sliding window
- Efficiently remove the obsolete, old stream data
- Compact Pattern Stream tree (CPS-tree) [1]
- Highly compact frequency-descending tree structure at runtime
- Efficient in terms of memory and time complexity
- Pane and window
- Insertion and restructuring

[1] Tanbeer, Syed Khairuzzaman and Ahmed, Chowdhury Farhan and Jeong, Byeong-Soo and Lee, Young-Koo, "Sliding window-based frequent pattern mining over data streams", in Information sciences, 179(22) pages 3843–3865, Elsevier, 2009

Clustering over Evolving Data Stream (DenStream)

Clustering over Evolving Data Stream

With limited memory and one-pass constraint one want to determine arbitrary number of clusters of arbitrary shape by efficiently handling outliers.

Use DenStream [2]

- Damped window model: Weights with time t are $f(t) = 2^{-\lambda.t}$. (other models landmark and sliding window)
- core-micro-cluster, potential-micro-cluster and outlier-micro-cluster structures
- Guarantees the precision of the weights of the micro-clusters

[2] Cao, Feng and Ester, Martin and Qian, Weining and Zhou, Aoying, "Density-Based Clustering over an Evolving Data Stream with Noise.", in International Conference on Data Mining, pages 328–339, vol 6, SIAM, 2006

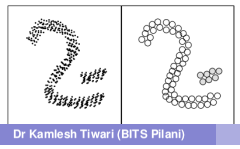
Clustering over Evolving Data Stream

- Beside limited memory and one-pass constraints, we require
  - No assumption on the number of clusters,
  - Discovery of clusters with arbitrary shape and
  - Ability to handle outliers
- DenStream [3], is a new approach for discovering clusters in an evolving data stream.
- Uses core-micro-cluster to summarize the clusters
- Along with potential core-micro-cluster and outlier micro-cluster structures
- Designed a pruning strategy that guarantees the precision of the weights of the micro-clusters
- User damped window model. Weights with time t are $f(t) = 2^{-\lambda.t}$. (other models landmark and sliding window)

[3] Cao, Feng and Ester, Martin and Qian, Weining and Zhou, Aoying, "Density-Based Clustering over an Evolving Data Stream with Noise.", in International Conference on Data Mining, pages 328–339, vol 6, SIAM, 2006

Clustering over Evolving Data Stream

- **Definition (core object)** It is an object in whose ϵ neighborhood the overall weight of data points is at least μ
- **Definition (density-area)** A density area is defined as the union of the ϵ neighborhoods of core objects
- **Definition (core-micro-cluster)** At time t it is defined as CMC(w, c, r) for a group of close points $p_{i_1}, p_{i_2}, ..., p_{i_n}$ with time stamp $T_{i_1}, T_{i_2}, ..., T_{i_n}$. $w = \sum_{j=1}^{n} f(t - T_{i_j})$, $w \geq \mu$ is the weight. $c = \frac{\sum_{j=1}^{n} f(t-T_{i_j})p_{i_j}}{w}$ is the center, $r = \frac{\sum_{j=1}^{n} f(t-T_{i_j})dist(p_{i_j},c)}{w}$, $r \leq \epsilon$ is the radius, where $dist(p_{i_j}, c)$ denotes the Euclidean distance between point p_{i_j} and center c
- When a clustering request arrives, each c-micro-cluster will be labeled to get the final result.



Clustering over Evolving Data Stream

Definition (potential-micro-cluster) A potential-micro-cluster (or p-micro-cluster) at time t for a group of close points $p_{i_1}, p_{i_2}, ..., p_{i_n}$ with time stamp $T_{i_1}, T_{i_2}, ..., T_{i_n}$ is defined as $\{\overline{CF^1}, \overline{CF^2}, w\}$. $w = \sum_{j=1}^{n} f(t - T_{i_j})$, $w \geq \beta\mu$ is the weight. β, $0 < \beta \leq 1$, is the parameter to determine the threshold of outlier relative to c-micro-clusters. $\overline{CF^1} = \sum_{j=1}^{n} f(t - T_{i_j})p_{i_j}$ is the weighted linear sum of the points. $\overline{CF^2} = \sum_{j=1}^{n} f(t - T_{i_j})p_{i_j}^2$ is the weighted squired linear sum of the points. Centre of p-micro-cluster is $c = \frac{\overline{CF^1}}{w}$ and the radius of a p-micro-cluster $r = \sqrt{\frac{\overline{CF^2}}{w} + (\frac{\overline{CF^1}}{w})^2}$, $r \leq \epsilon$

Clustering over Evolving Data Stream

Definition (outlier-micro-cluster) An outlier-micro-cluster (or o-micro-cluster) at time t for a group of close points $p_{i_1}, p_{i_2}, ..., p_{i_n}$ with time stamp $T_{i_1}, T_{i_2}, ..., T_{i_n}$ is defined as $\{\overline{CF^1}, \overline{CF^2}, w, t_0\}$. The definition of w, $\overline{CF^1}$, $\overline{CF^2}$ center and radius are the same as p-micro-cluster. $t_0 = T_{i_1}$, denotes the creation time of o-micro-cluster which is used to define the life span of o-micro-cluster. However $w < \beta\mu$.

Note: p-micro-cluster and o-micro-cluster can be maintained incremently.

Clustering Algorithm has two parts:

- Online part of micro-cluster maintenance
- Offline part of generation of final clusters, on demand of user

Merging of P

p-micro-clusters and o-micro-clusters are maintained in an online way.

Algorithm 1 Merging (p)

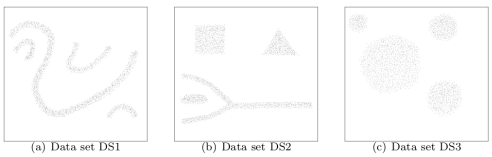
```
Try to merge p into its nearest p-micro-cluster c_p;
if r_p (the new radius of c_p) ≤ ε then
    Merge p into c_p;
else
    Try to merge p into its nearest o-micro-cluster c_o;
    if r_o (the new radius of c_o) ≤ ε then
        Merge p into c_o;
        if w (the new weight of c_o) > βμ then
            Remove c_o from outlier-buffer and create a
            new p-micro-cluster by c_o;
        end if
    else
        Create a new o-micro-cluster by p and insert it
        into the outlier-buffer;
    end if
end if
```


DenStream Algorithm

Algorithm 2 DenStream (DS, ϵ, β, μ, λ)

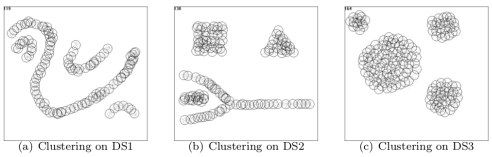
```
T_p = ⌈(1/λ) log(βμ/(βμ−1))⌉;
Get the next point p at current time t from data
stream DS;
Merging(p);
if (t mod T_p)=0 then
    for each p-micro-cluster c_p do
        if w_p(the weight of c_p)< βμ then
            Delete c_p;
        end if
    end for
    for each o-micro-cluster c_o do
        ξ = (2^{−λ(t−t_o+T_p)} − 1)/(2^{−λT_p} − 1);
        if w_o(the weight of c_o)< ξ then
            Delete c_o;
        end if
    end for
end if
if a clustering request arrives then
    Generating clusters;
end if
```


Performance



(a) Data set DS1 (b) Data set DS2 (c) Data set DS3

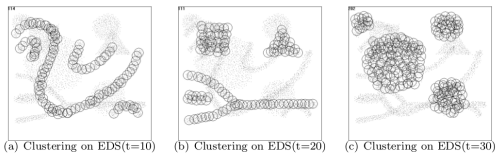
Figure 4: Synthetic data sets



(a) Clustering on DS1 (b) Clustering on DS2 (c) Clustering on DS3

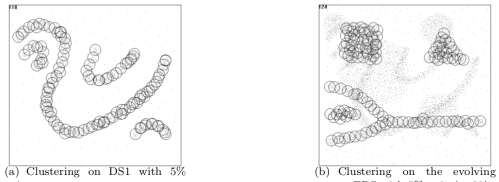
Figure 5: Clustering on DS1, DS2 and DS3

Performance



(a) Clustering on EDS(t=10) (b) Clustering on EDS(t=20) (c) Clustering on EDS(t=30)

Figure 6: Clustering on the evolving data stream EDS



(a) Clustering on DS1 with 5% noise (b) Clustering on the evolving stream EDS with 5% noise(t=20)

Figure 7: Clustering on data streams with noise

Performance

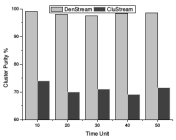


Figure 8: Clustering quality(EDS data stream, horizon=2, stream speed=2000)

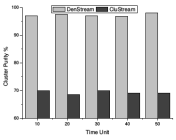


Figure 9: Clustering quality(EDS data stream, horizon=10, stream speed=1000)

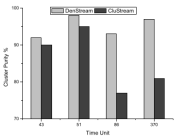


Figure 10: Clustering quality(Network Intrusion data set, horizon=1, stream speed=1000)

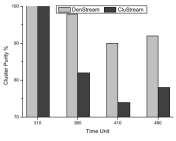


Figure 11: Clustering quality(Network Intrusion data set, horizon=5, stream speed=1000)

Performance

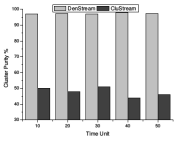


Figure 12: Clustering quality(EDS data stream with 1% noise, horizon=2, stream speed=2000)

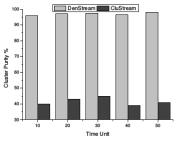


Figure 13: Clustering quality(EDS data stream with 5% noise, horizon=10, stream speed=1000)

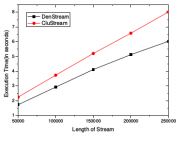


Figure 14: Execution time vs. length of stream(Netw Intrusion data set)

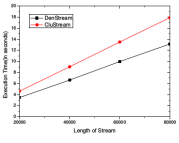


Figure 15: Execution time vs. length stream(Charitable Donation data set)

Performance

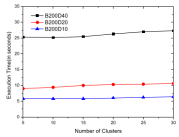


Figure 16: Execution time vs. number of clusters

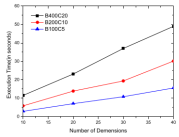


Figure 17: Execution time vs. dimensionality

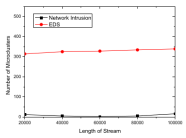


Figure 18: Memory usage

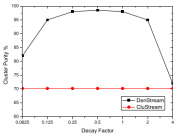


Figure 19: Clustering quality vs. decay factor λ

Thank You!

Thank you very much for your attention!