Precision variable anonymization method supporting transprecision computing
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Precision variable anonymization method supporting transprecision computing

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The era of Big data

- Many IoT equipment are built in our daily life and gathers various data
  - Smart meters
    - Automatically gathers power consumption data in every fixed time interval
    - The conventional power meters are changed into smart meters[1]

The secondary use of the Big data is gaining attention

- Power consumption data
  - Demand response service[2]
    - Gives out message to power users to save energy and cut the peak of the power consumption
Objective

- Issues in the secondary use of Big data
  - Privacy issue
    - Private information is invaded
    - Power consumption data
      - Violates one’s lifestyle
    - Anonymization gaining attention for this issue
  - Energy issues for computing the data
    - Many services are invented due to the growth of the data
      - More service will enlarge the energy of the server
    - Transprecision computing is gaining attention for solving the issue

A demand for a new method, which preserves the privacy and lowers power consumption
Related works (1/2)

- **k-anonymity**
  - One privacy standard for anonymization
  - At least k number of tuples observed inside a q-block.
- **Identifier**
  - An attribute, which can detect a person individually
  - Deleted
- **Quasi-identifier**
  - An attribute, which can detect a person by combining it with other attributes
  - Anonymized
- **Sensitive attribute**
  - An attribute necessary for the analyst
  - Preserved

<table>
<thead>
<tr>
<th>Identifier</th>
<th>Quasi-identifier</th>
<th>Sensitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Gender</td>
<td>Age</td>
</tr>
<tr>
<td>Mike</td>
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<td>25</td>
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<tr>
<td>Matthew</td>
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<td>28</td>
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<tr>
<td>Andy</td>
<td>Male</td>
<td>29</td>
</tr>
</tbody>
</table>

$k = 3$
Related works (2/2)

- Transprecision computing
  - One method of approximate computing
  - Precision variable computation
    - Enables to compute in the chosen precision
  - Open transprecision computing project (Oprecomp)
    - A project in the EU, which focus on the transprecision
      - CEA, IBM Zurich
  - By lowering the precision of the computing, the energy consumption of the computation will be reduced
    - 8~20% electricity reduction
  - Applications are simulated by using transprecision
    - k-nn, Mandelbrot-set
Connection

- Issues in the research fields
  - Anonymization
    - No consideration of energy in the computation
  - Transprecision computing
    - No consideration about privacy

- Connection
  - Transprecision computing
    - Accepts the computation error to reduce energy for computation
  - Anonymization
    - Accepts the error to preserve privacy

A new privacy preserving method that fits the feature of the transprecision computing should be made.
Proposed method

- Precision variable anonymization method supporting transprecision computing
  - The method has the parameters for level of anonymization and level of precision
    - Gives a trade-off between information loss and computational cost

- Steps
  - Use k-member clustering to group the data
  - Anonymize the exponent bit
  - Reduce the mantissa bit to chosen precision and anonymize the mantissa bit
K-member clustering

- K-member clustering
  - Clusters the data to maintain at least k data values in each cluster
- Steps
  1. Choose the point furthest from a randomly chosen point.
  2. Gather k data values nearest from the point chosen in Step 1.
  3. Choose the furthest point from the center of the cluster and repeat Step 2.
  4. Execute Step 3 repeatedly until there are less than $k - 1$ non-clustered points.
  5. Add each left data value to the nearest cluster
Anonymize the exponent bit

- **Exponent bits**
  - Change the exponent bit into the most appeared exponent in the cluster
  - If the exponent is larger than before change the mantissa to 0 and if smaller than before change the mantissa to 1

<table>
<thead>
<tr>
<th>value</th>
<th>sign</th>
<th>exponent</th>
<th>mantissa</th>
<th>cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>18.12</td>
<td>0</td>
<td>10000011</td>
<td>001…11000010</td>
<td>1</td>
</tr>
<tr>
<td>17.56</td>
<td>0</td>
<td>10000011</td>
<td>000…11100001</td>
<td>1</td>
</tr>
<tr>
<td>15.17</td>
<td>0</td>
<td>10000010</td>
<td>111…01010001</td>
<td>1</td>
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<td>1</td>
</tr>
<tr>
<td>16</td>
<td>0</td>
<td>10000011</td>
<td>000…00000000</td>
<td>1</td>
</tr>
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Reduce and anonymize mantissa bit

- Mantissa bits
  - Change least number of bits into 0 chosen according to the precision
  - Change the mantissa bit into the most appeared bit in the cluster

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<tr>
<td>16</td>
<td>0</td>
<td>10000011</td>
<td>000…00000000</td>
<td>1</td>
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</thead>
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<tr>
<td>17.227</td>
<td>0</td>
<td>10000011</td>
<td>000…11000000</td>
<td>1</td>
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The relationship between precision and MAPE

- Proposed method gave less precision with higher MAPE
- Less precision means less power consumption
  - Precision can be chosen by the anonymized data application
The relationship between $k$ and MAPE

- The MAPE of anonymization data only rises 0.14% compared to the conventional when the precision is 16bit.
- The larger the anonymity level is, the error by precision lowers.
Evaluation (3/3)

- Evaluation of demand and response service and power consumption

- Demand and response service
  - The service curtails top 15% power users to 85% of the maximum power consumption

- Energy consumption simulation of the computation
  - Number of floating operation multiplied by the size of mantissa
    - The number of operations means the cycles of instruction
    - The size of mantissa = the length of the critical path
The relationship between the error of service and the simulated energy consumption

- Energy consumption of the computation can be reduced to 15% when $k = 2$ and 18% when $k = 3,4$
Conclusion

- Showed a connection between anonymization and transprecision computing
- Made an anonymization method, which has parameter of $k$ and precision
  - Gave a trade-off between information loss and computational cost by deleting the mantissa bits
- Float32 anonymized data could be changed to float16 data with only 0.14% error increase
- Using this anonymization method the power consumption of the service can be reduced to 16% in average.
Thank you for your attention