Precision variable anonymization method supporting transprecision computing

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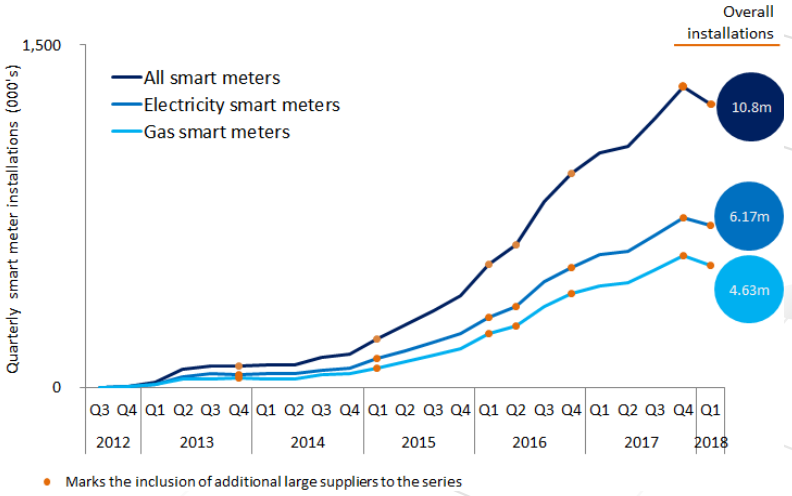
Background

- 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[3]
    - 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[4]
    - 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 analysist
    - Preserved

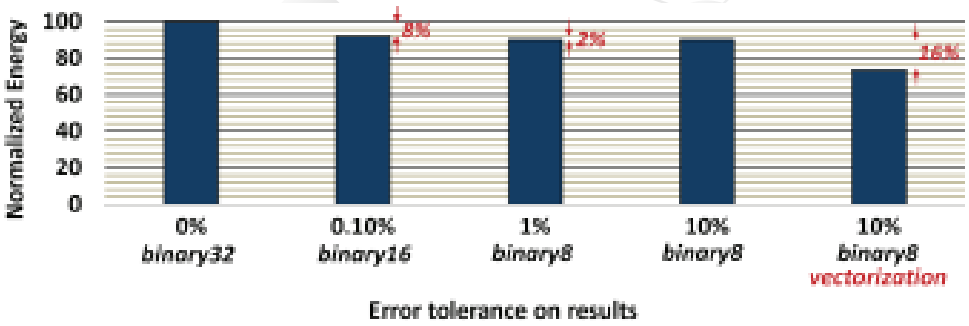
Identifier	Quasi-identifier		Sensitive
Name	Gender	Age	Disease
Mike	Male	25	Aids
Matthew	Male	28	Cancer
Andy	Male	29	Cancer

$k = 3$

Name	Gender	Age	Disease
Mike	Male	2*	Aids
Matthew	Male	2*	Cancer
Andy	Male	2*	Cancer

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

value	sign	exponent	mantissa	cluster
18.12	0	10000011	001…11000010	1
17.56	0	10000011	000…11100001	1
15.17	0	10000010	111…01010001	1

value	sign	exponent	mantissa	cluster
18.12	0	10000011	001…11000010	1
17.56	0	10000011	000…11100001	1
16	0	10000011	000…00000000	1

Reduce and anonymize mantissa bit

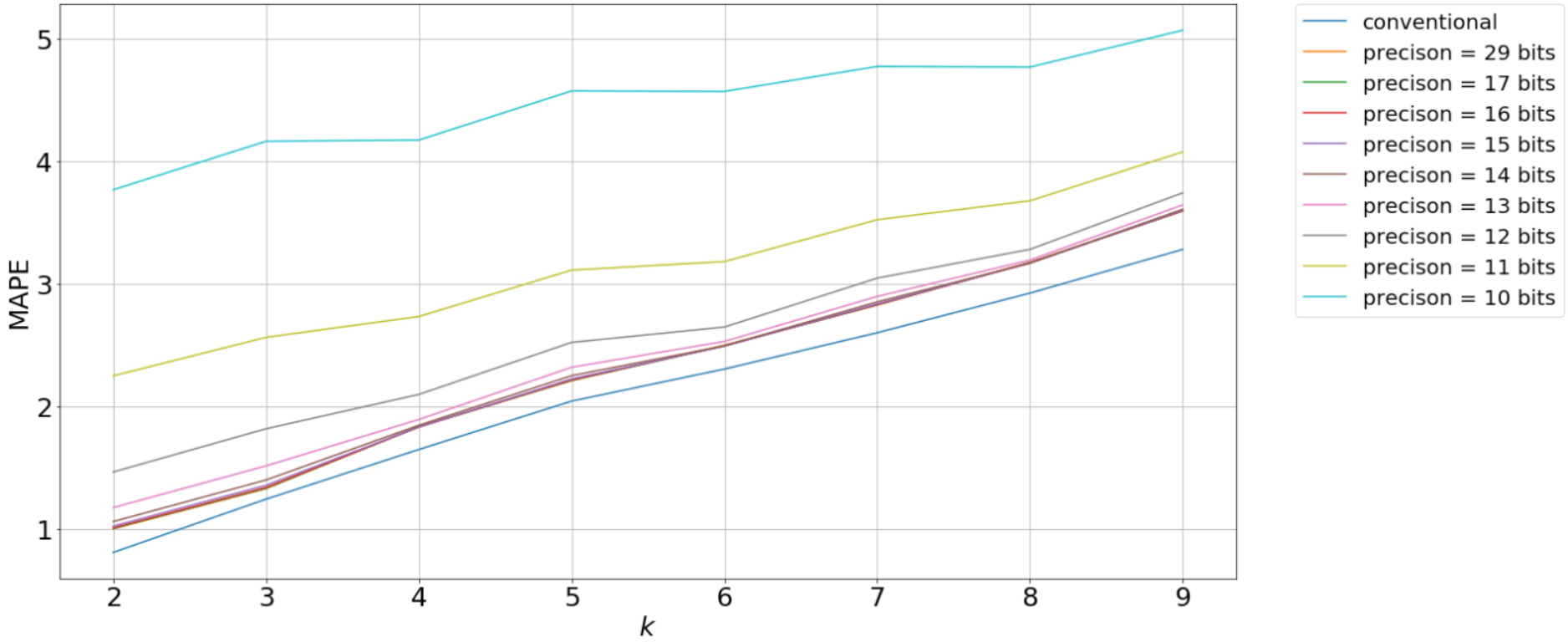
- Mantissa bits
  - Change least number of bits into 0 chosen according to the precision
  - Change the mantissa bit into the most appeared bit in the cluster

value	sign	exponent	mantissa	cluster
18.12	0	10000011	001…11000010	1
17.56	0	10000011	000…11100001	1
16	0	10000011	000…00000000	1

value	sign	exponent	mantissa	cluster
17.227	0	10000011	000…11000000	1
17.227	0	10000011	000…11000000	1
17.227	0	10000011	000…11000000	1

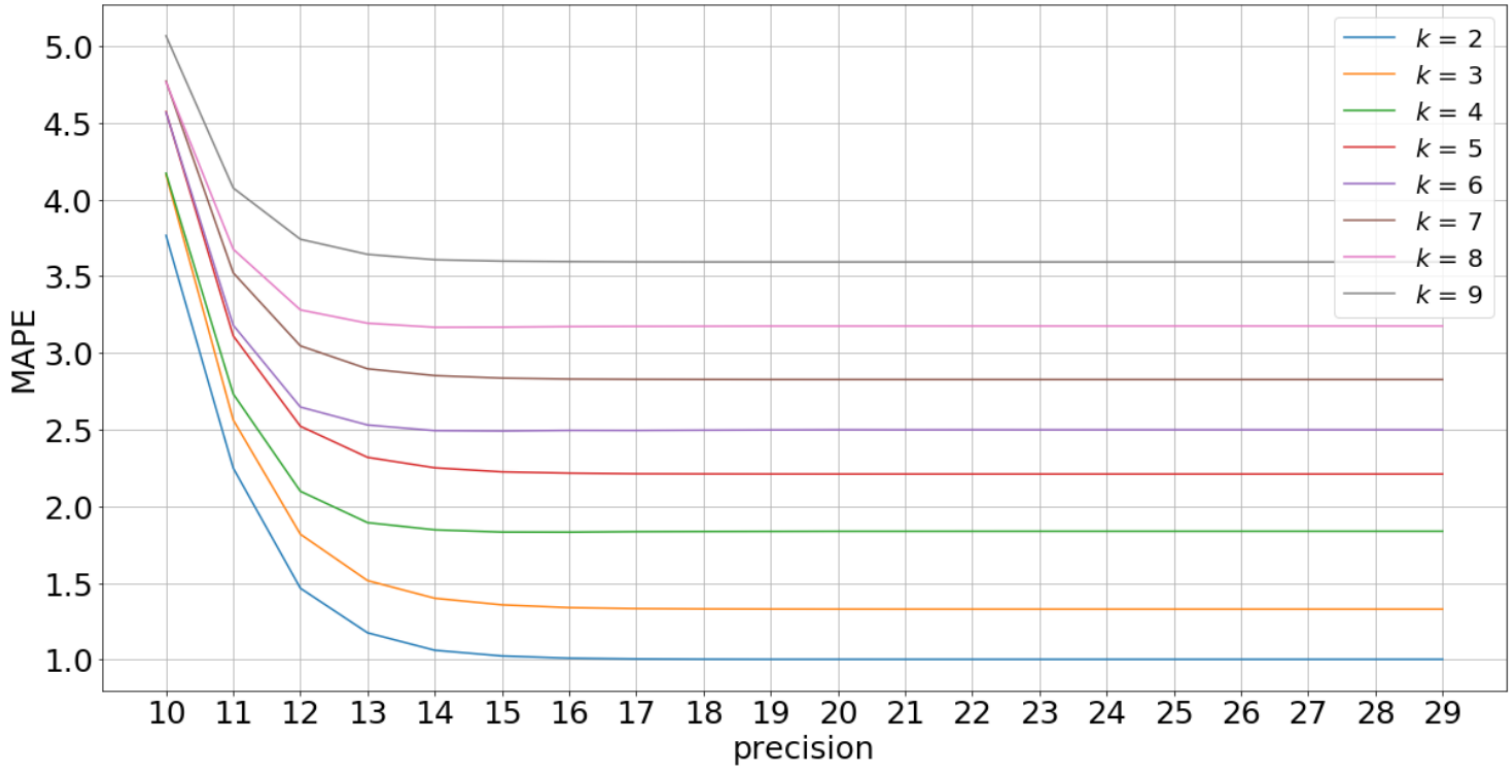
Evaluation(1/3)

- 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



Evaluation(2/3)

- 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



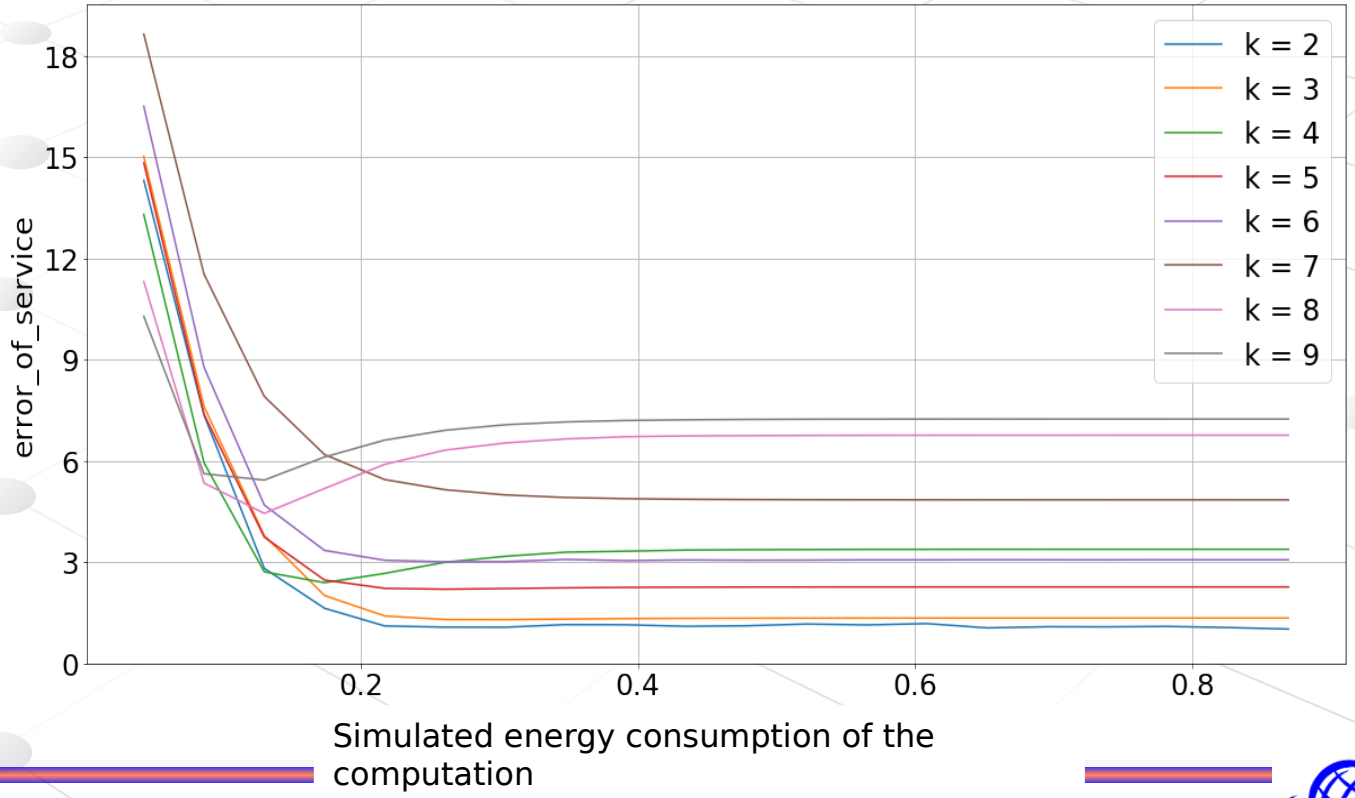
Evaluation(3/3)

- 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

Evaluation(3/3)

- 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