Federated Learning for Data Streams

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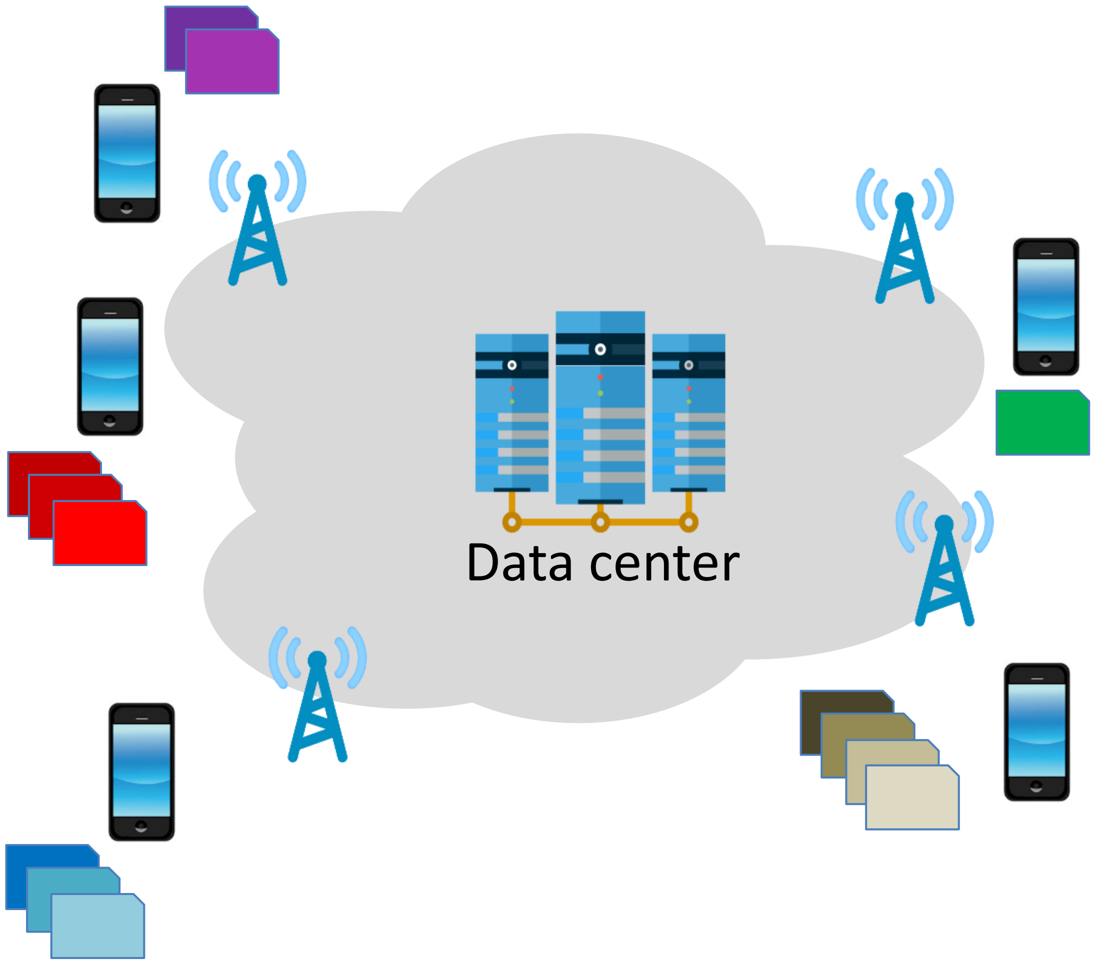
From Cloud Machine Learning to Federated Learning



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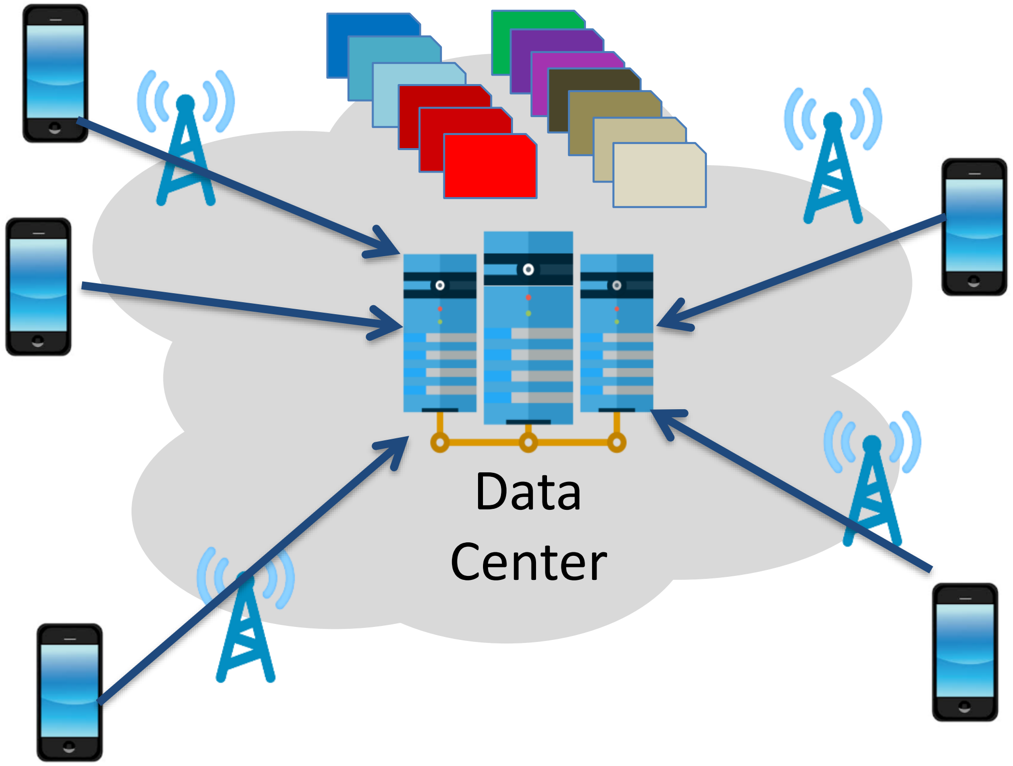

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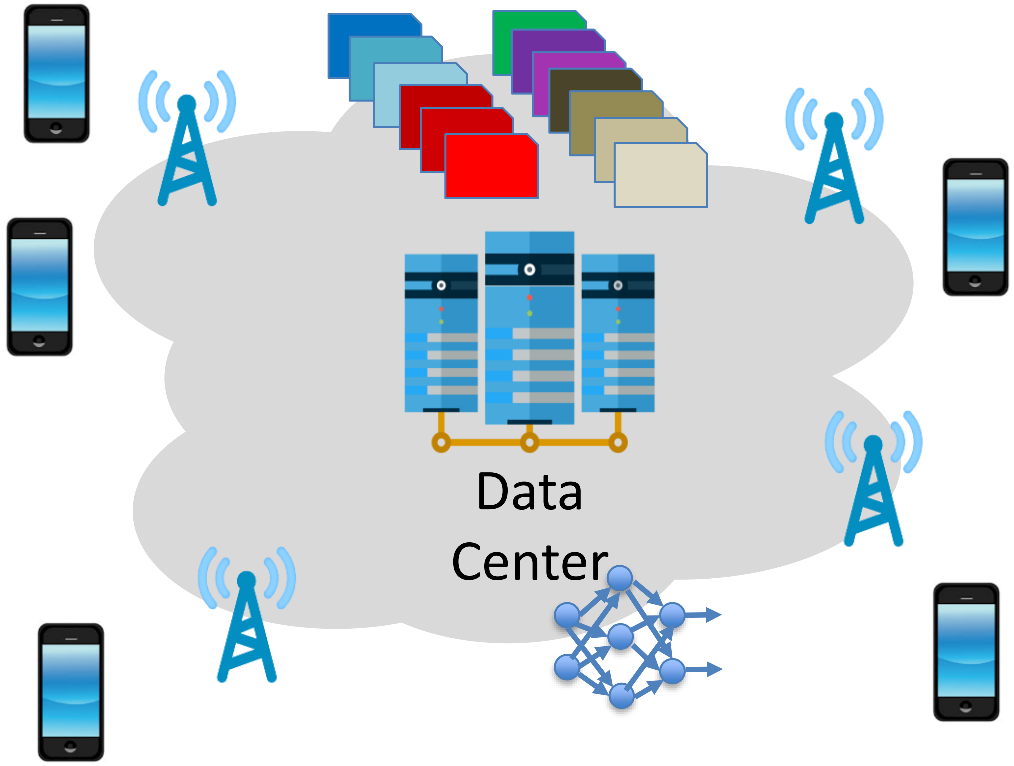

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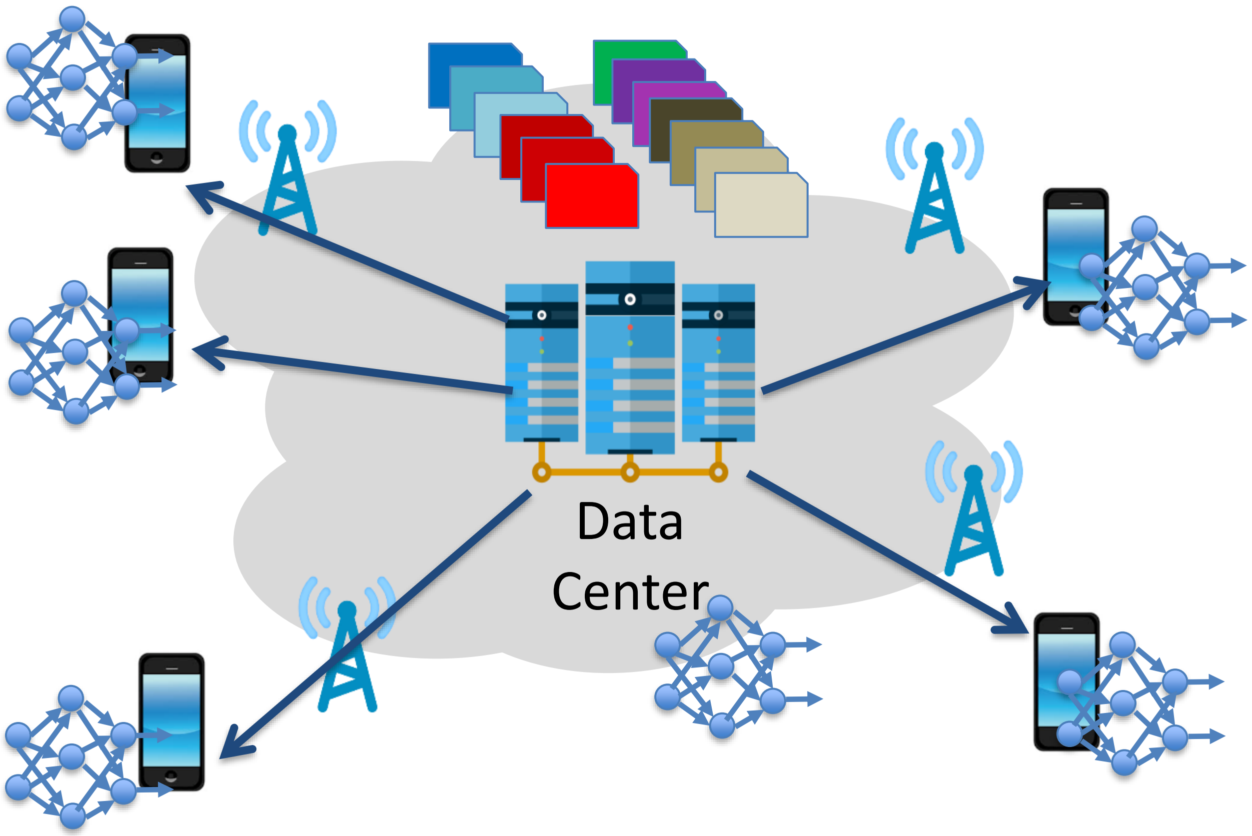

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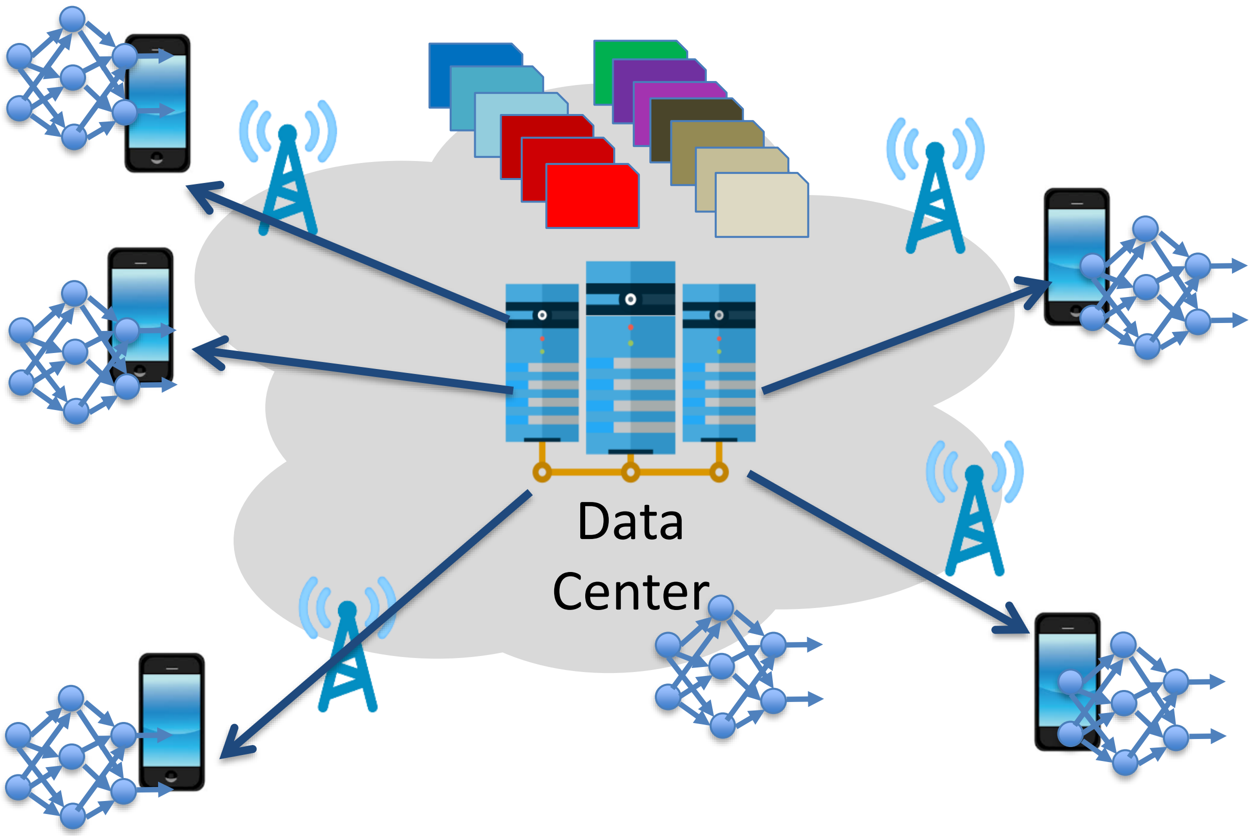

Limitations:

1. communication cost
2. privacy concerns

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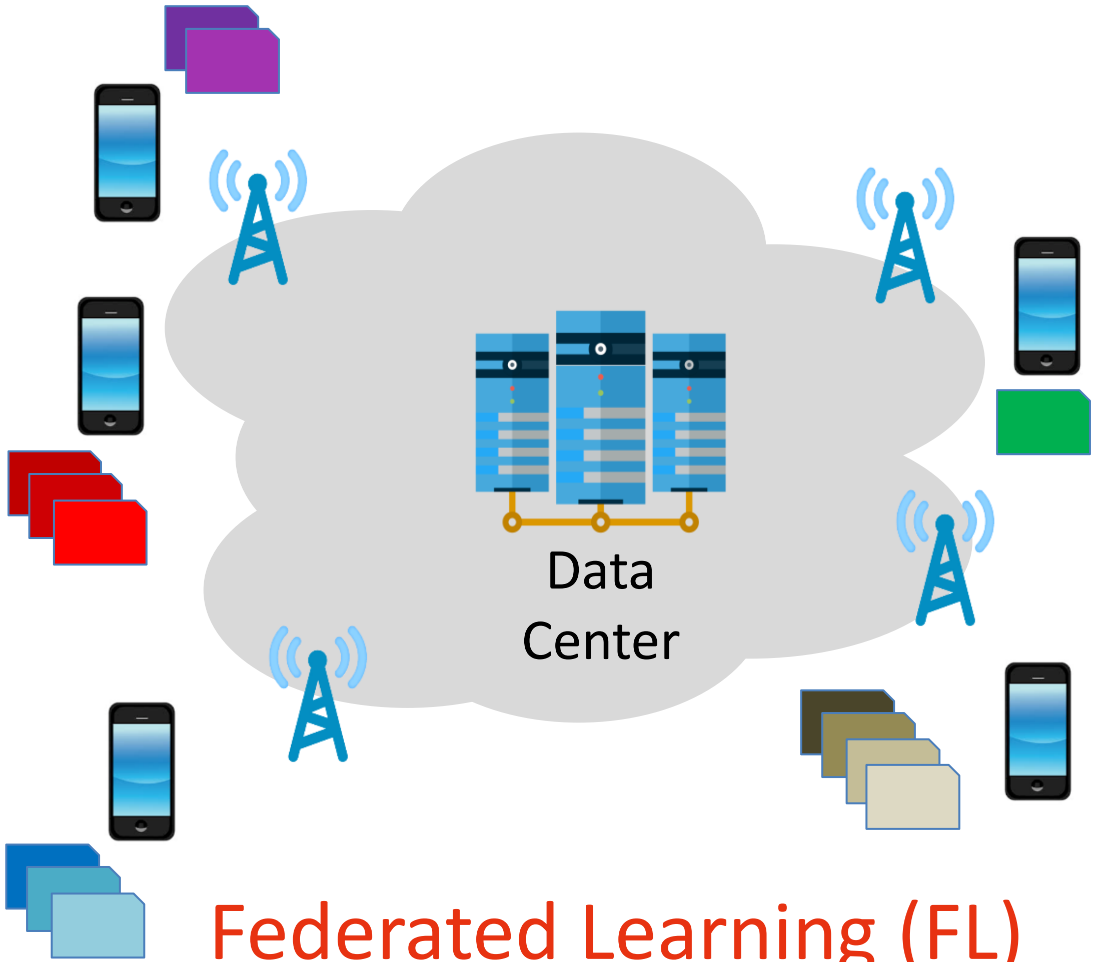

Federated Learning (FL)

Solution:

- keep clients' data on device
- only exchange model's parameters

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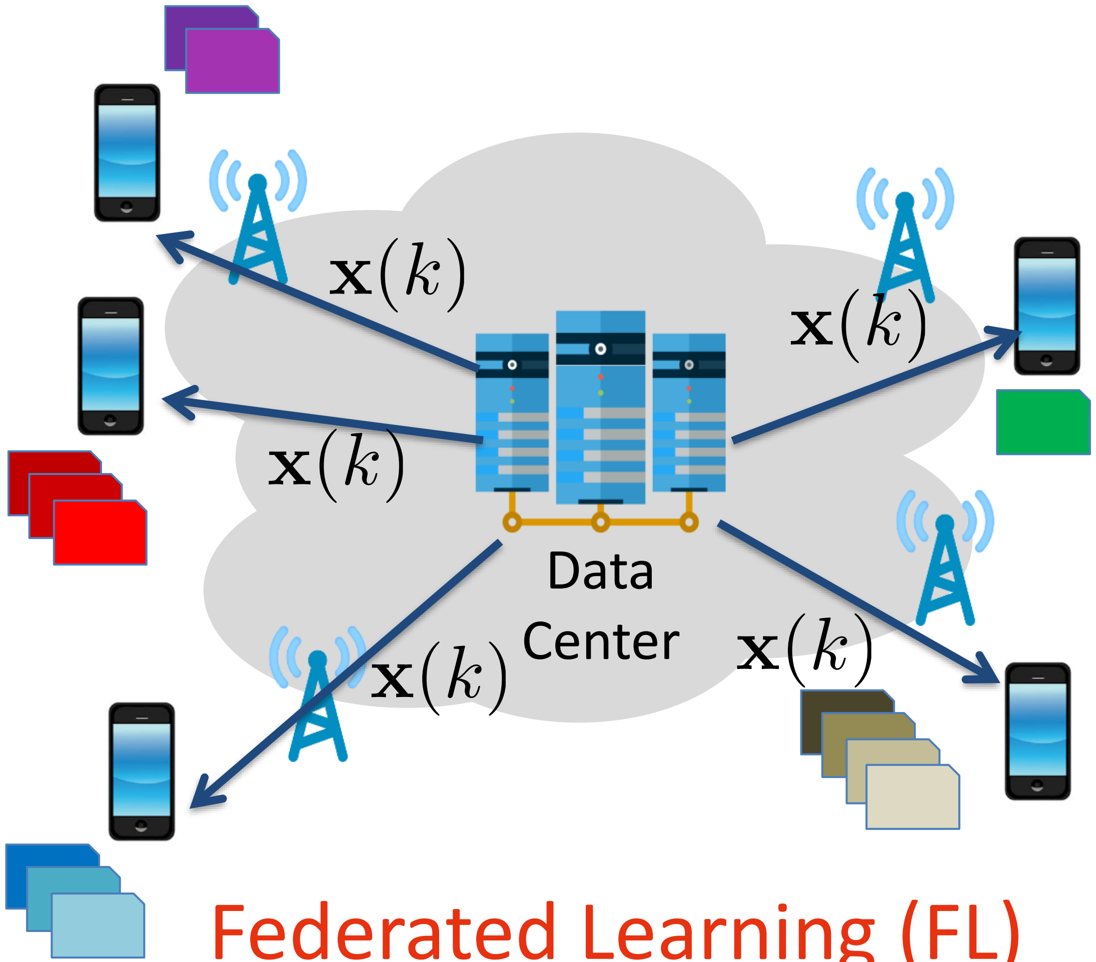

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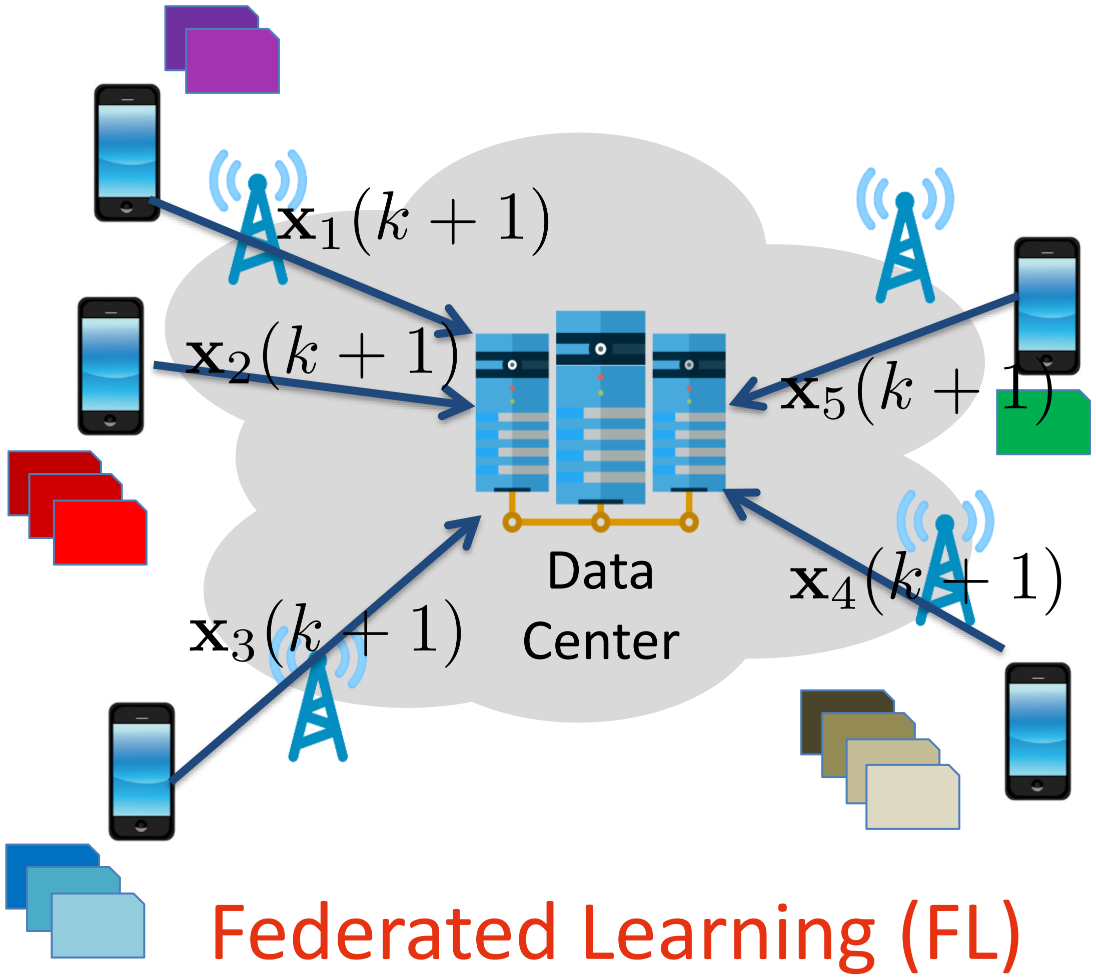

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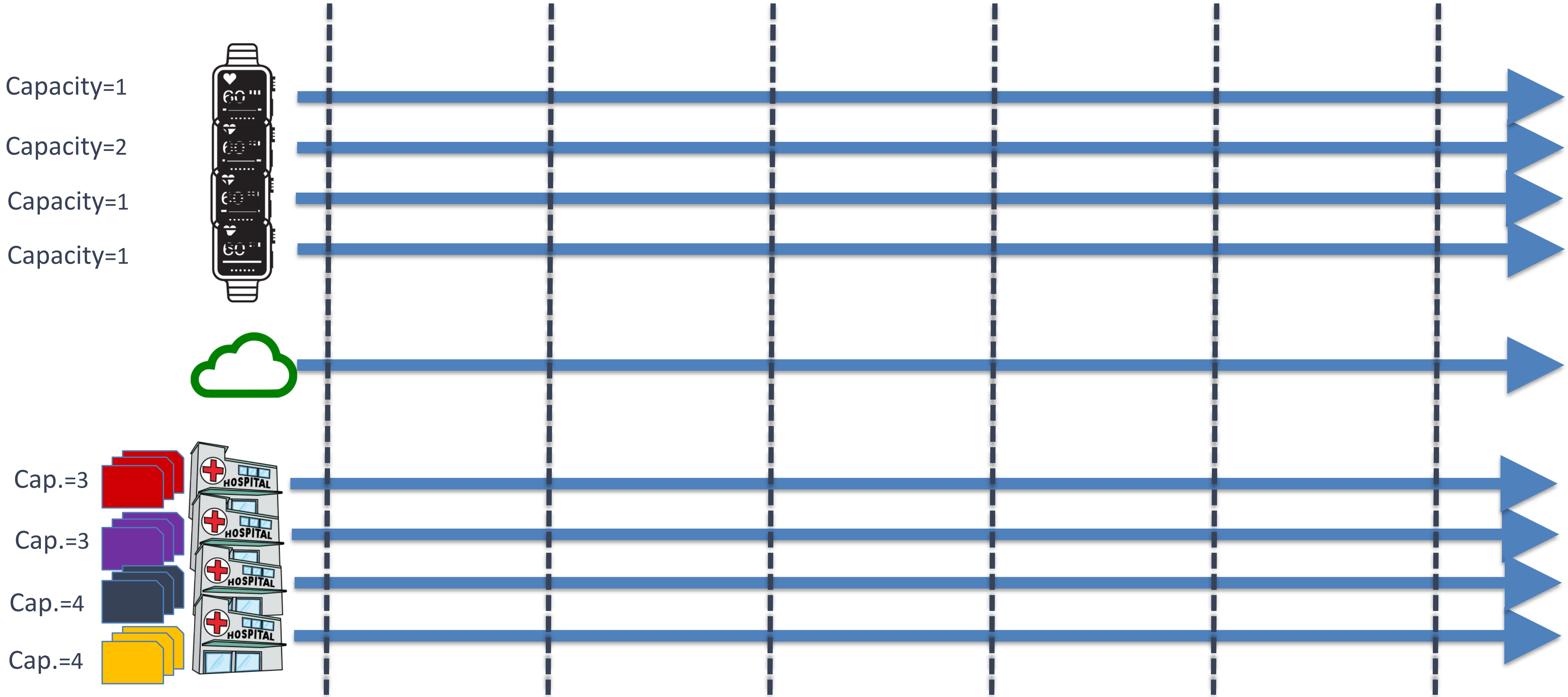

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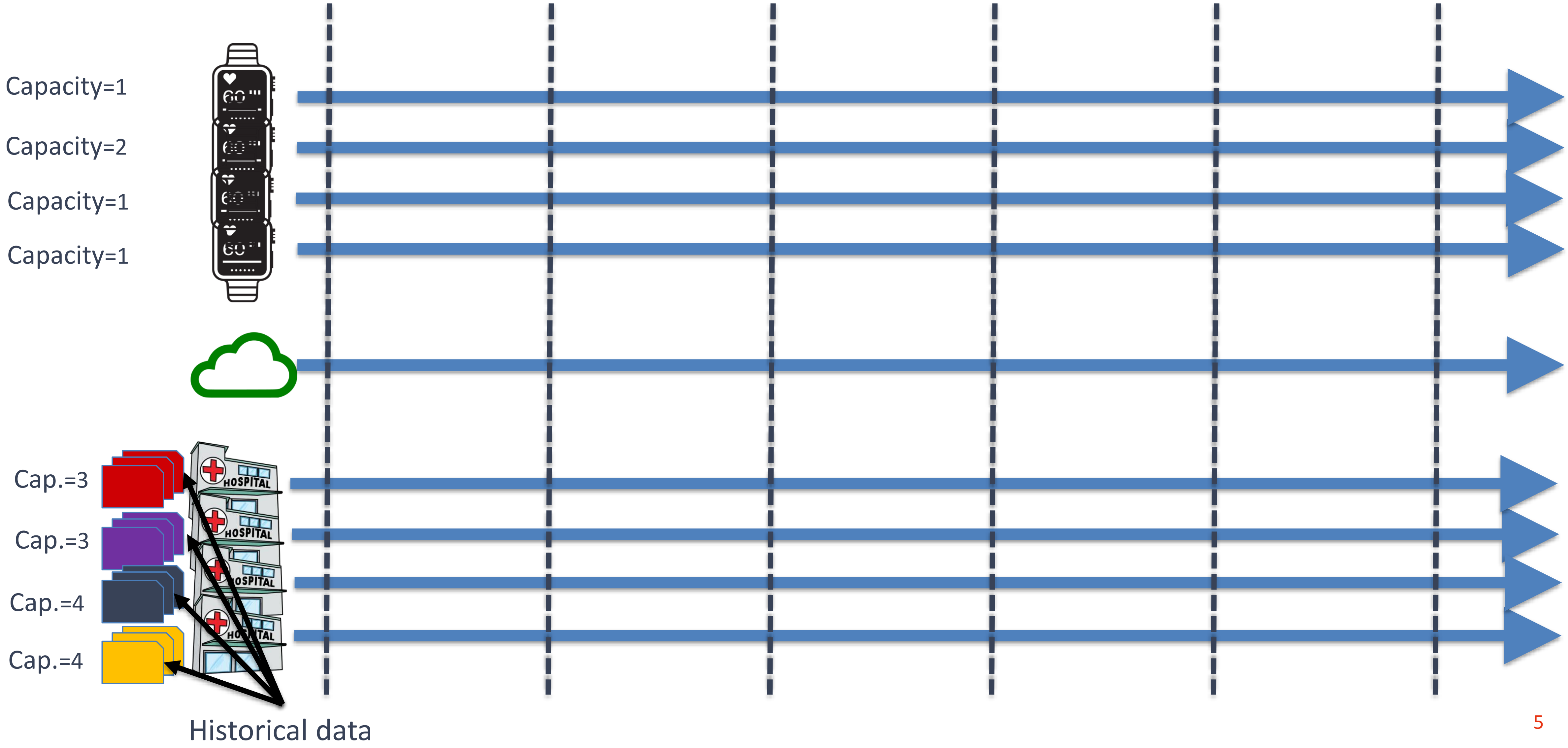

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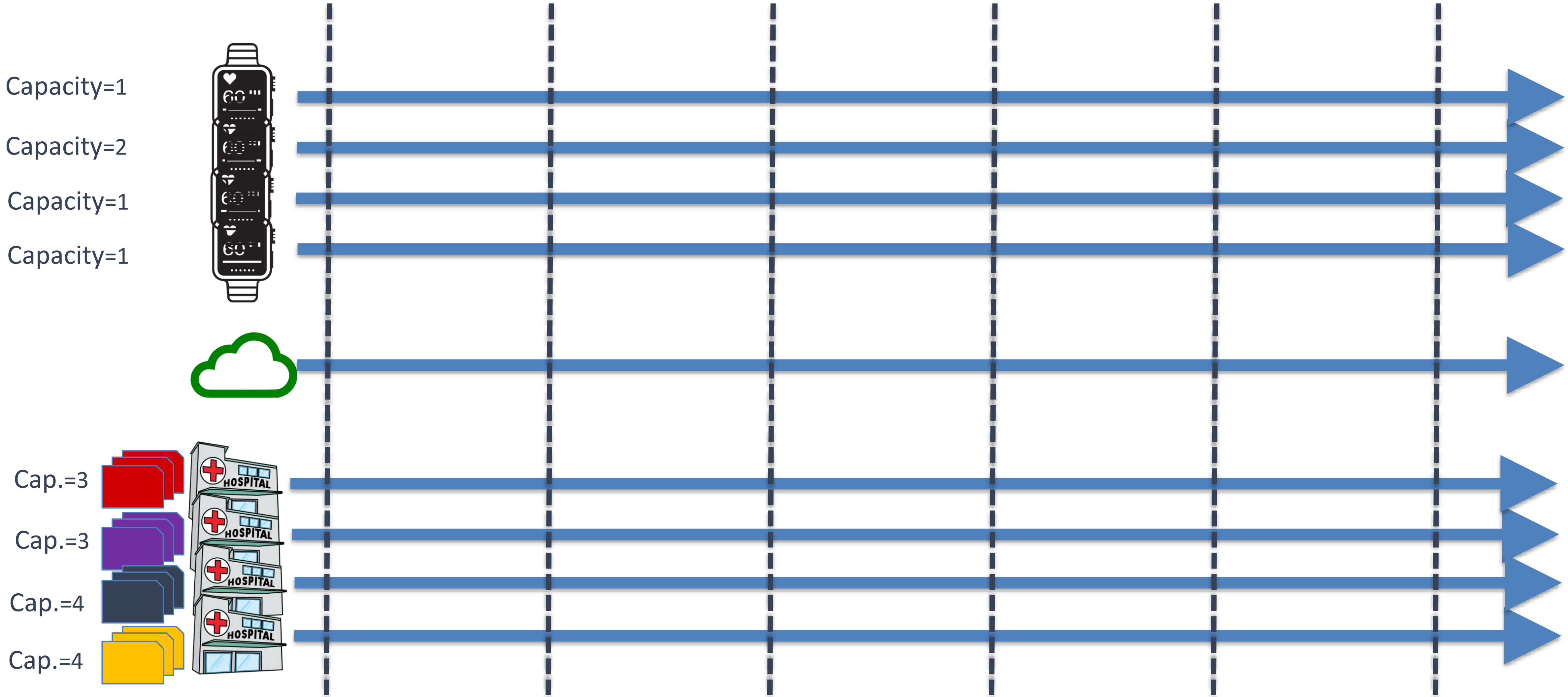

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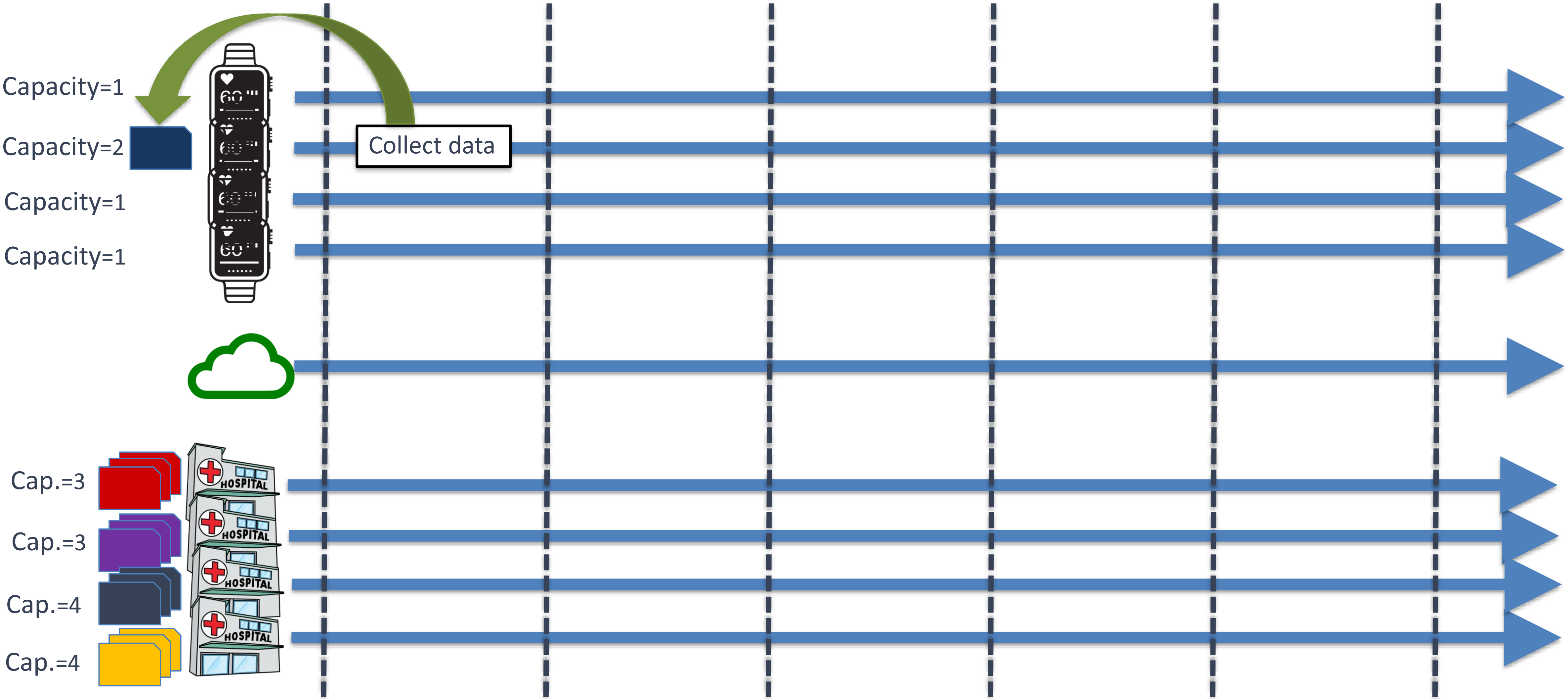

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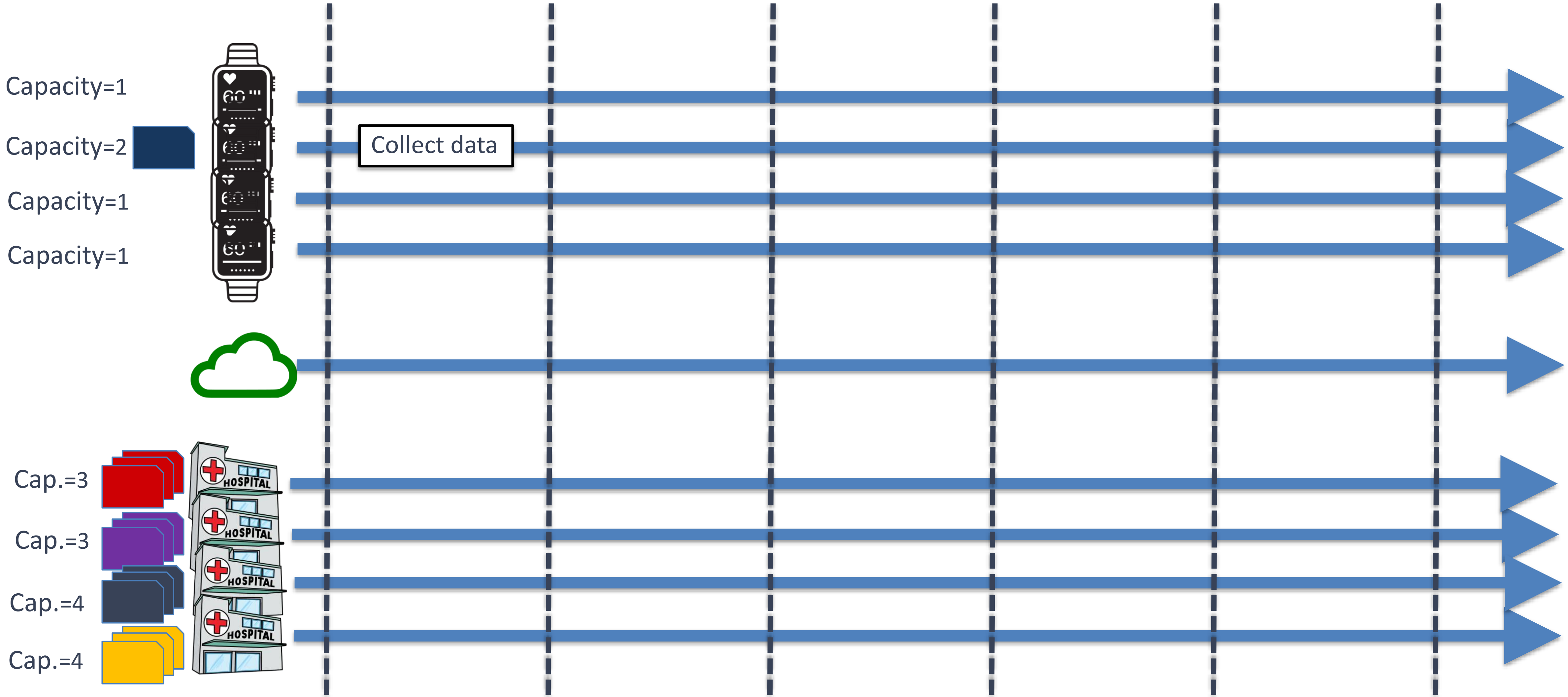

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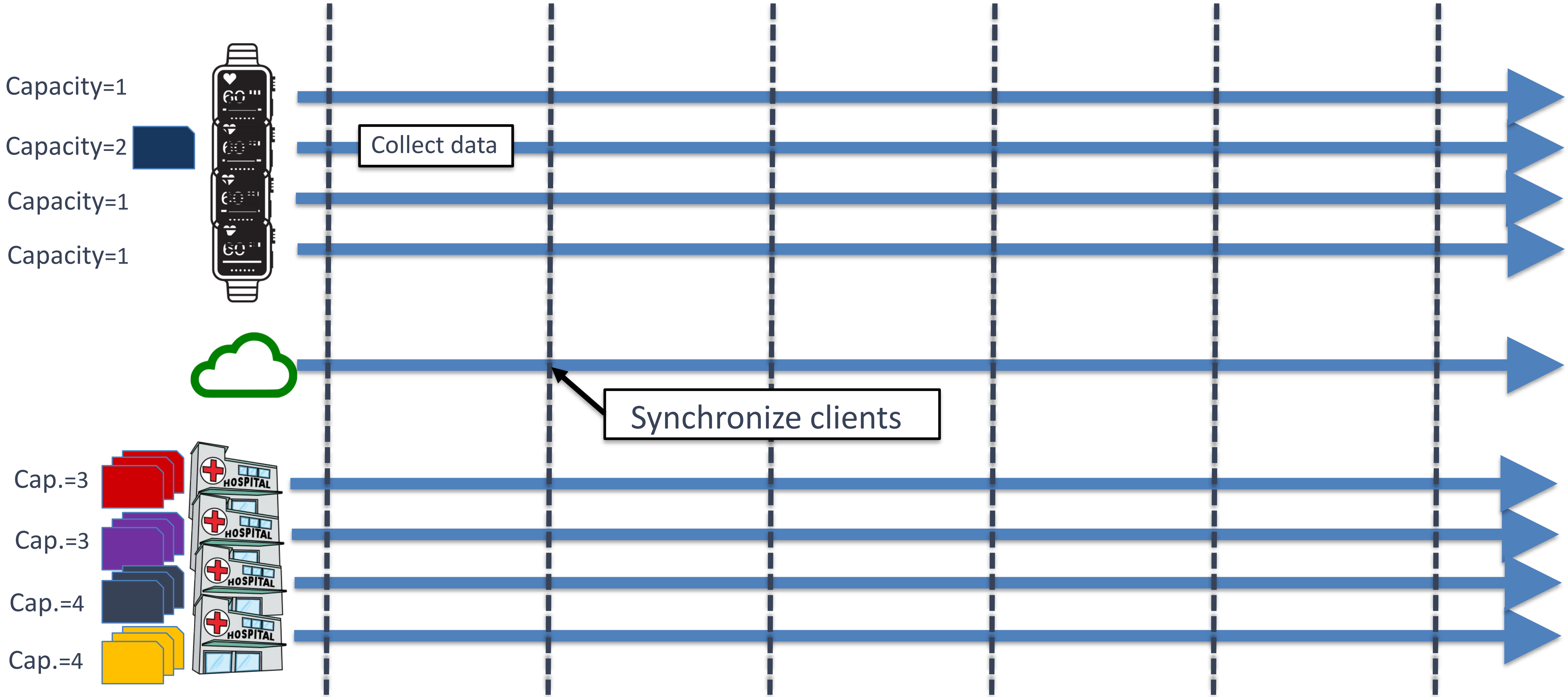

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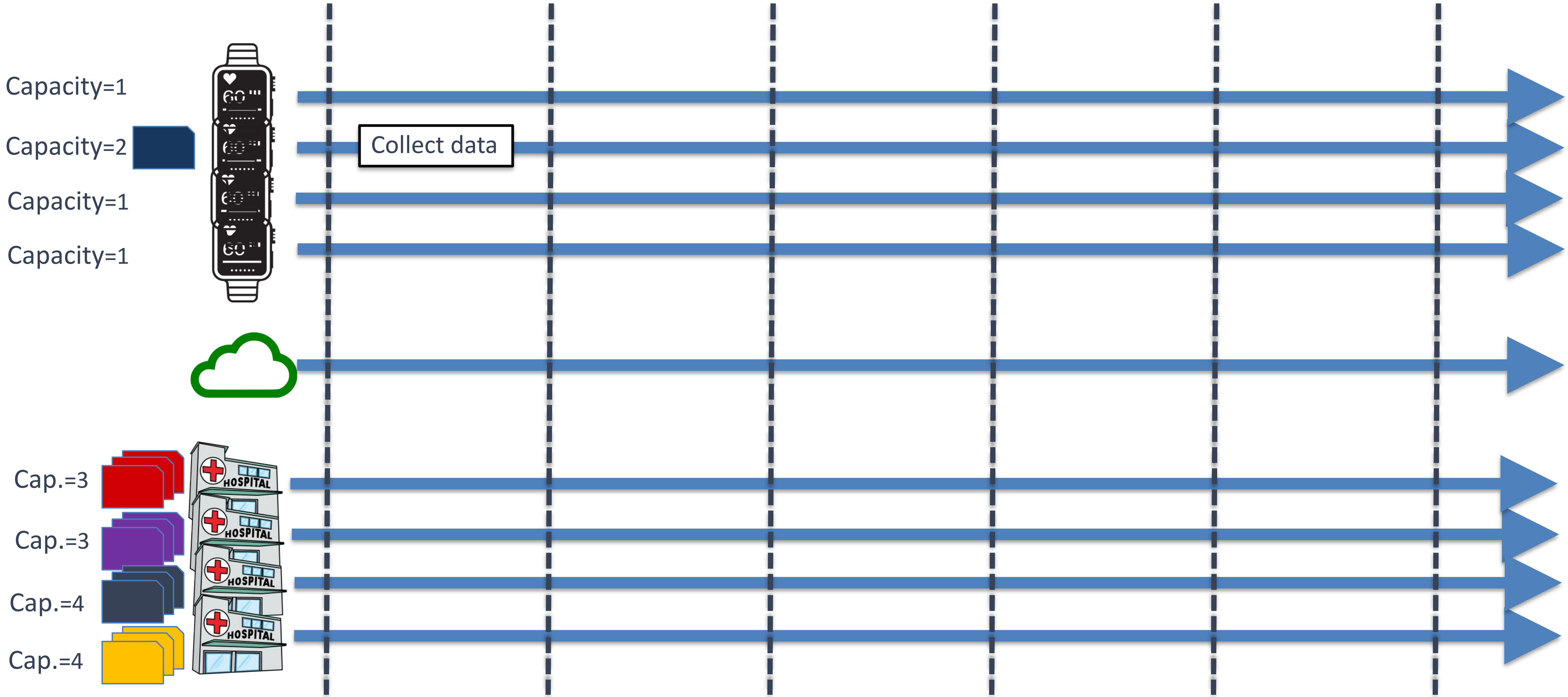

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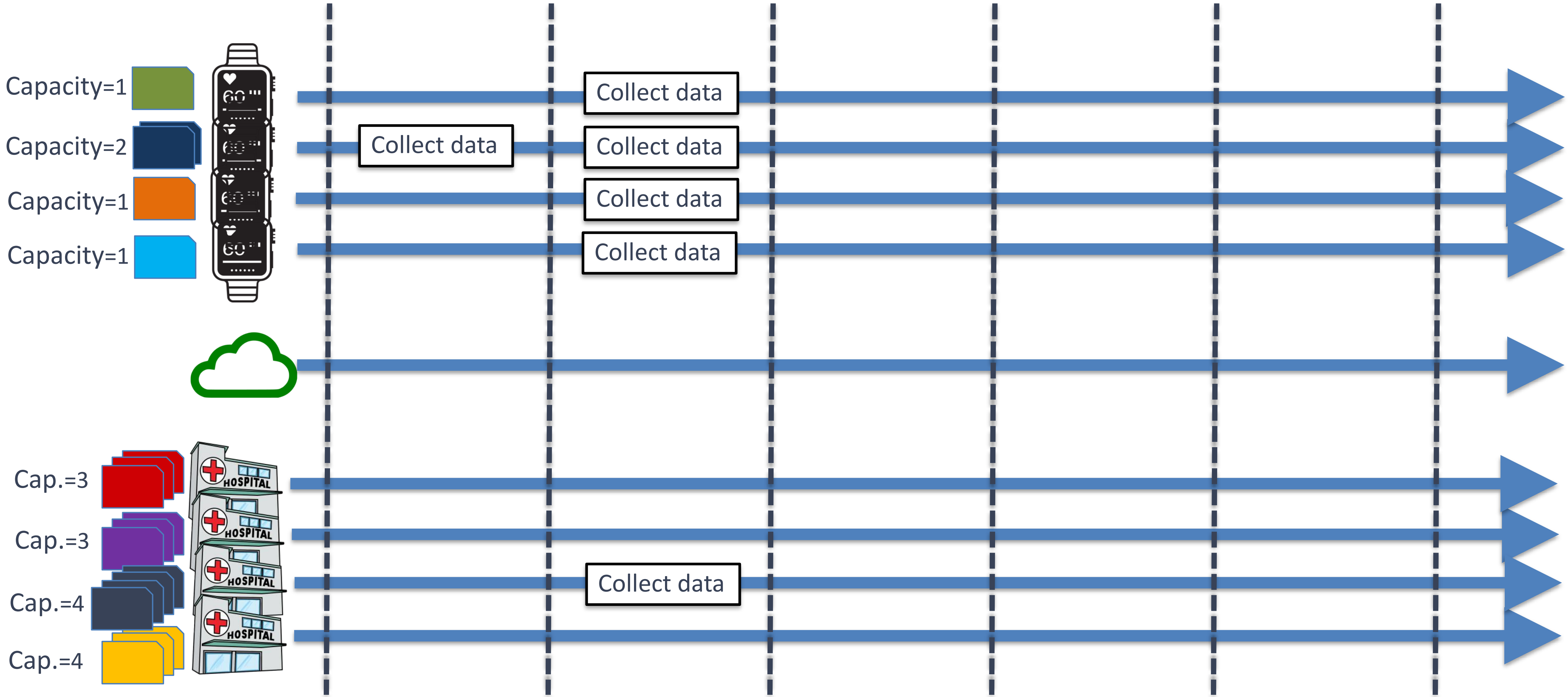

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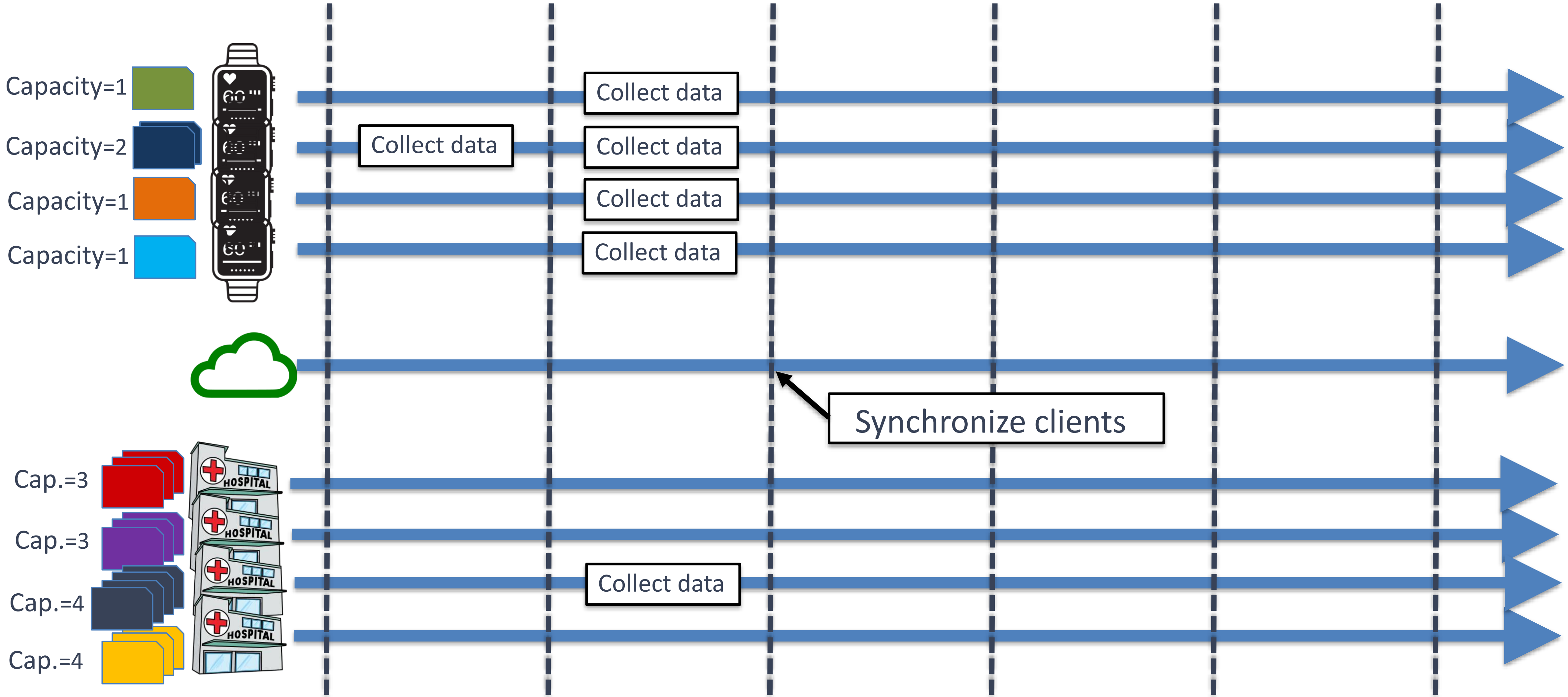

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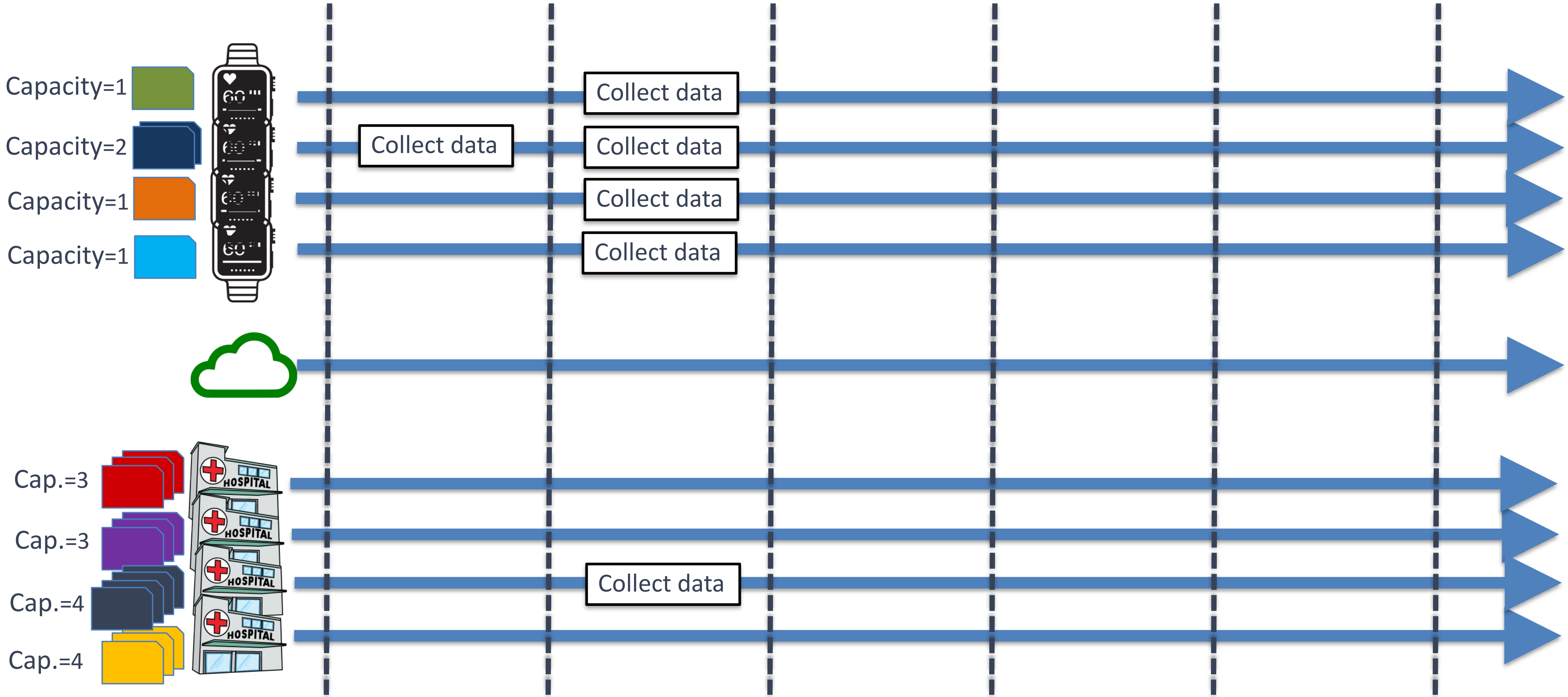

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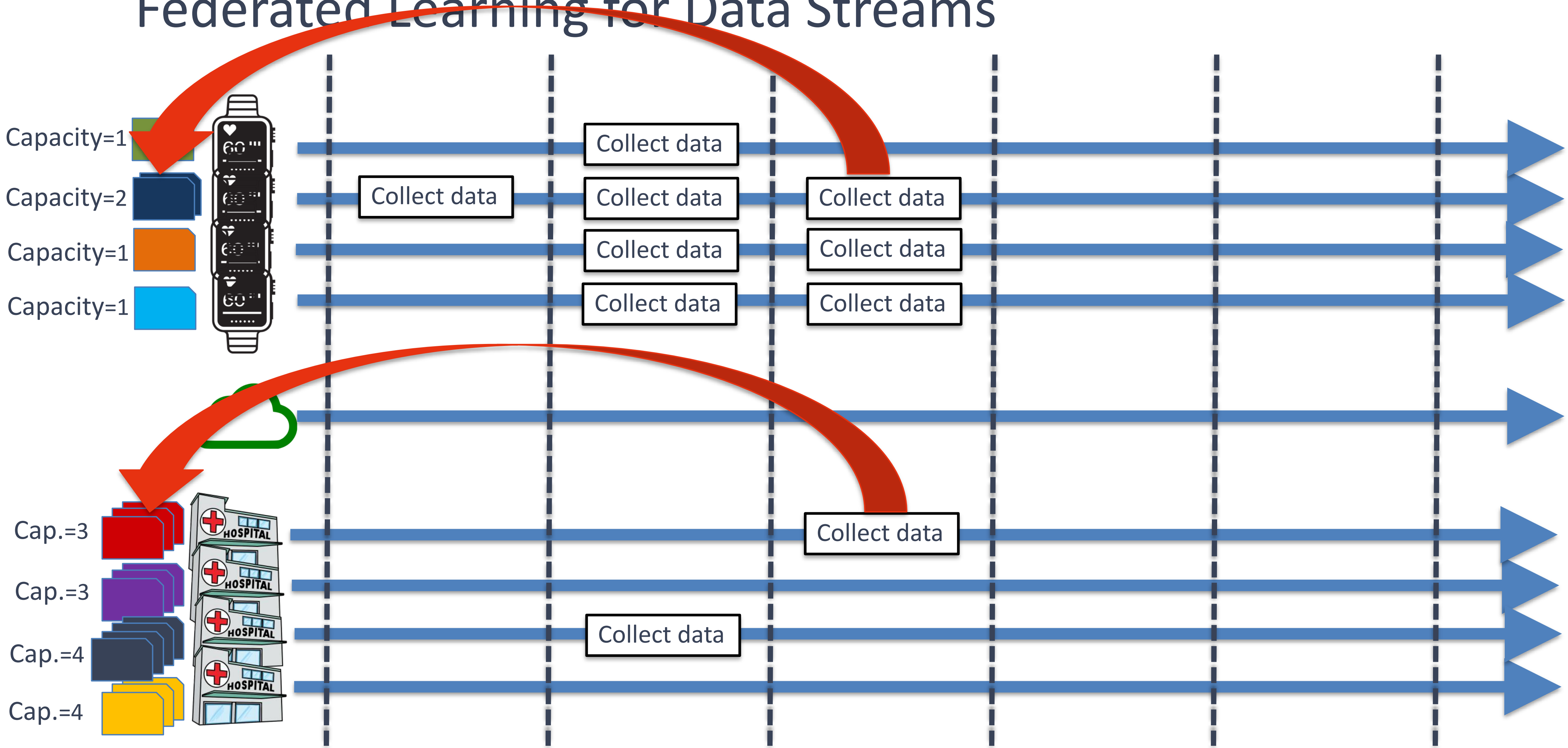

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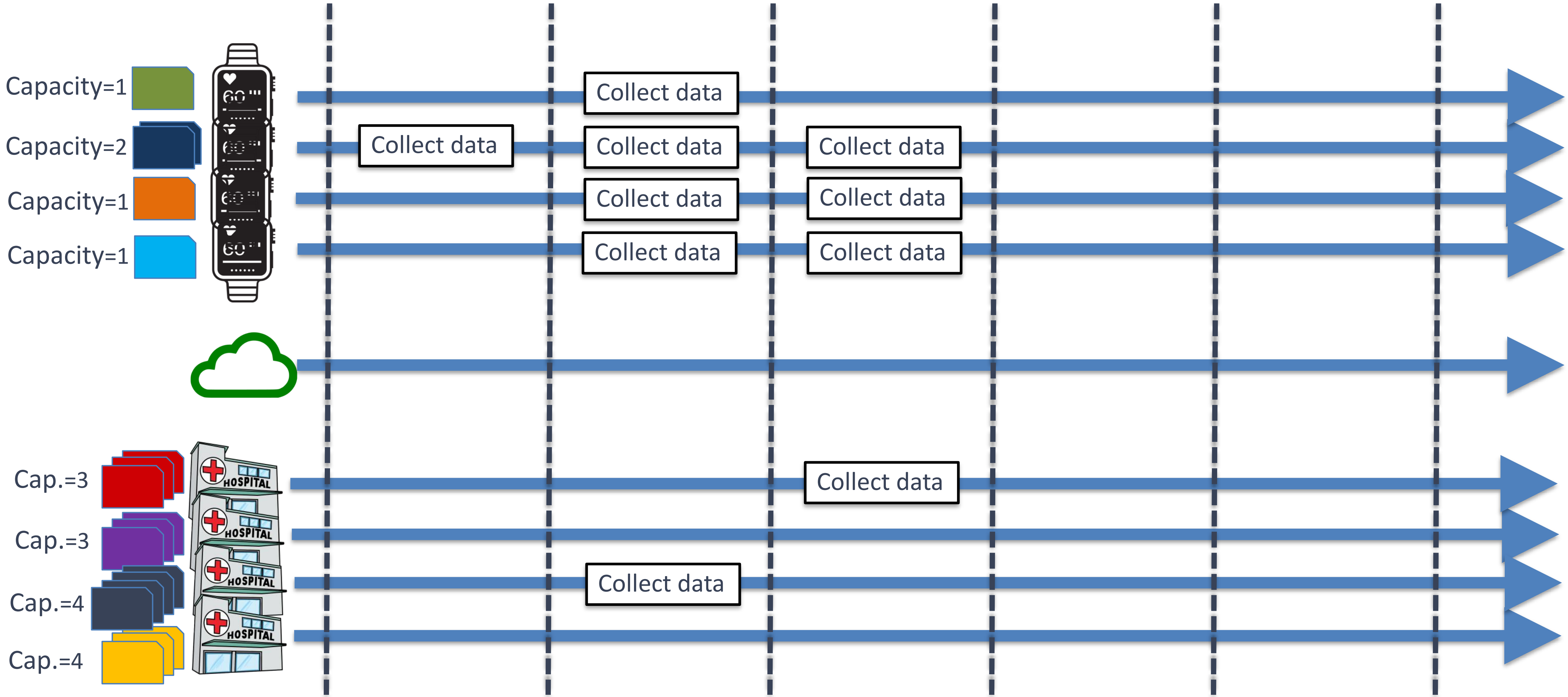

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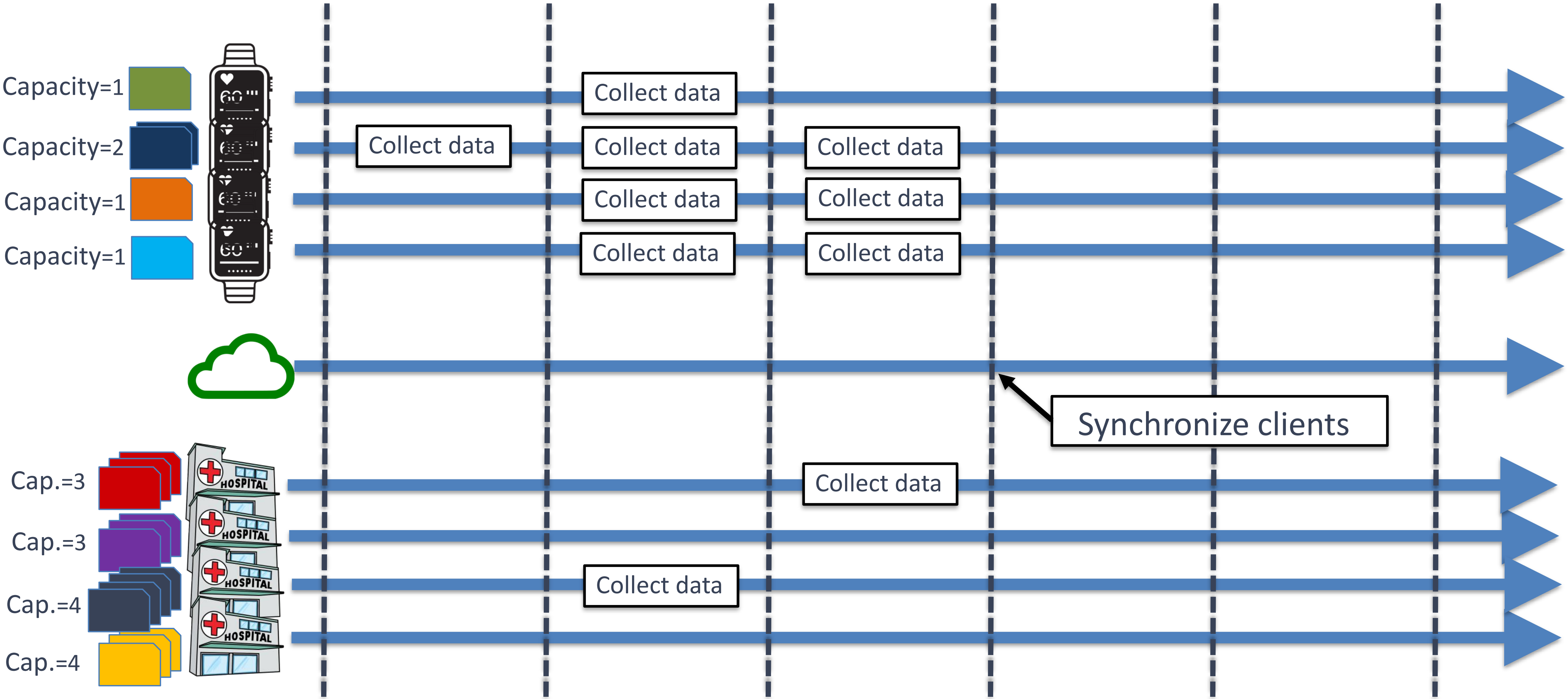

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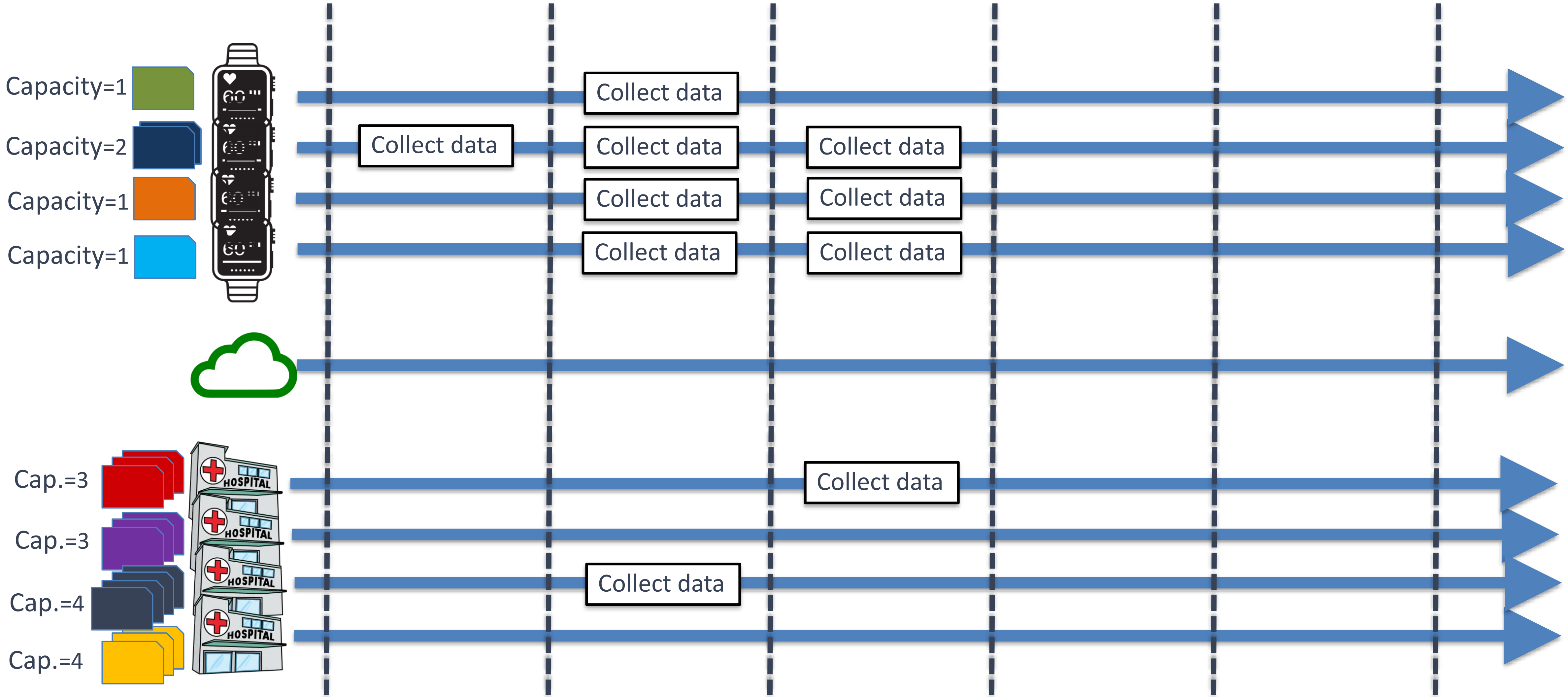

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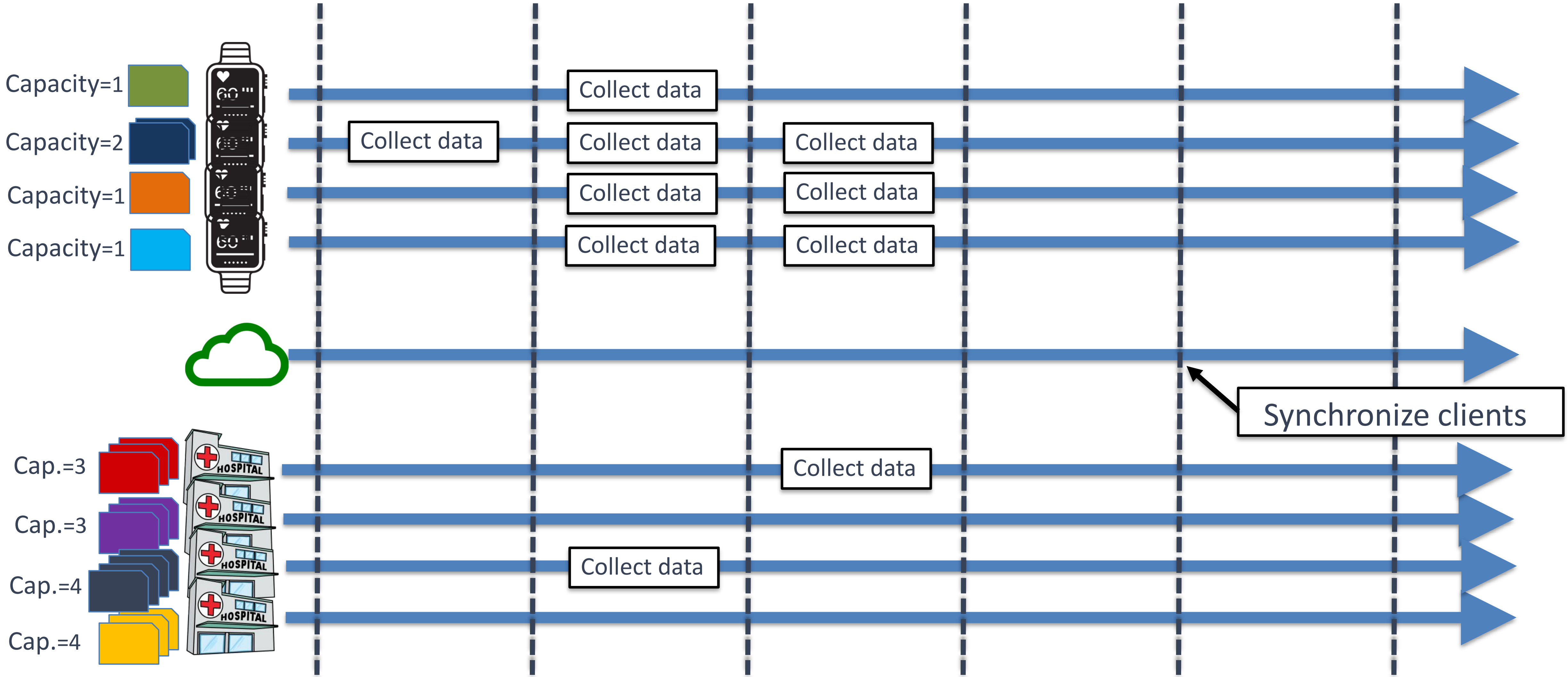

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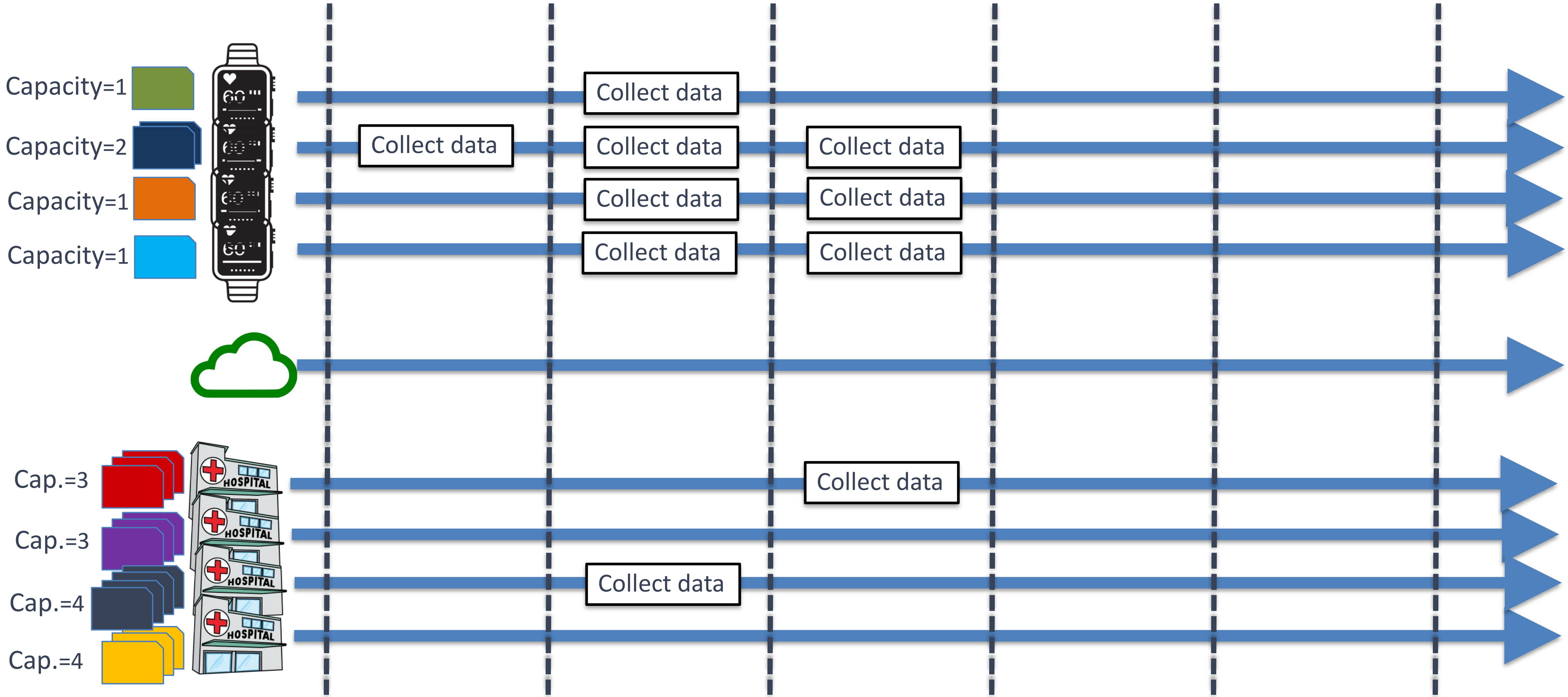

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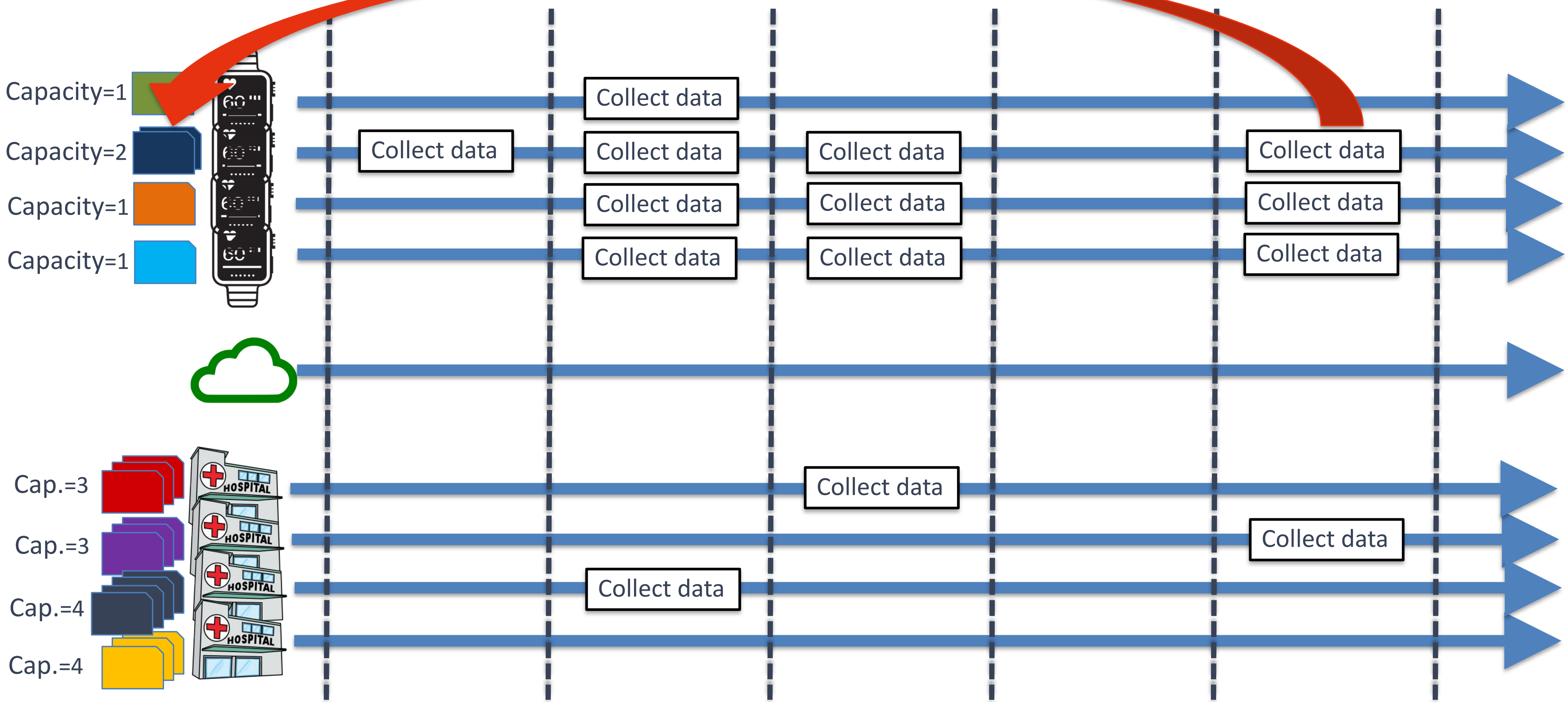

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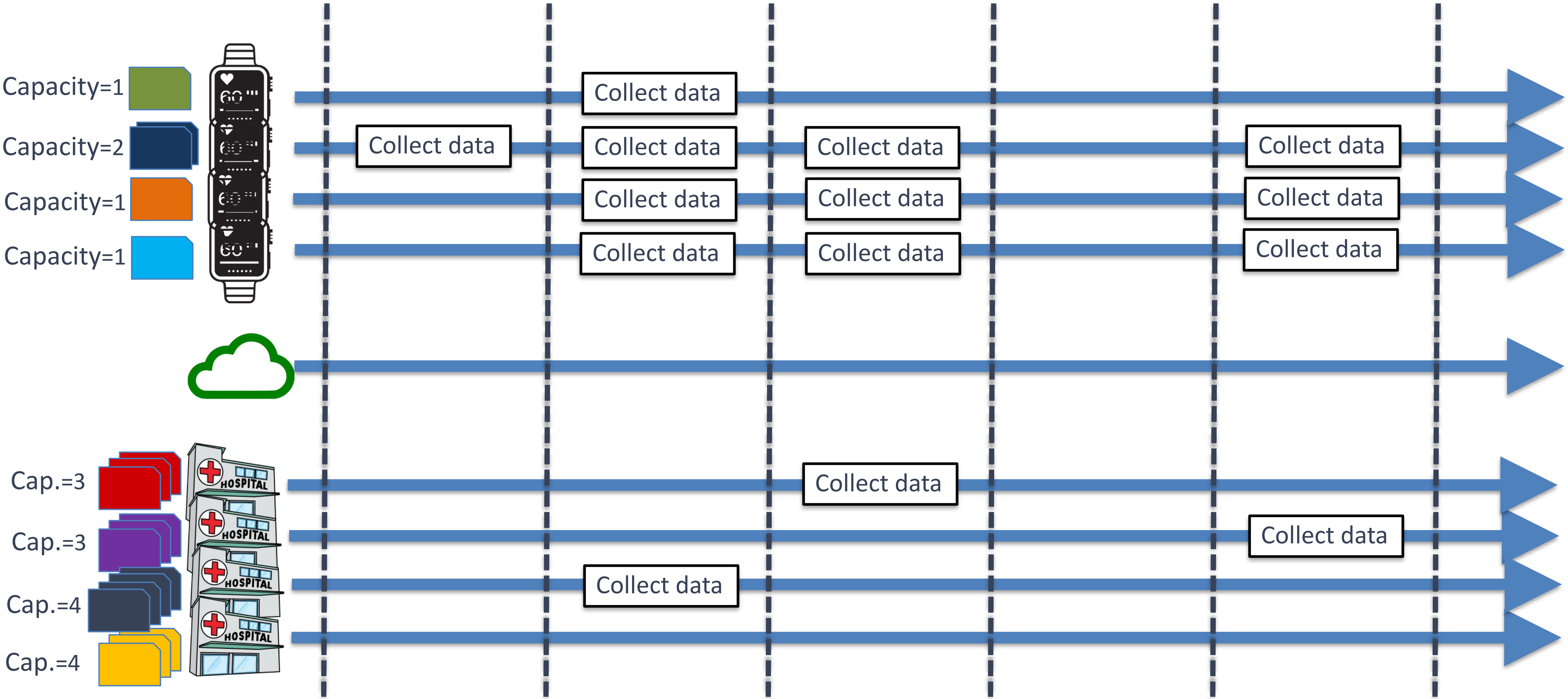

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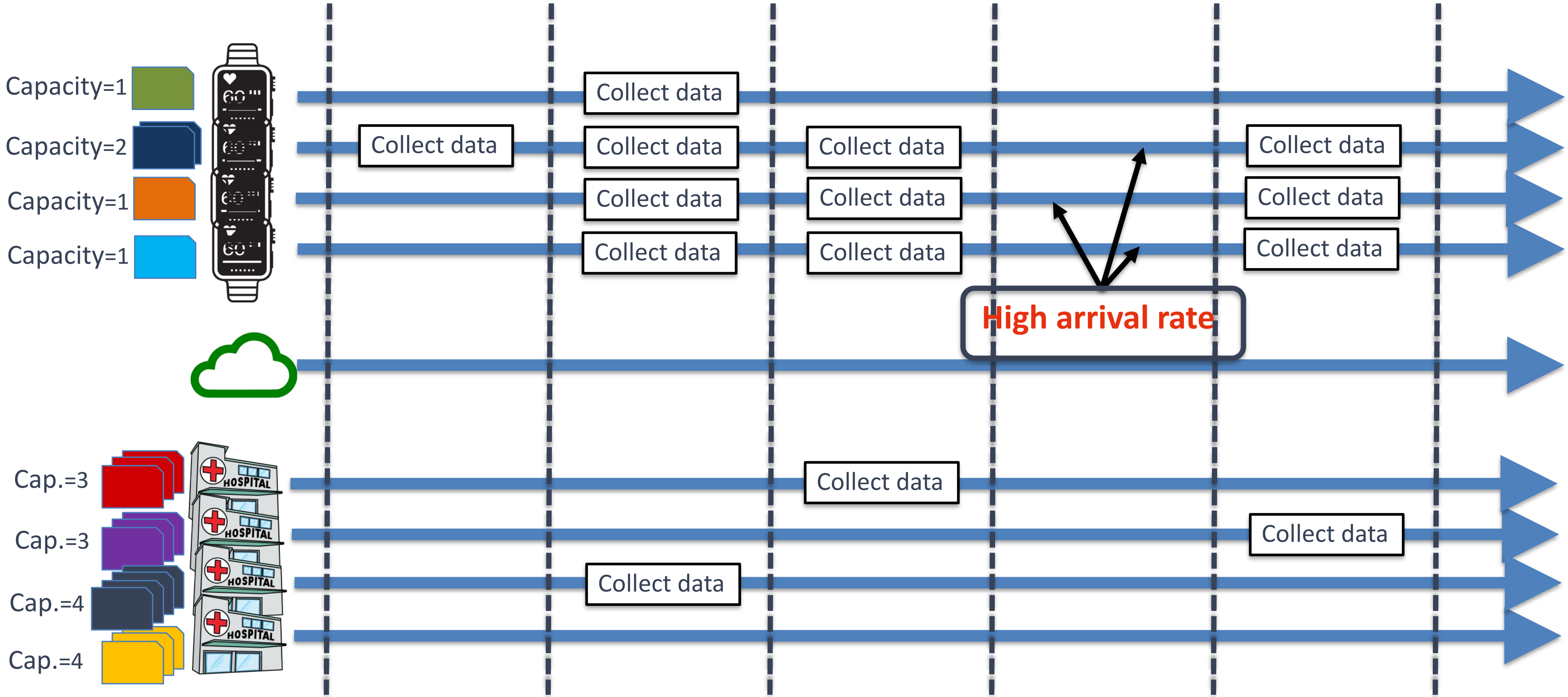

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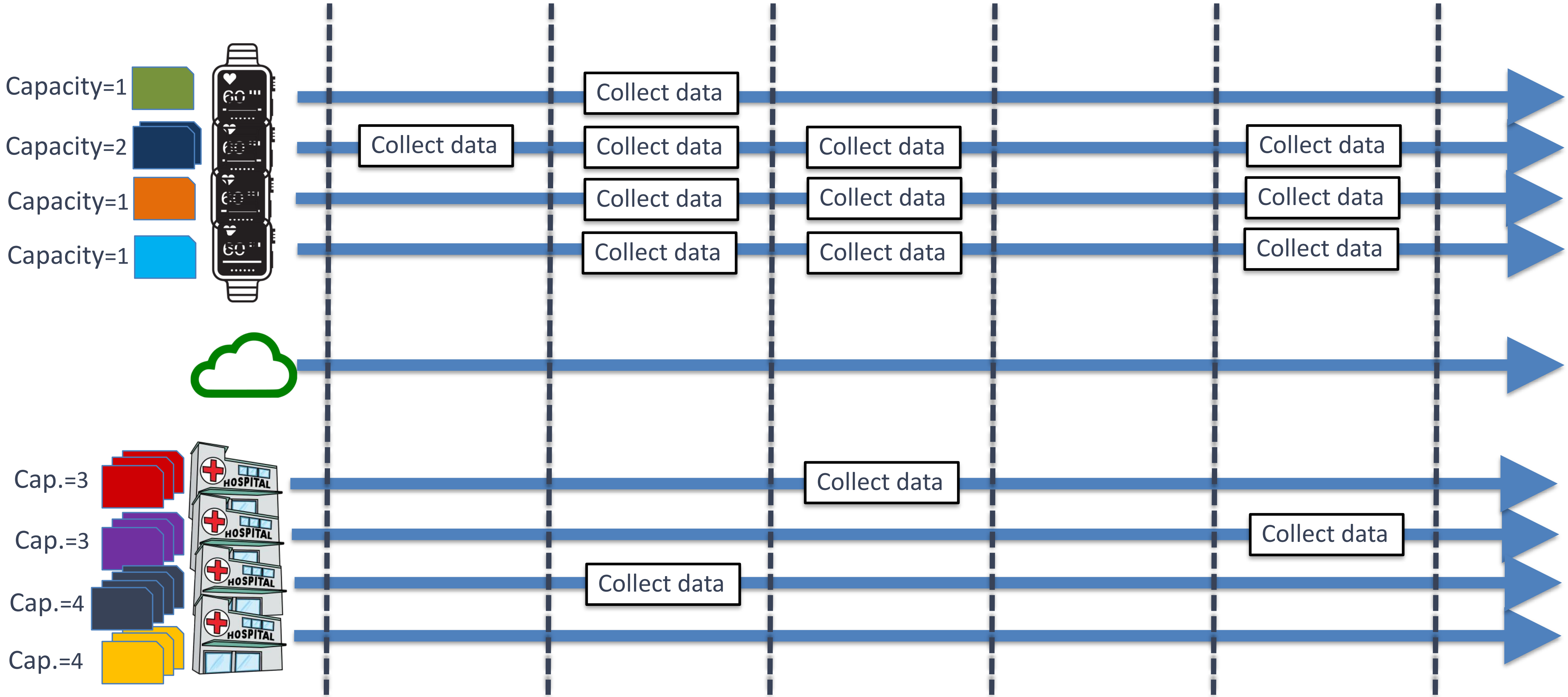

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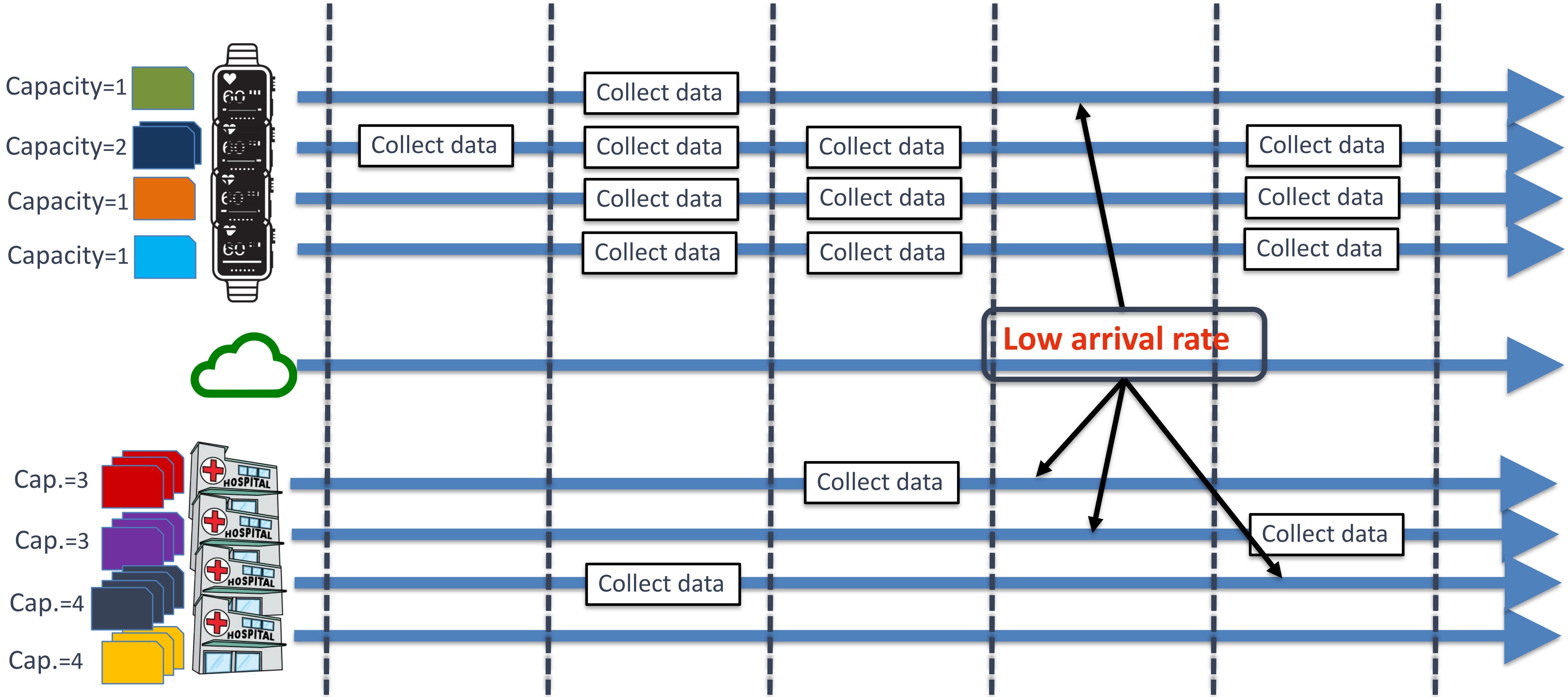

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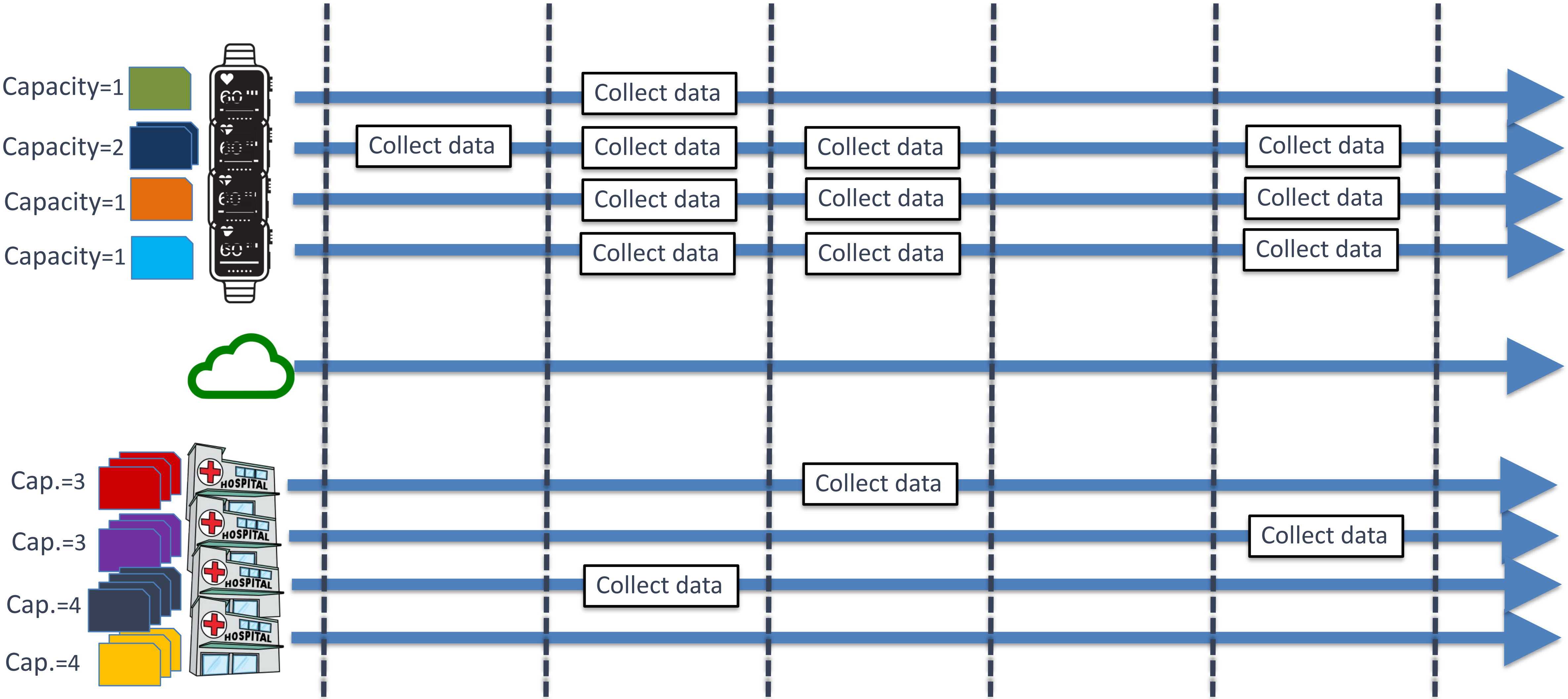

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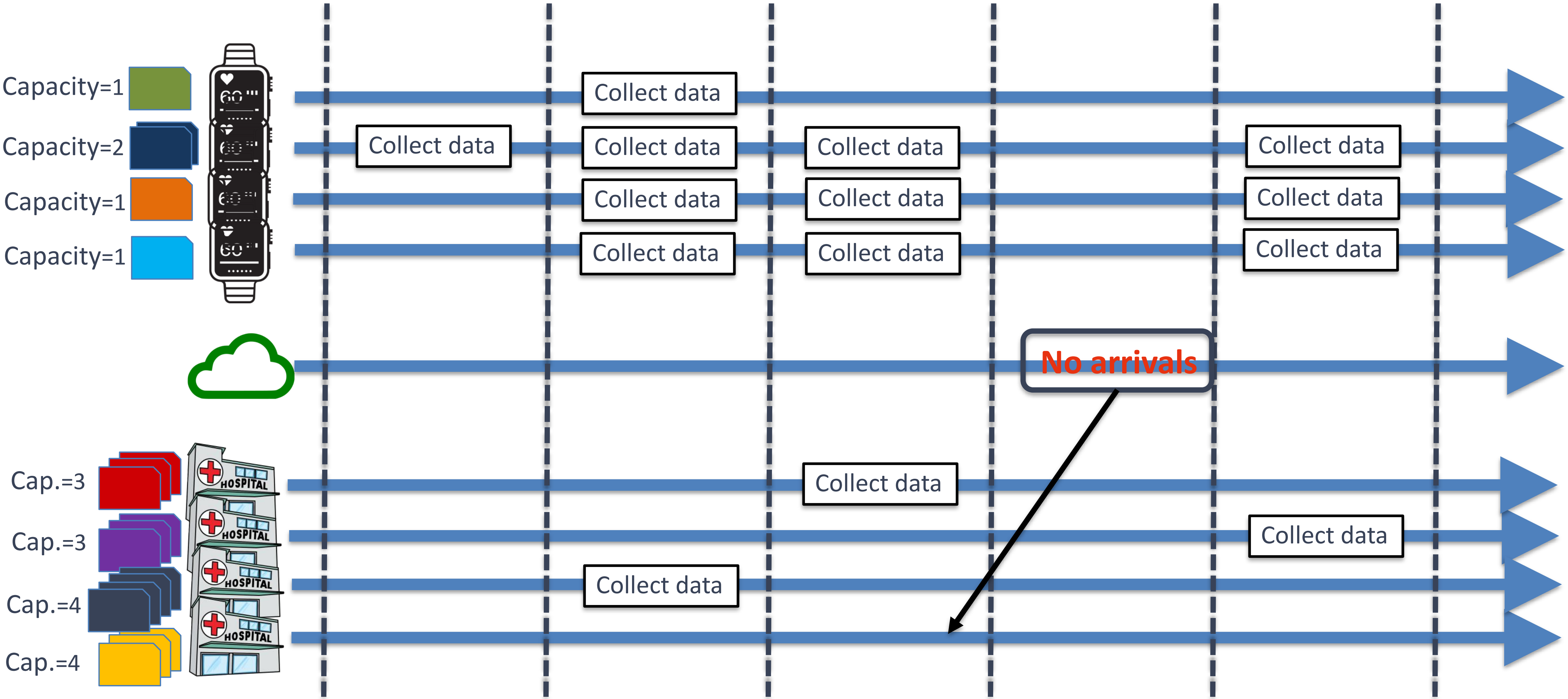

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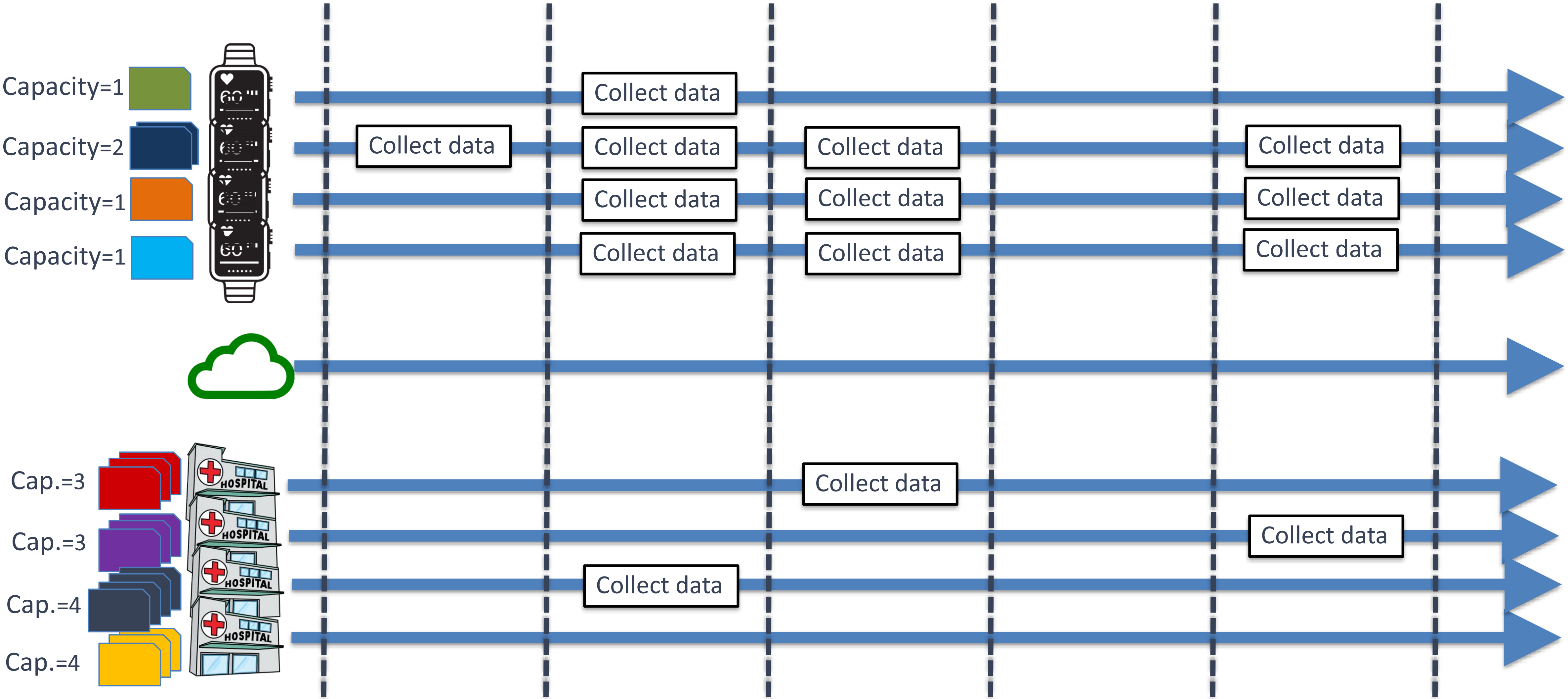

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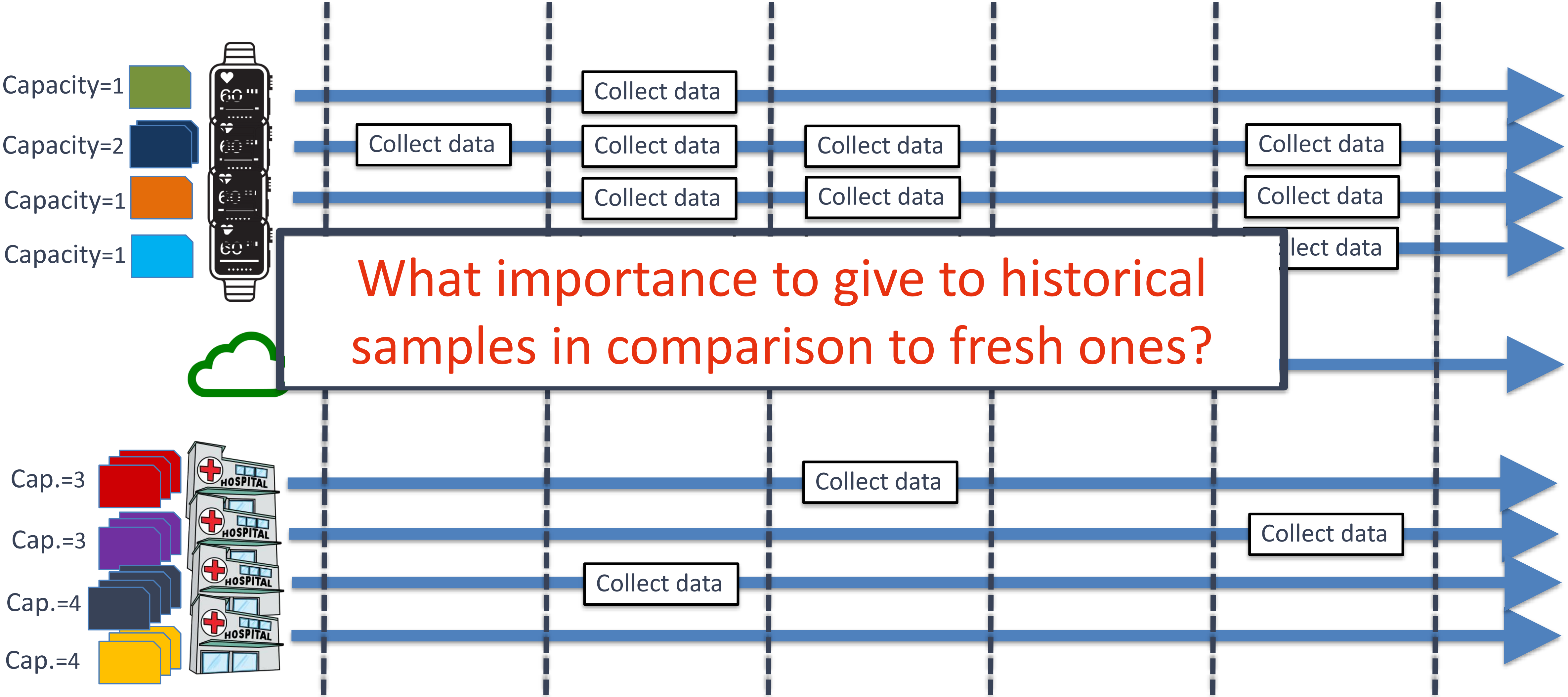

What importance to give to historical samples in comparison to fresh ones?

Federated Learning for Data Streams

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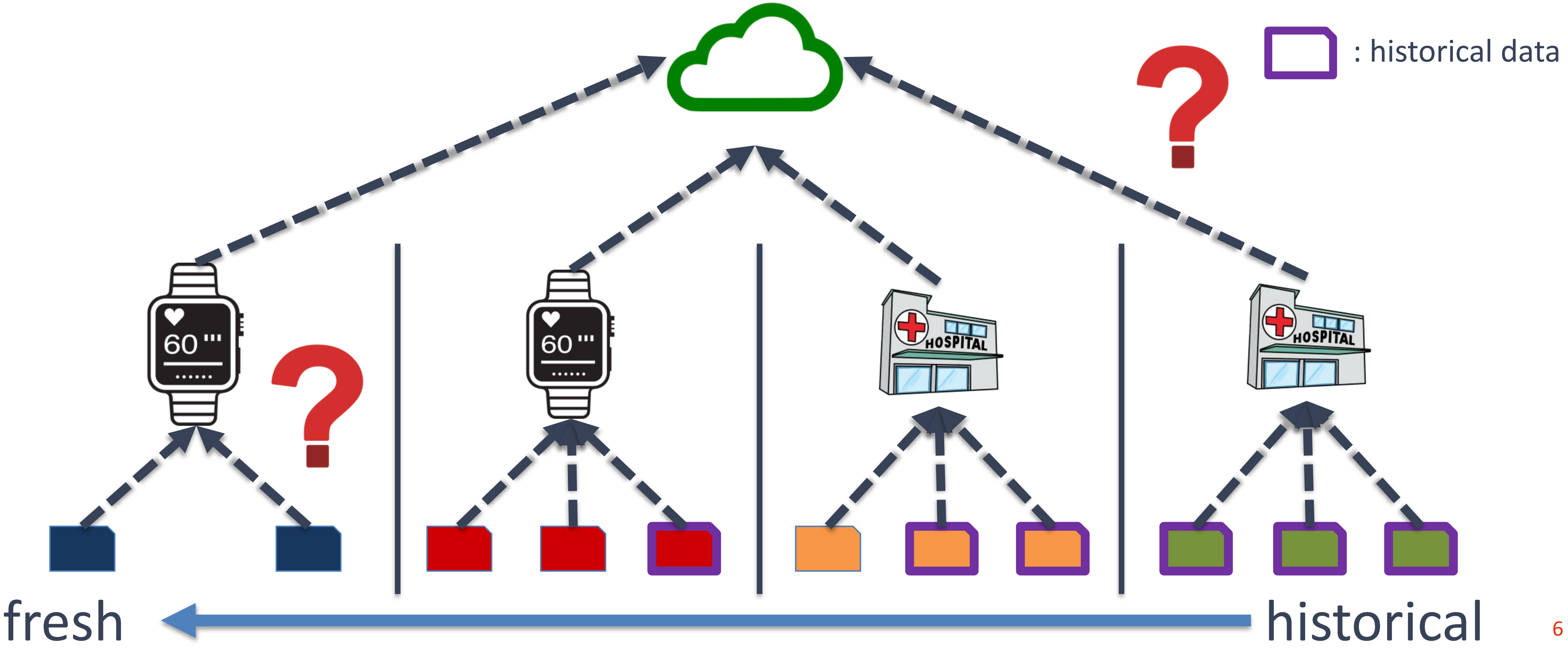
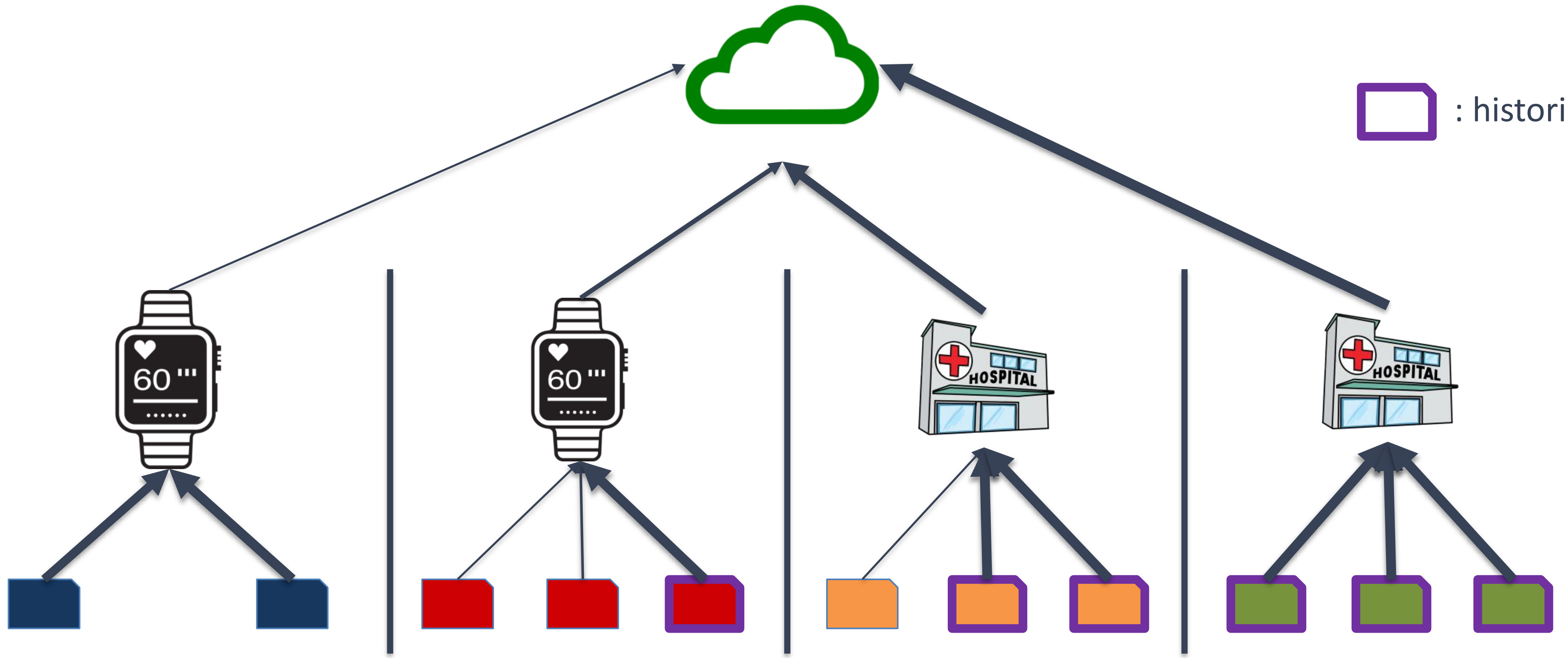
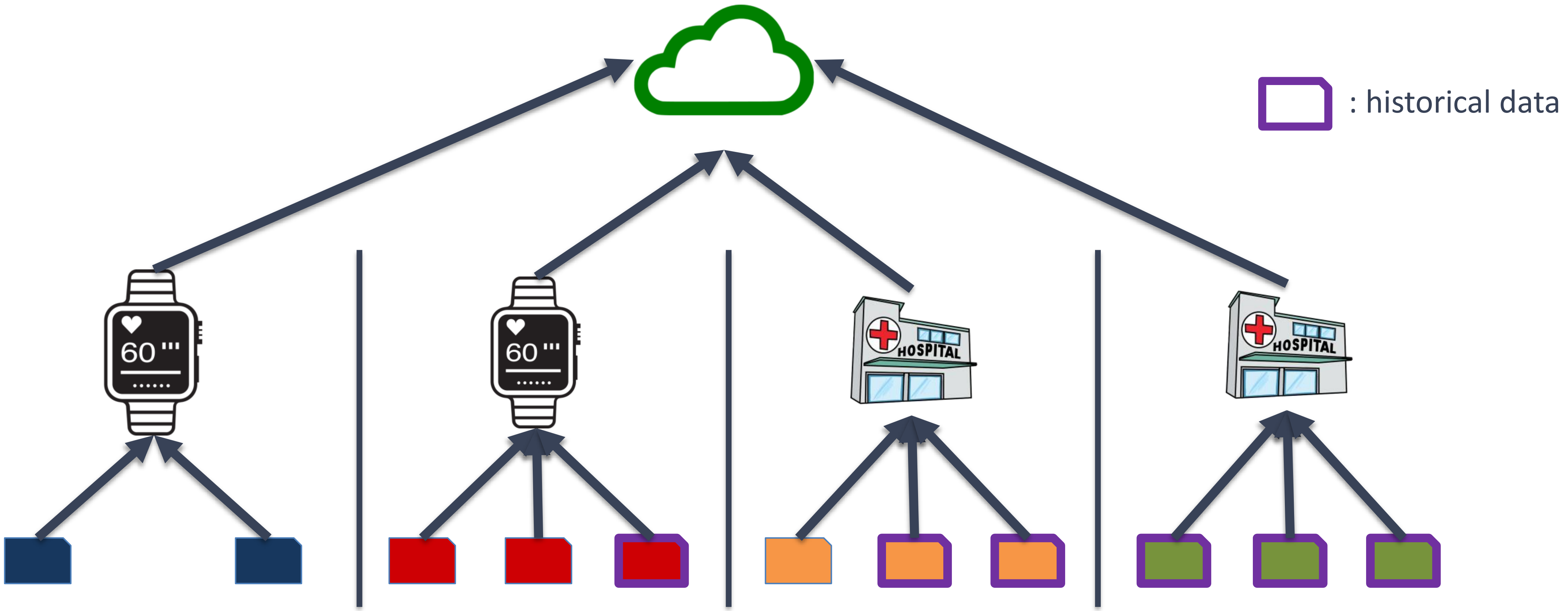


“Historical” strategy



: historical data

“Uniform” strategy



Theoretical Analysis

Reminder: error decomposition in ML

"True Error" = "Optimization Error" + "Generalization Error" + "Approximation Error"

"**Optimization Error**" is large when gradients are noisy

"**Generalization Error**" is large when few samples are available

"**Approximation Error**" only depends on the hypothesis space (model architecture)

Theoretical Analysis

"Historic"

- small variance
- small efficient number of samples
- low optimization error
- high generalization error

"Uniform"

- large variance
- large efficient number of samples
- high optimization error
- low generalization error

Theoretical Analysis

"Historic"

- sma
- sma

  samples
- low optimization error
- high generalization error

"Uniform"

- mber of

  samples
- high optimization error
- low generalization error

Is there a better compromise than these two extreme strategies?

Theoretical Analysis

Is there a better compromise than these two extreme strategies?

- ➢ The answer is "**usually YES**"

Theorem (informal)

\# clients

client importance

$$\text{True Error} \leq c_0 + c_1 \cdot \sqrt{\sum_{m=M_{\text{hist}}+1}^{M} p_m^2} + c_2 \cdot \sqrt{\sum_{m=1}^{M} \frac{p_m^2}{n_m}}.$$

\# historical clients

relative size

Practical Algorithm

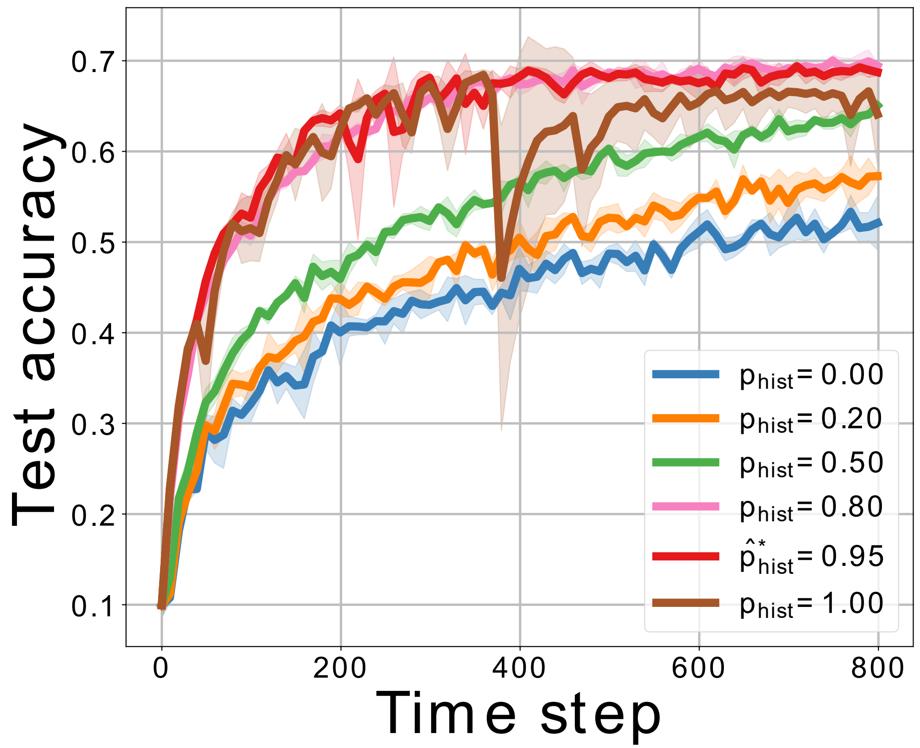
1. estimate the constants on historical data

2. optimize the upper-bound

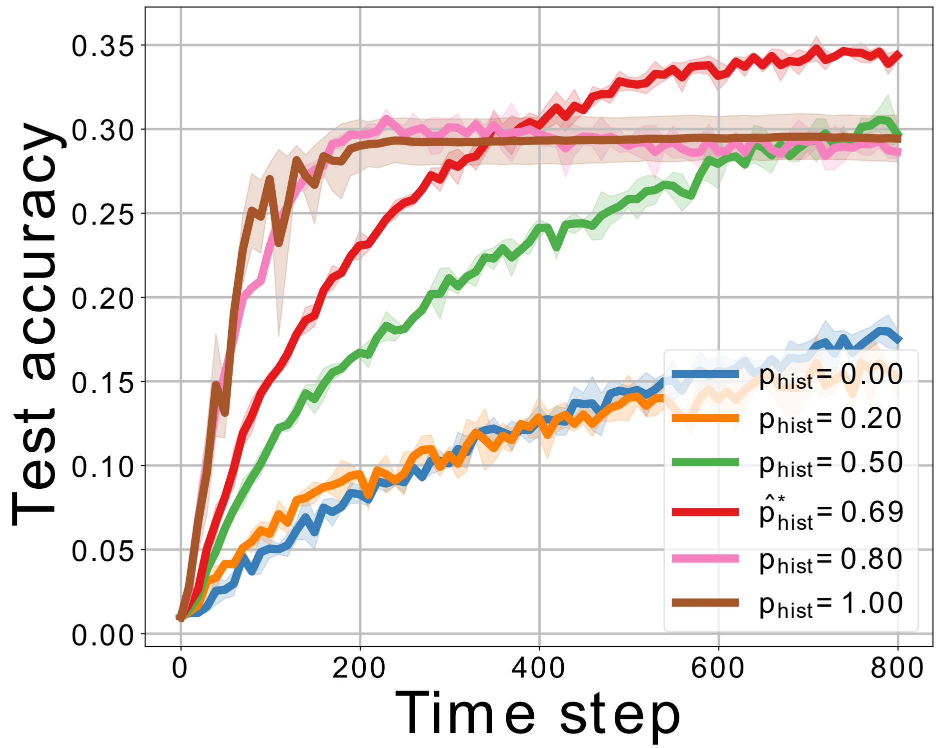
3. run federated averaging with the resulting weights

Experimental Results

Scenario with large number of historical samples (50%)



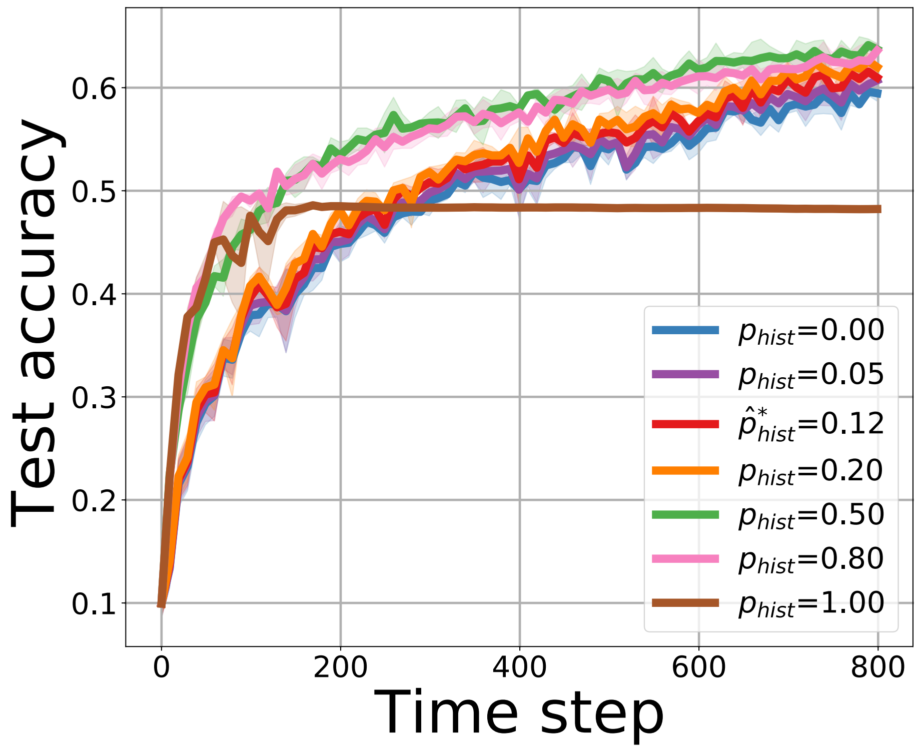
CIFAR-10



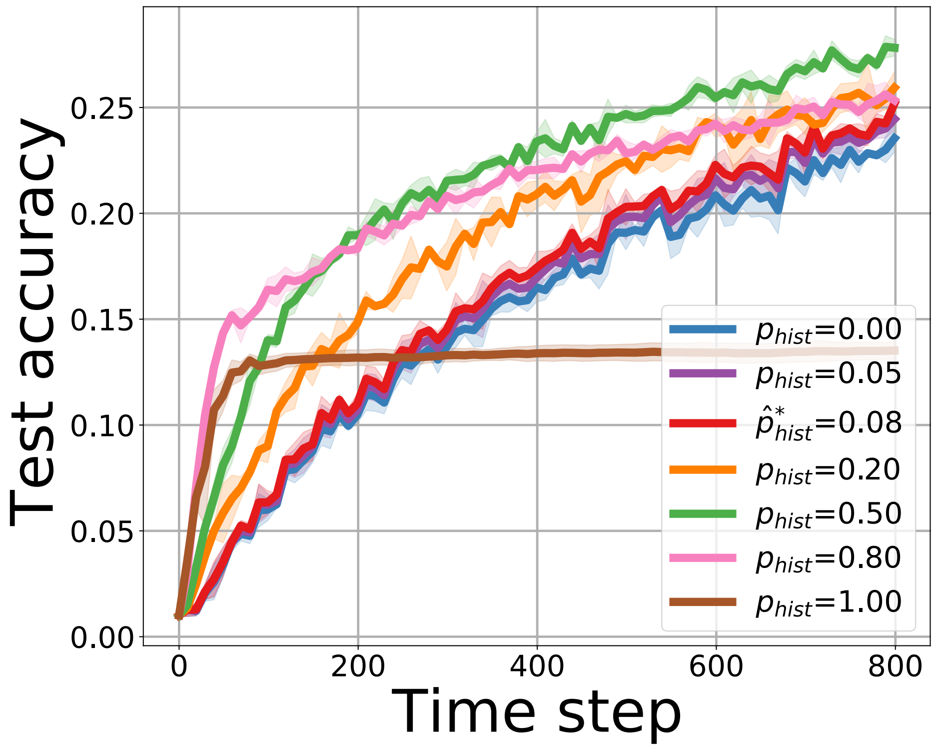
CIFAR-100

Experimental Results

Scenario with a few historical samples (5%)



CIFAR-10



CIFAR-100

Conclusion

1. Formalize the problem of federated learning for data streams
2. Theoretical analysis reveals a new generalization-optimization tradeoff
3. Practical algorithm to decide the relative importance samples

Questions