Privacy-preserving machine learning

@MLRS

Bangkok, Thailand

Aug 11, 2019

Mijung Park

Privacy & your data

- Increasingly more and more devices collect & stream your data

Internet & emails

[Lookeen]

Home appliances

[LG newsroom]

Drones

[Intogagets]

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[Electronic Frontier Foundation via Wikimedia Commons]

Worry:
A few corporations
own your data
& might abuse them!

My name is Cayla!

- Cayla is a children's smart toy, that can have interactive conversations with kids

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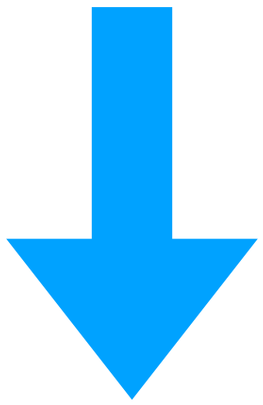
- Issue 1: Conversations streamed to company's server
- Issue 2: anybody who has a bluetooth connection can hack this doll.

Threat!



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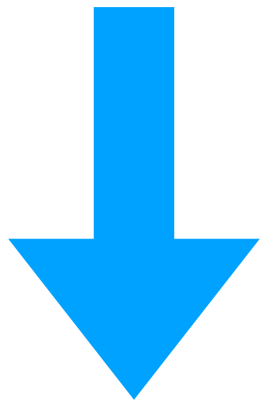

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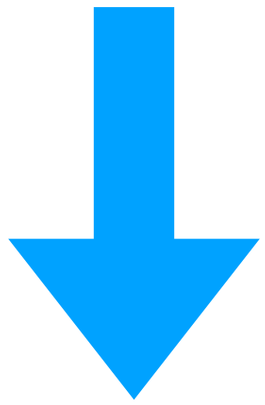

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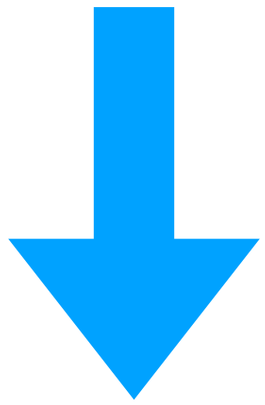
Philanthropic reason!



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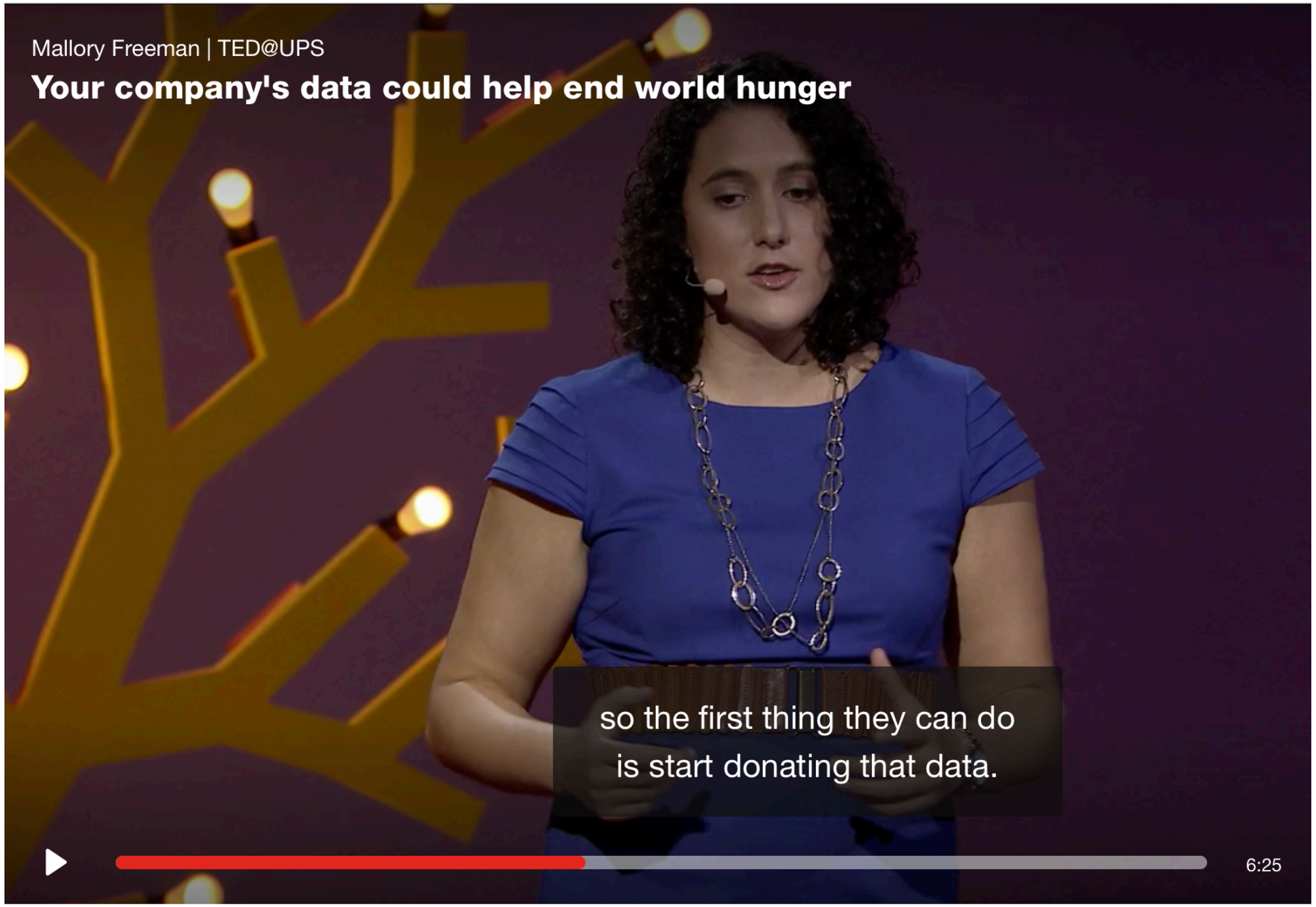
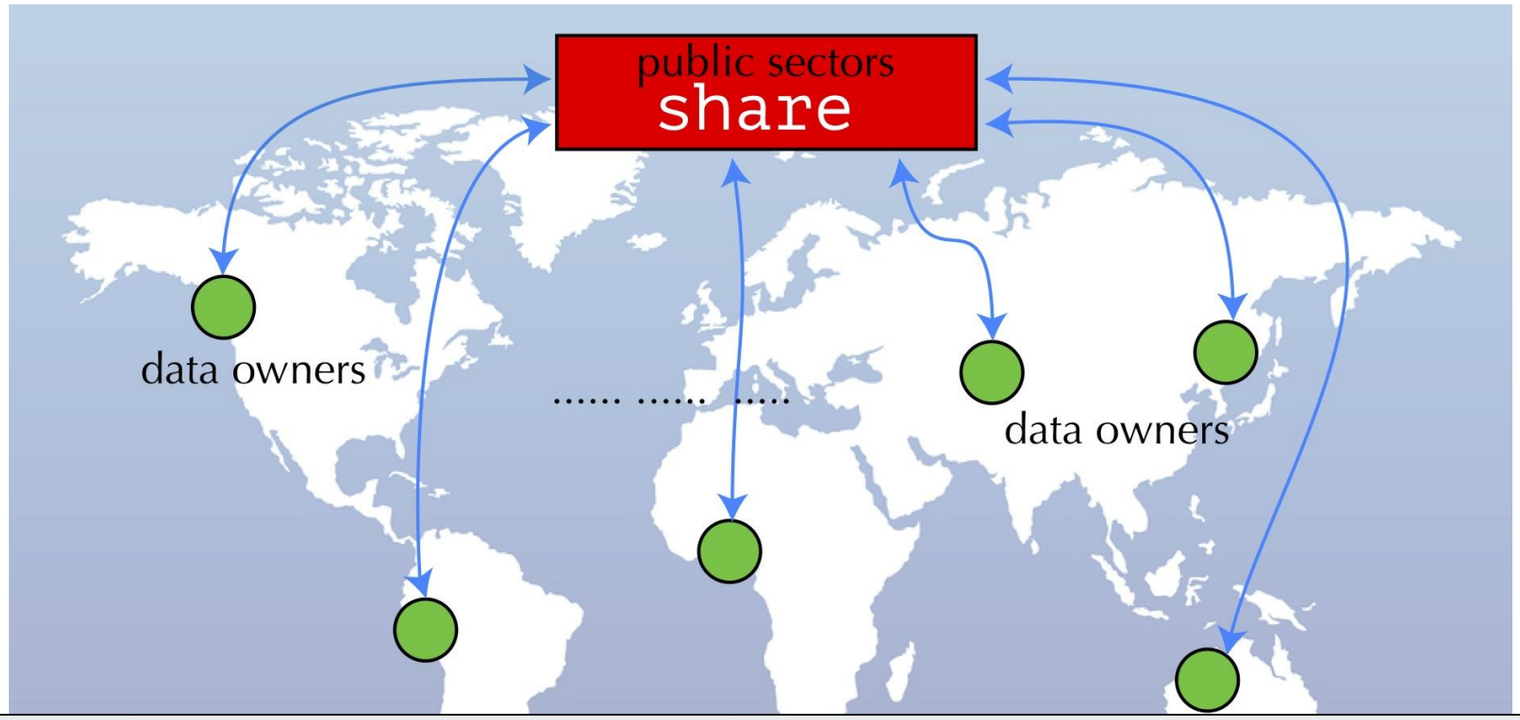


- Emphasising the importance of sharing data for public good

Data philanthropy

[United Nations Global Pulse]



"--- think of big data as a new kind of natural resource – infinitely renewable, increasingly ubiquitous – but … has fallen into the hands of… industry …Data has a social opportunity – and we have a social responsibility – …data reaches the people who need it most."

[Director of UN Global Pulse]

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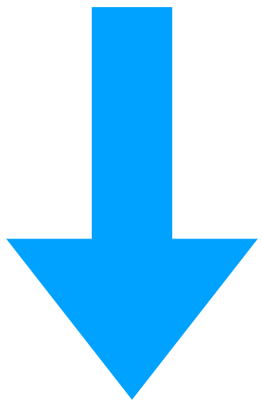
Philanthropic reason!



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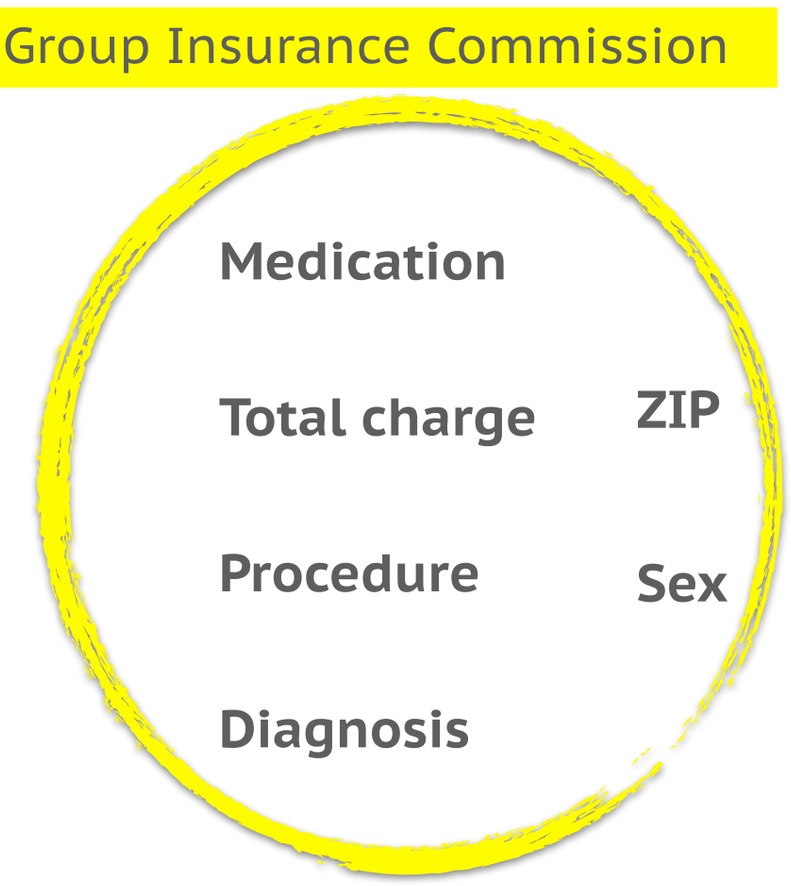

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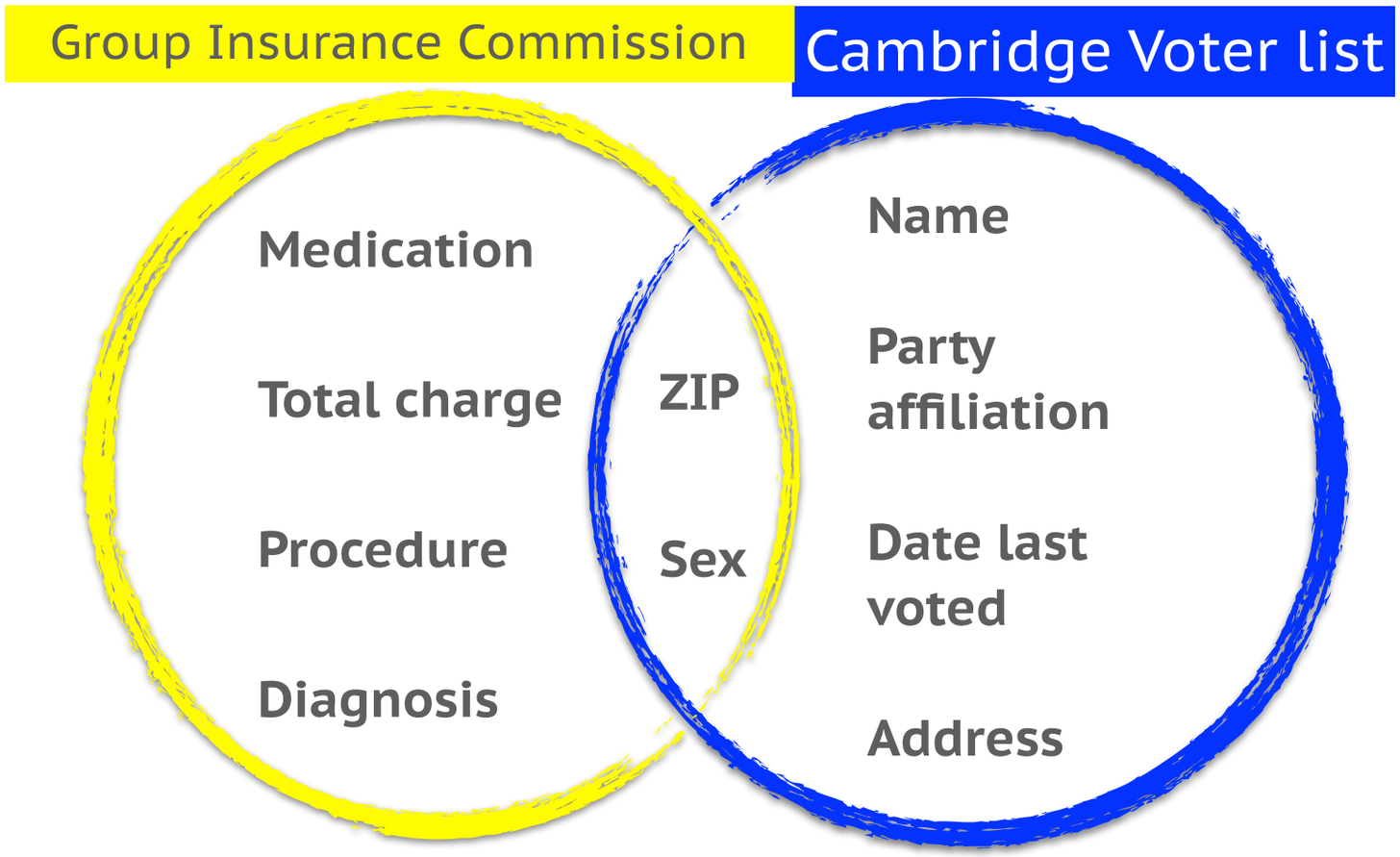

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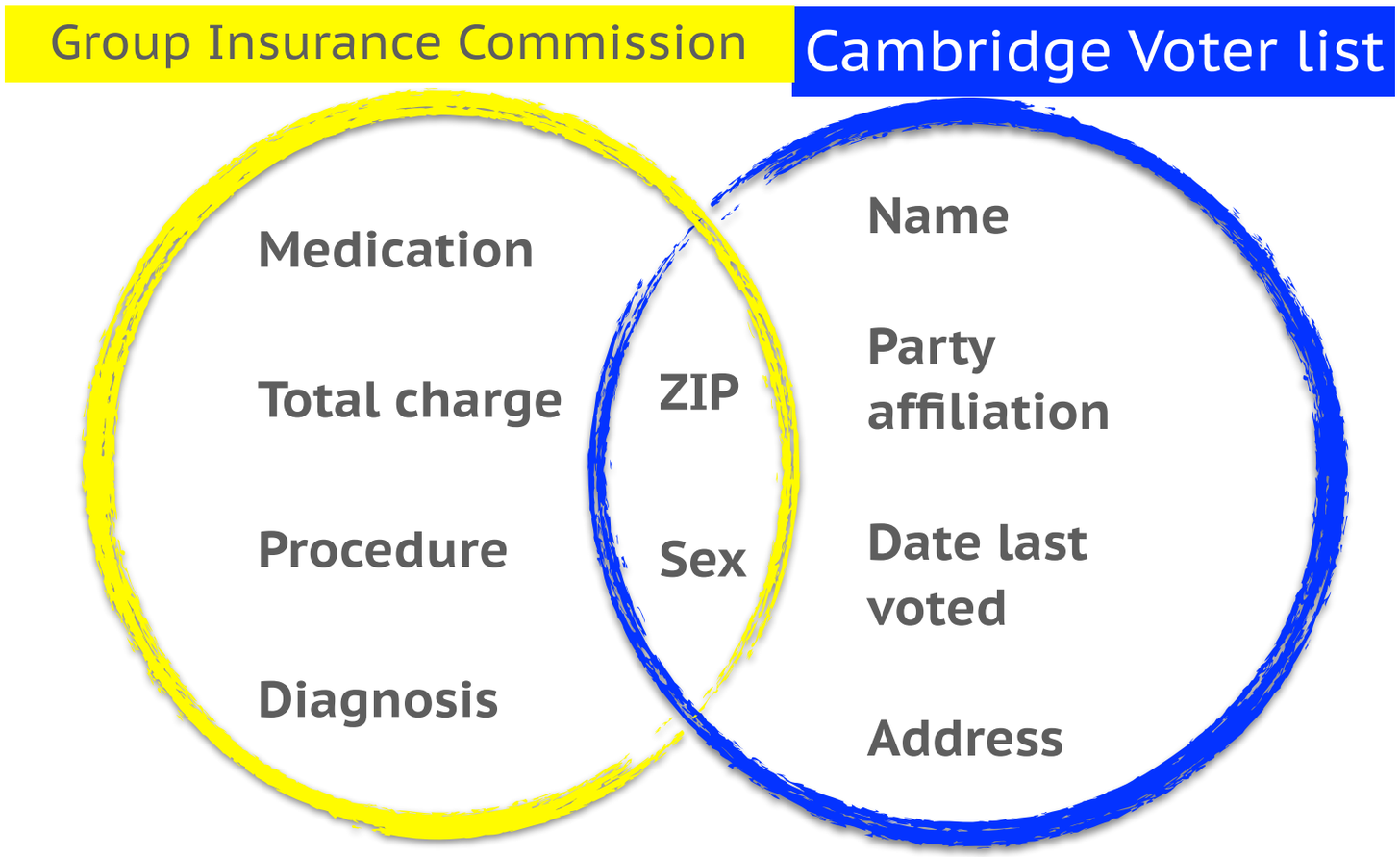

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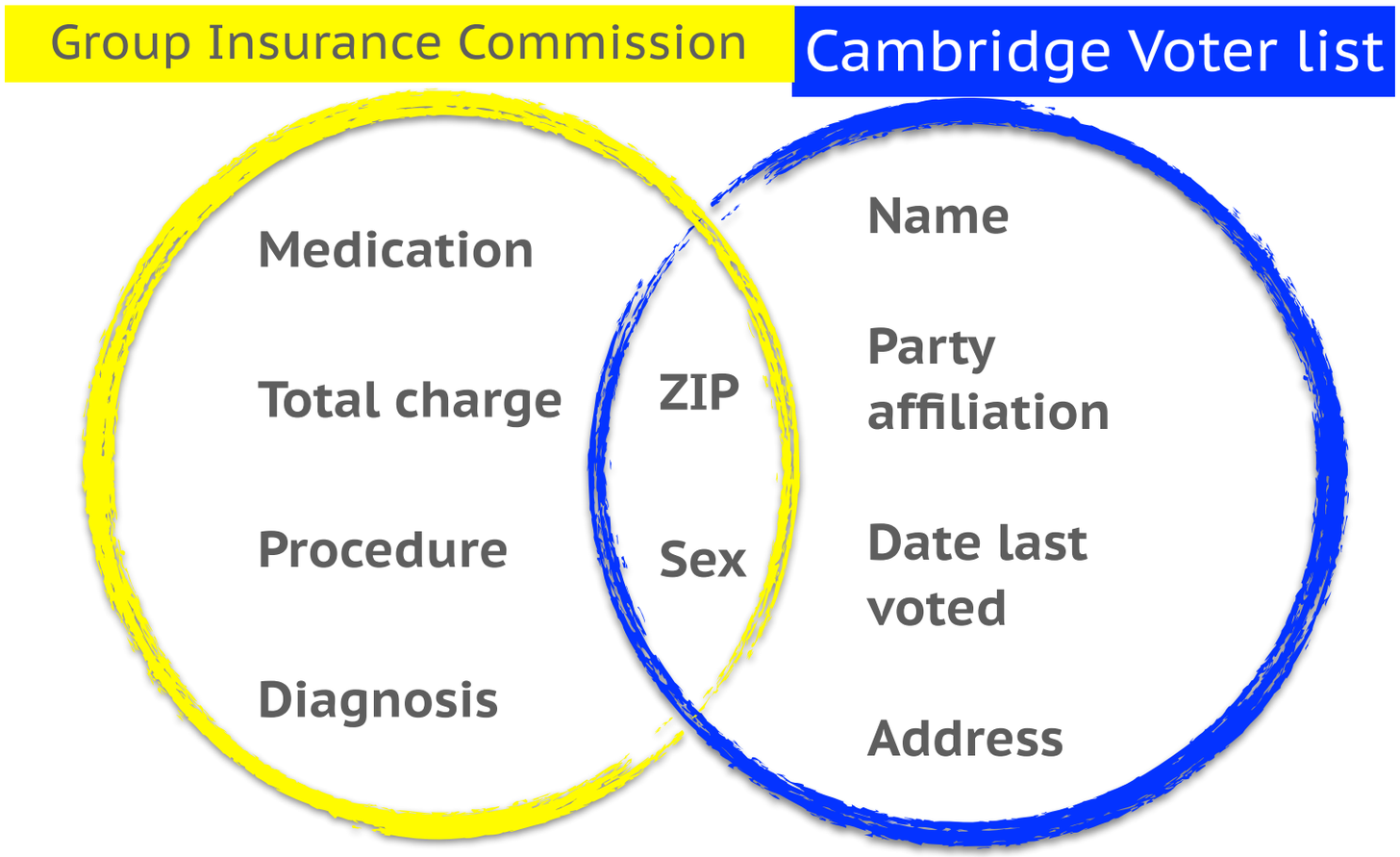

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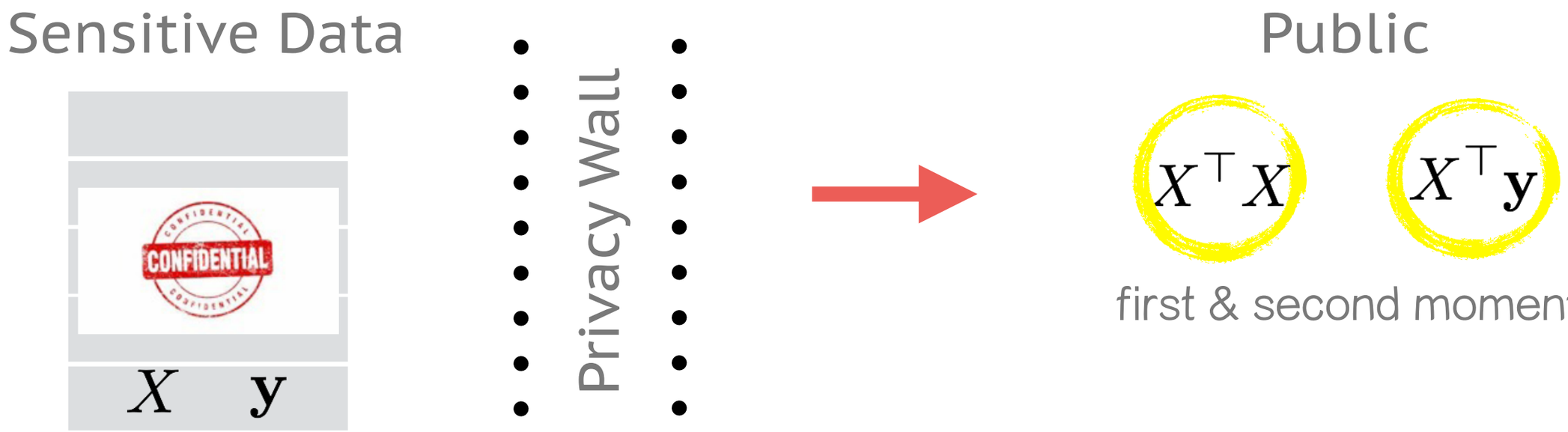
Governor William Weld!

What about releasing statistics?



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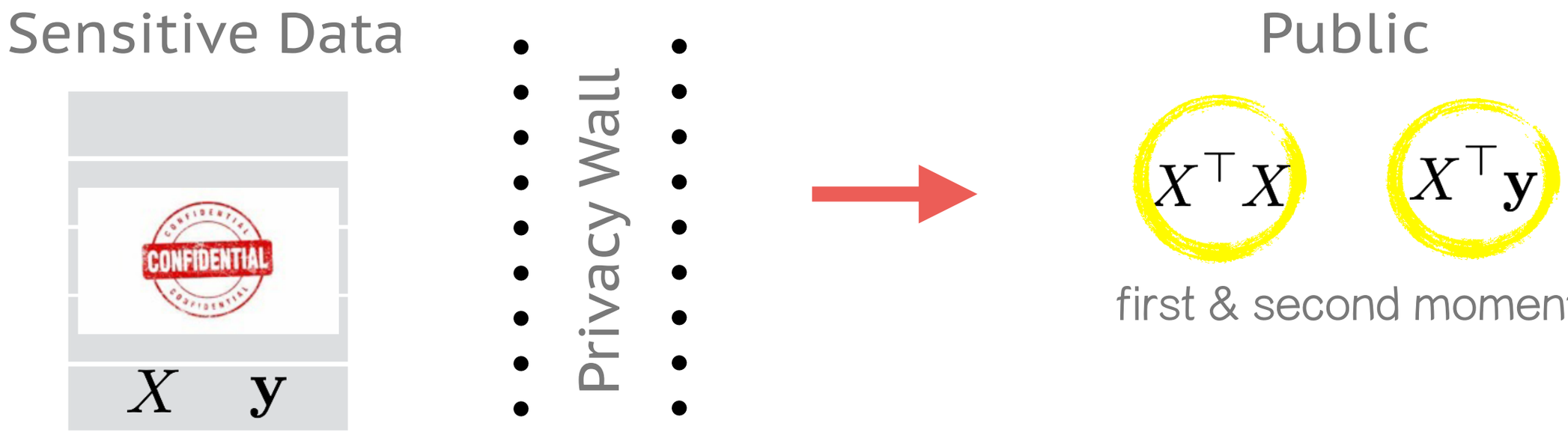

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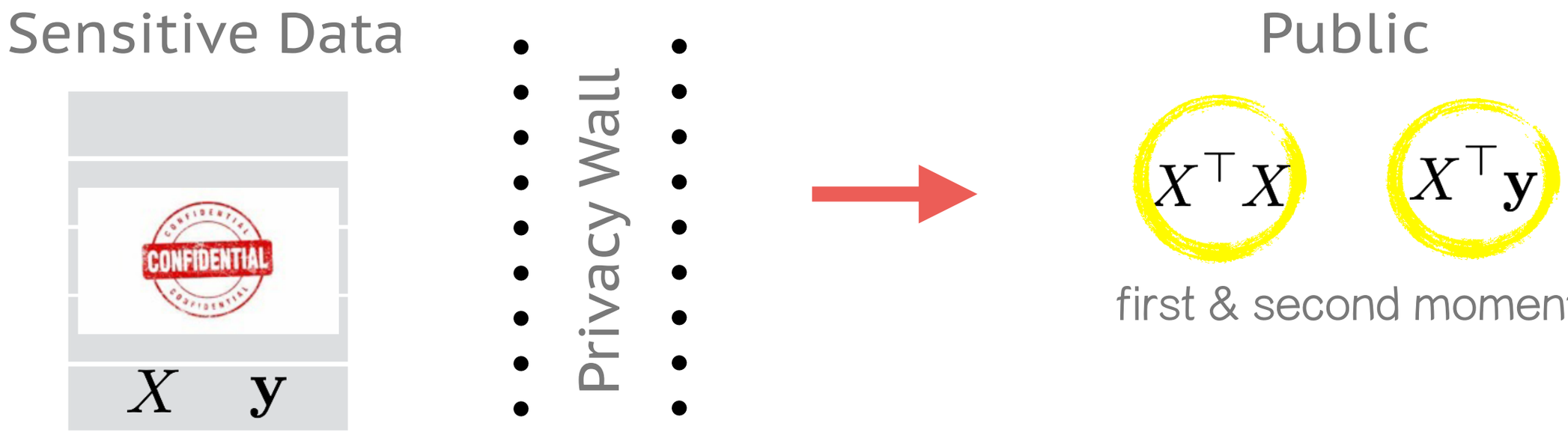

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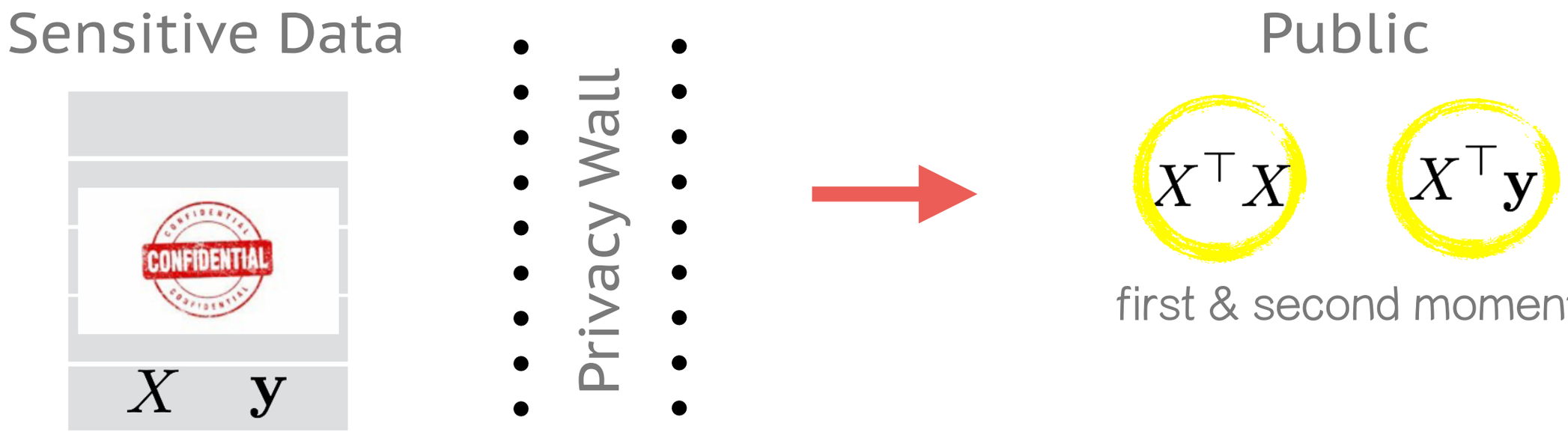

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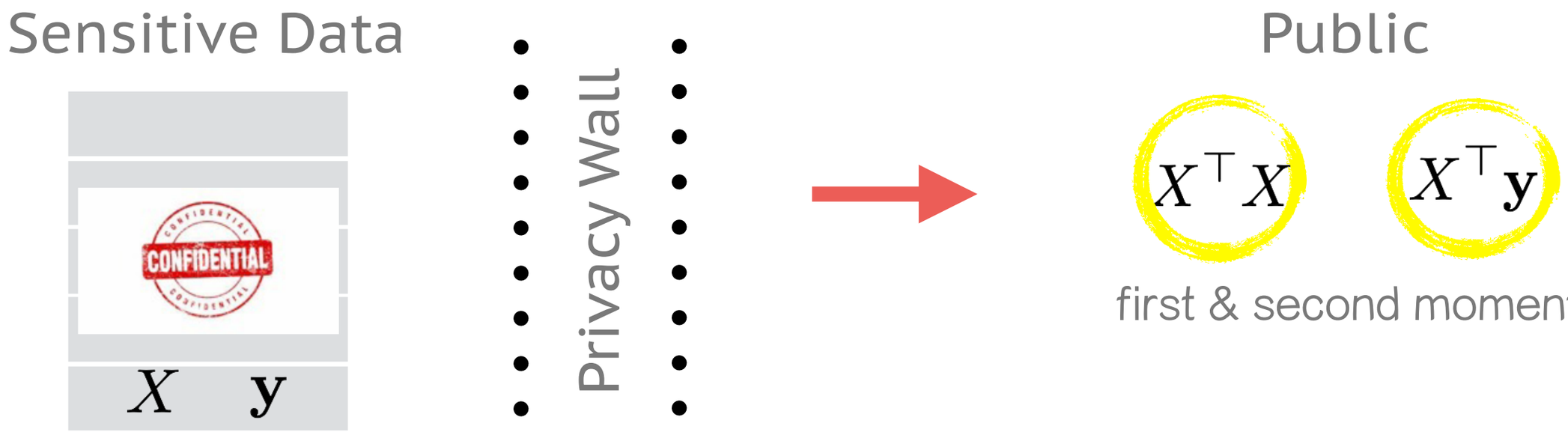

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$\hat{\boldsymbol{\theta}}_{ls} = (X^\top X)^{-1} X^\top \mathbf{y}$

→

$y_n \approx \hat{\boldsymbol{\theta}}_{ls}{}^\top \mathbf{x}_n$

Statistically sound prediction of sensitive attributes

Simply anonymising data is unsafe!

Releasing statistics of data is unsafe!

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⋮

We need a provably strong privacy notion!

Privacy definition

Differential privacy!

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[Dwork 06]

Differential privacy is the statistical science of trying to learn as much as possible about a group while learning as little as possible about any individual in it.

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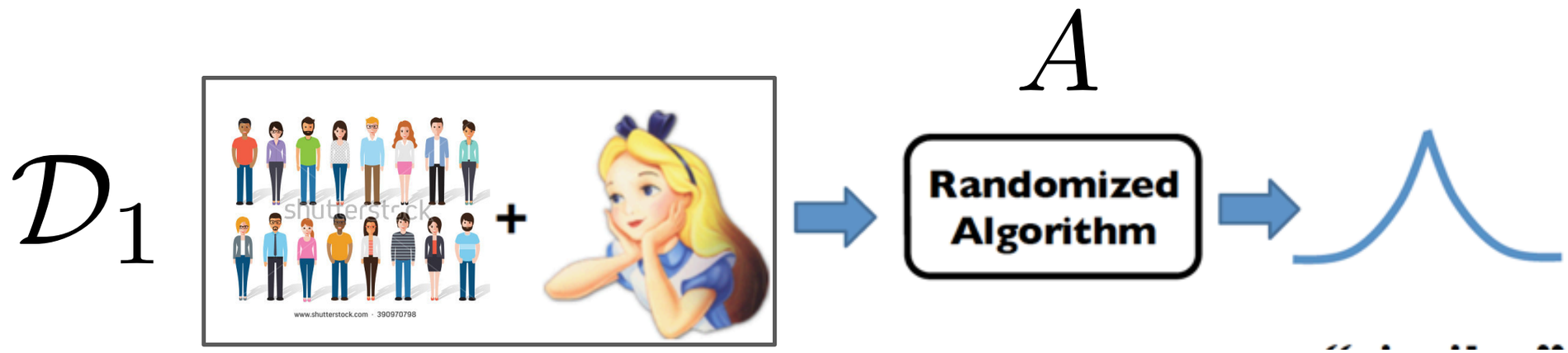

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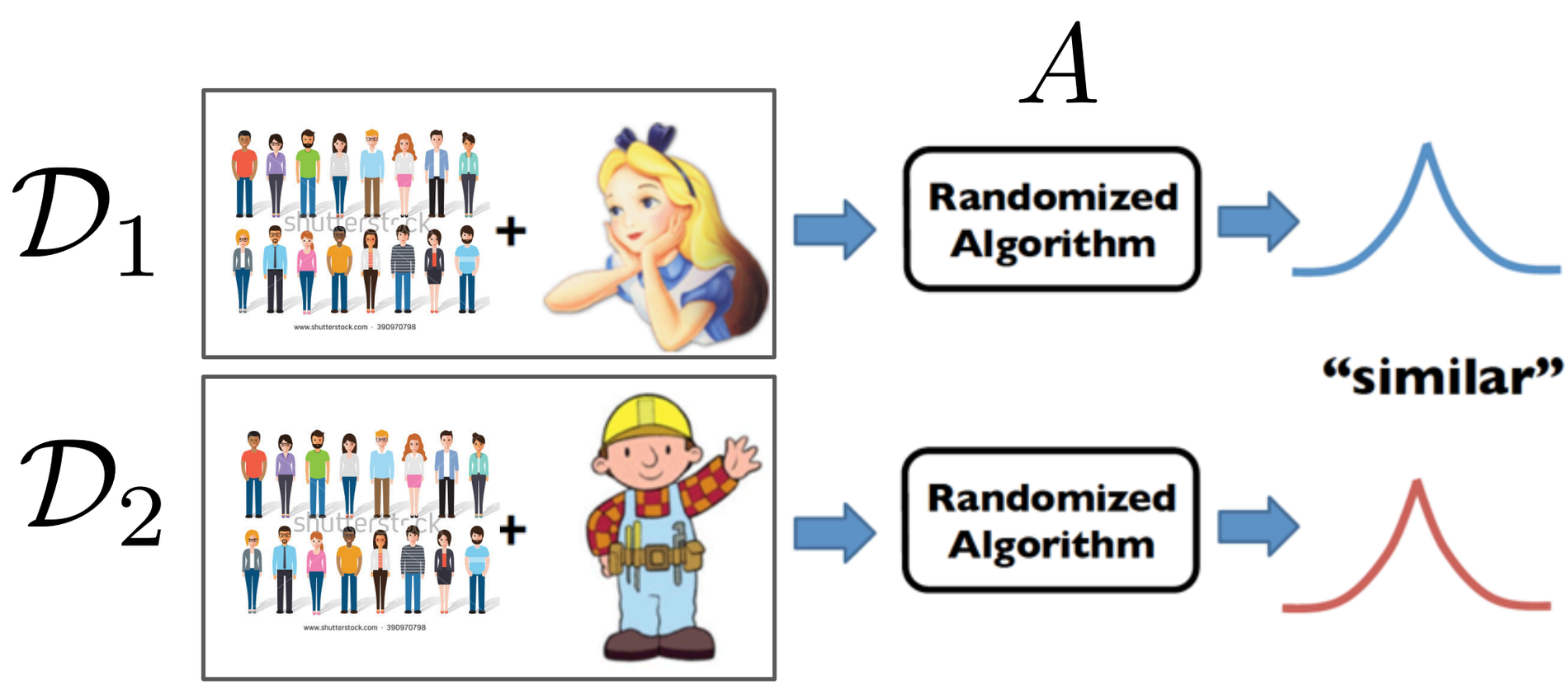

An algorithm is differentially private, if

A is epsilon-DP, if $|L^{(o)}| \leq \epsilon$

for all o and all pairs of datasets

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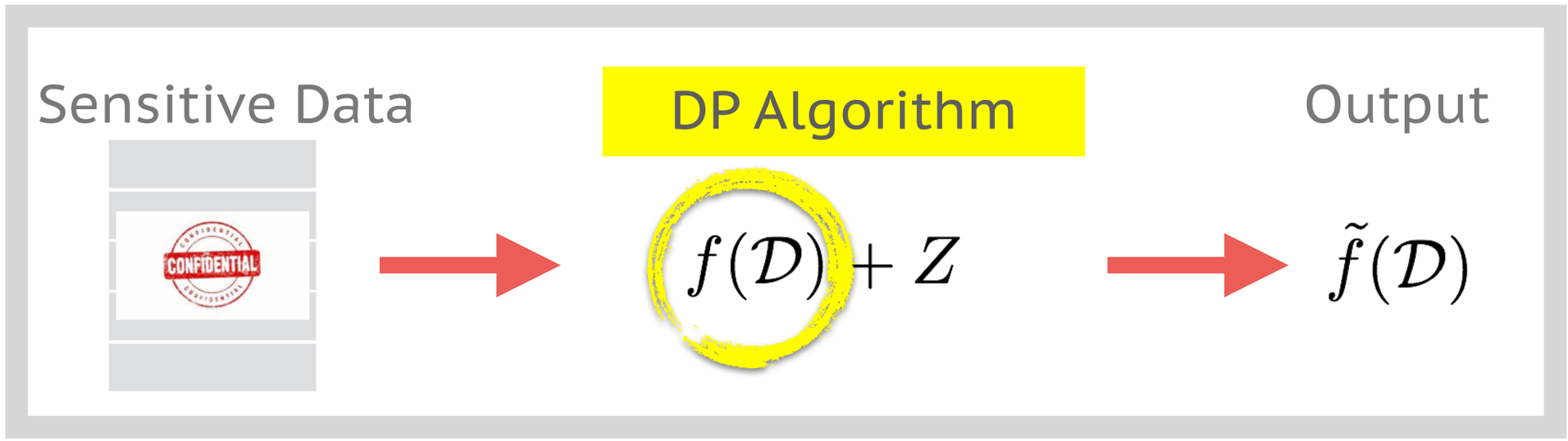
- Epsilon quantitatively measures how much the risk to an individual privacy may increase due to that individual's data inclusion in the inputs to the algorithm.

How to develop a DP Algorithm?

[Global Sensitivity Method, DMNS06]



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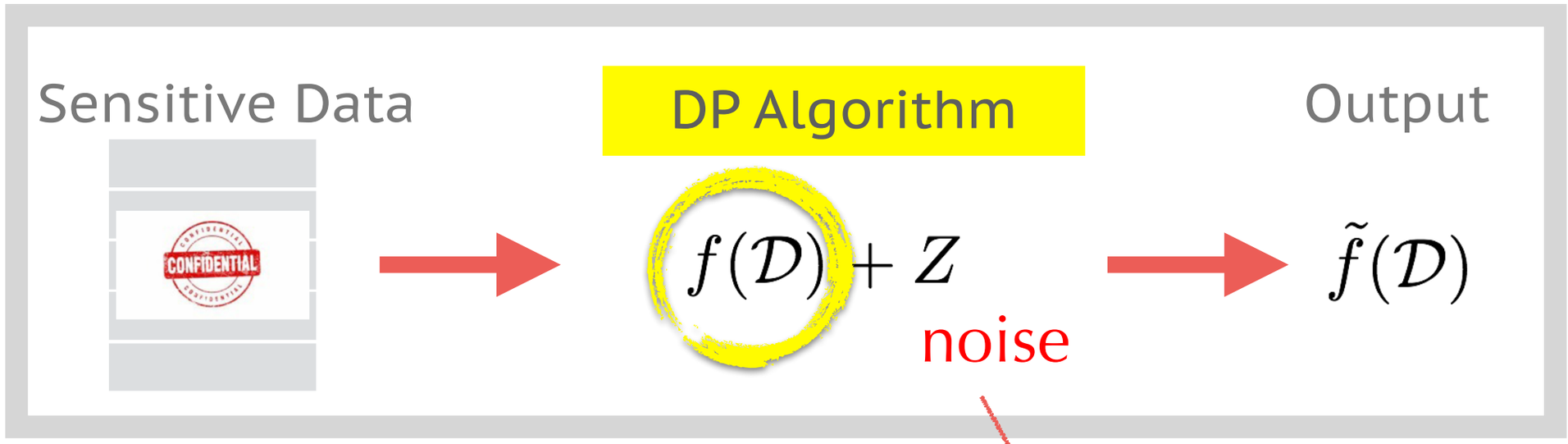

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Sensitivity

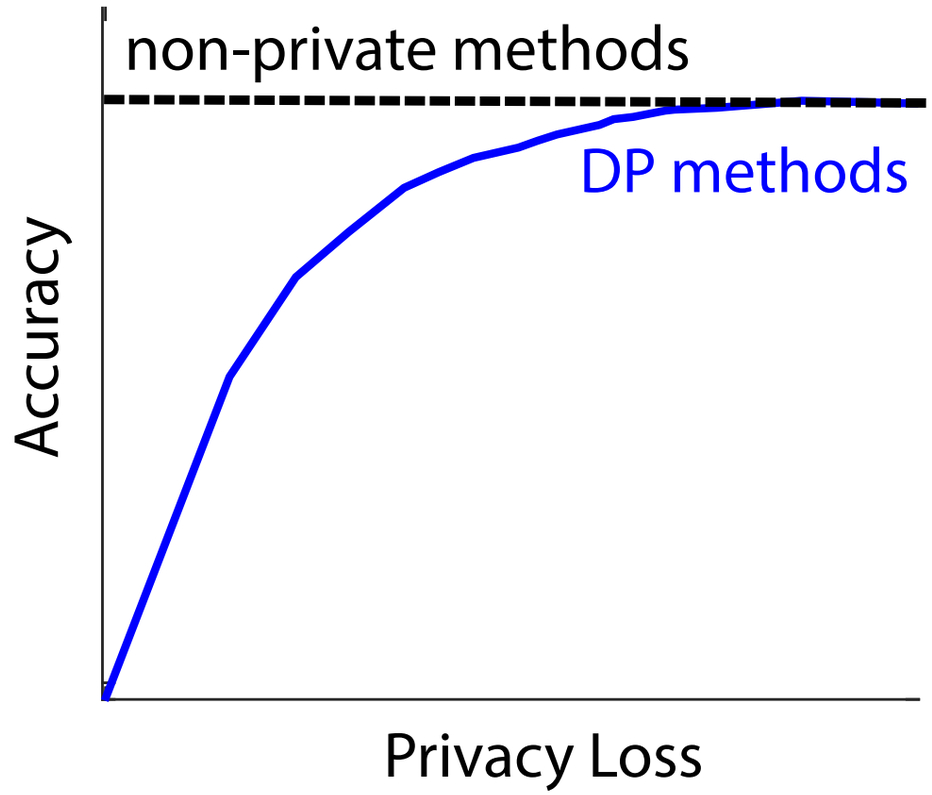
privacy loss

$$S(f) = \max_{D(\mathcal{D},\mathcal{D}')=1} |f(\mathcal{D}) - f(\mathcal{D}')|$$

maximum over all pairs of datasets

Privacy & Accuracy Trade-off

$$\text{noise} \propto \frac{\text{sensitivity}}{\text{privacy loss}}$$



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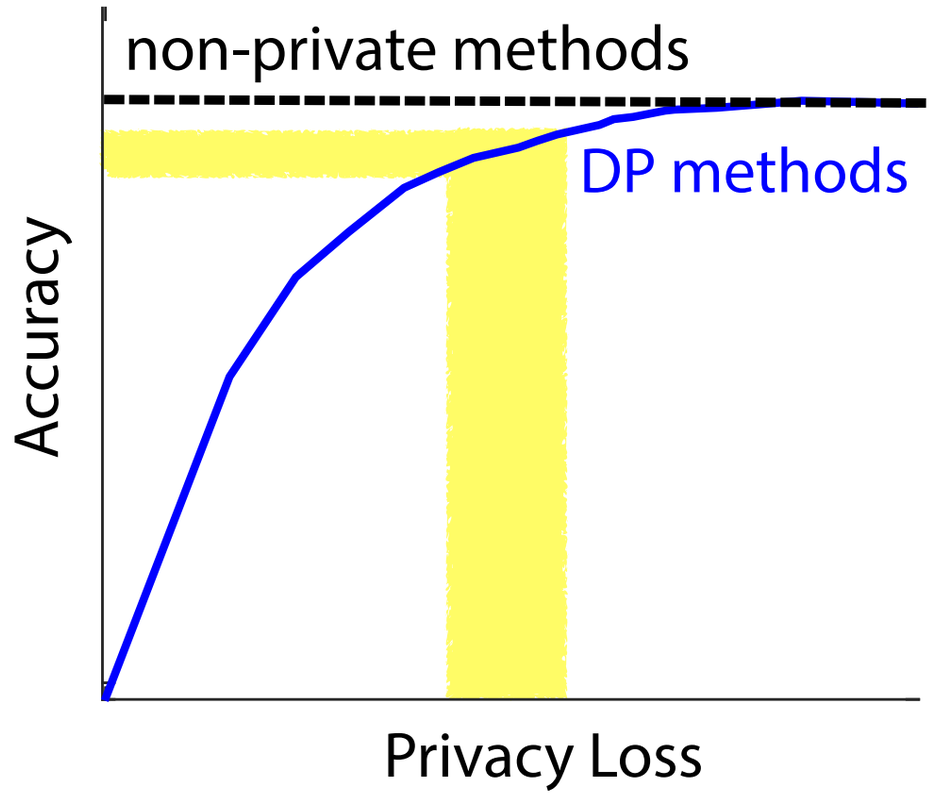

Good DP-ML algorithms:

provide accurate

& differentially private outputs

Example

DP mechanisms

Laplace Mechanism

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Input: Monthly salary $x_1, x_2, \cdots, x_N$

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Sensitivity: $S(\bar{x}) = \max_{\mathcal{D}, \mathcal{D}'} |\bar{x} - \bar{x}'|$

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Privacy loss

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Add Gaussian noise $f(\mathcal{D}) + Z$

$$Z \sim \mathcal{N}(0, \sigma^2)$$

noise standard deviation: $\sigma \geq \dfrac{c(\delta)S(f)}{\epsilon}$

Approximate DP: $P(L^{(o)} > \epsilon) \leq \delta$

Privacy loss

$(\epsilon, \delta) - \mathrm{DP}$

Pure DP holds w.p. at least $1 - \delta$

DP Mechanisms

- Laplace mechanism: provides a pure DP guarantee

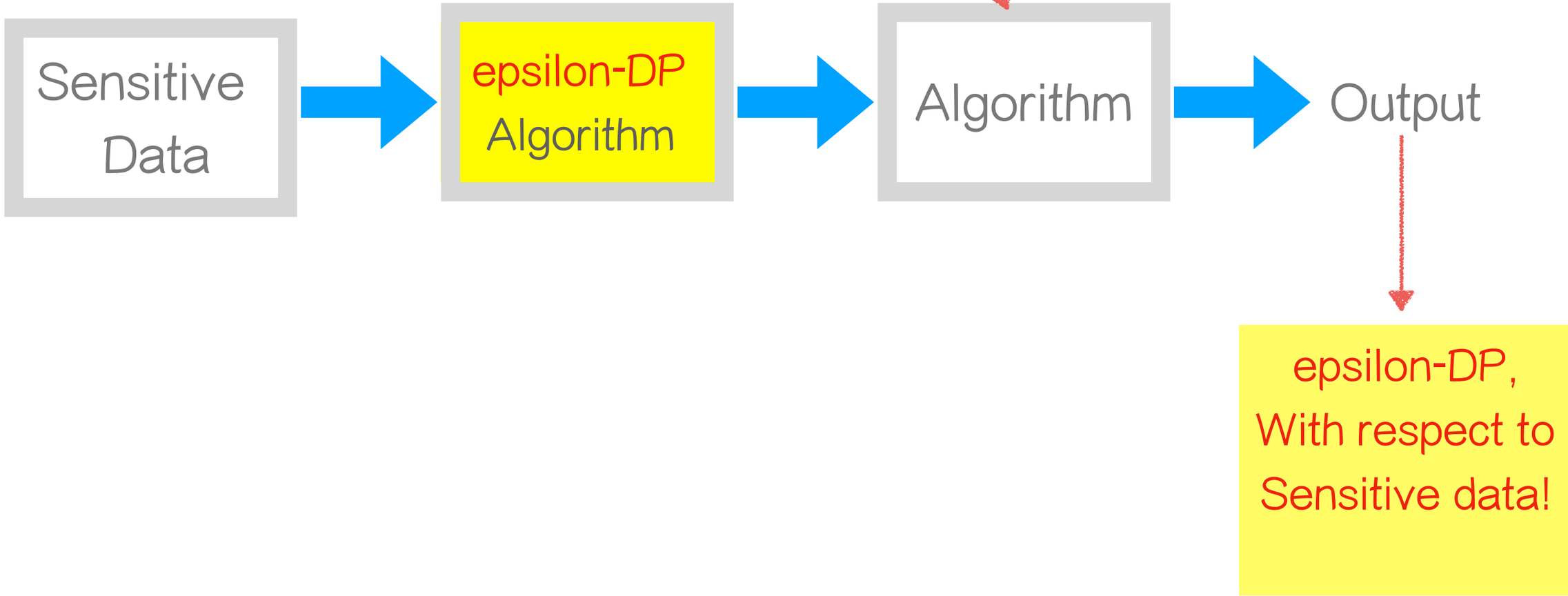
- Gaussian mechanism: provides an approximate DP guarantee

- There are more mechanisms. See [Algorithmic foundations of differential privacy, Dwork & Roth 2014].

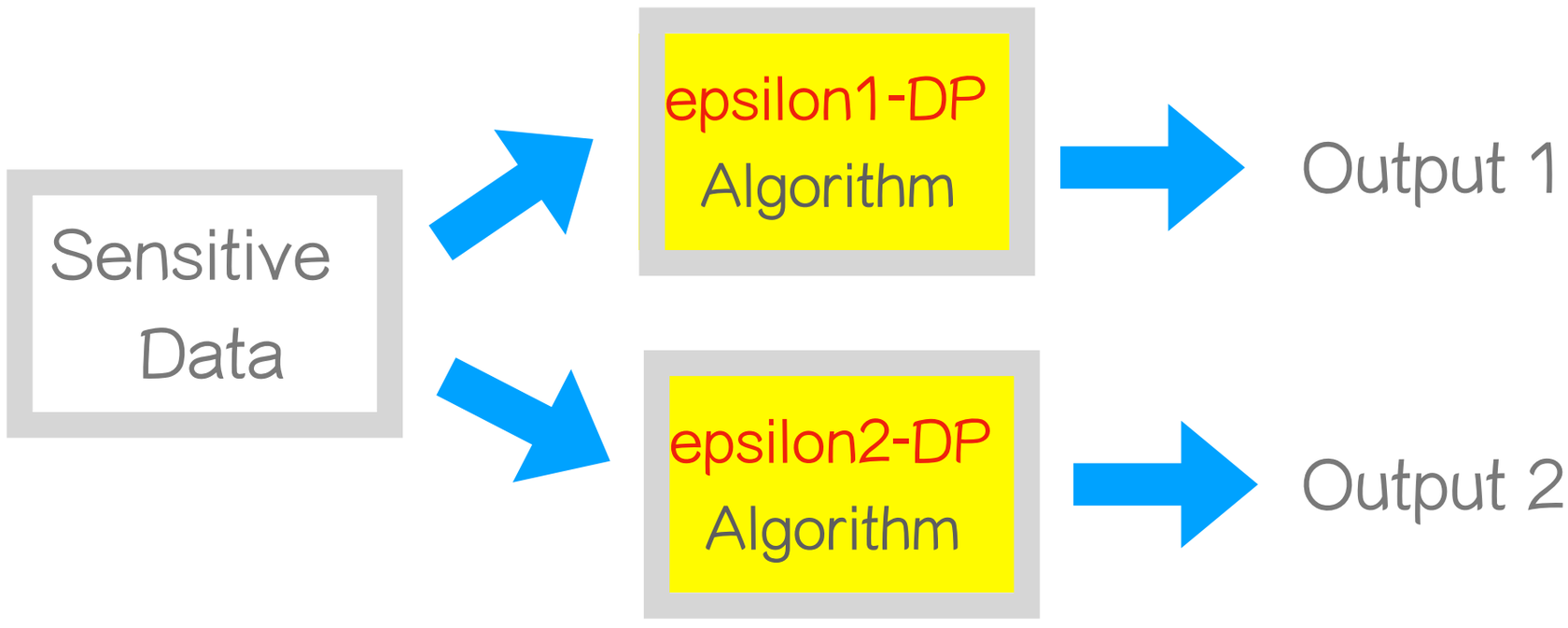
Properties of DP

1. Postprocessing invariance

- Differential privacy is immune to post-processing:



2. Composition



- Union of output 1 (from epsilon1-DP algorithm) & output 2 (from epsilon2-DP algorithm) is (epsilon1+epsilon2)-DP!
- More refined composition methods do exist! e.g., [Abadi et al,16]

Key properties of DP

- Post-processing invariance

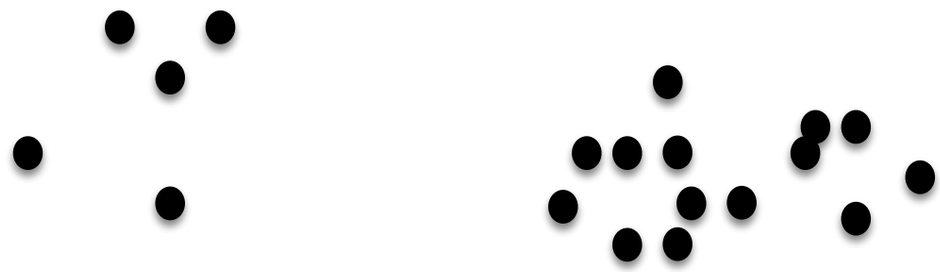
- Composition : introduces challenges to make iterative algorithms in ML differentially private!

Examples of DP-ML algorithms

Clustering & density estimation

Mixture of Gaussians

For clustering & density estimation



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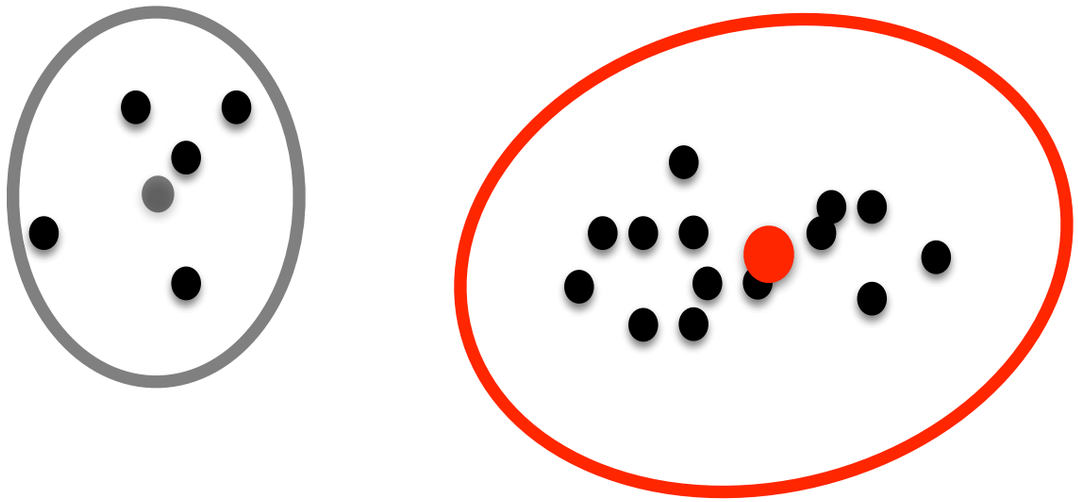

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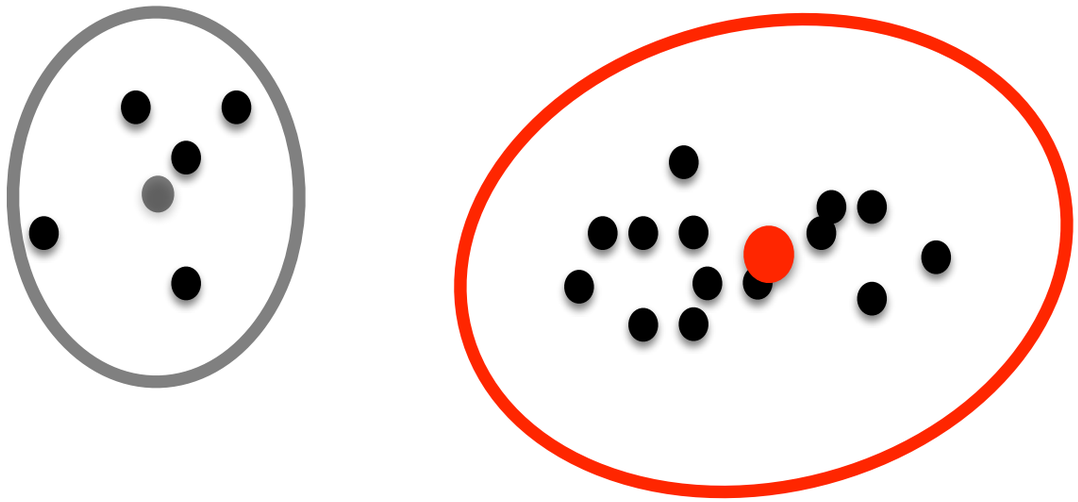

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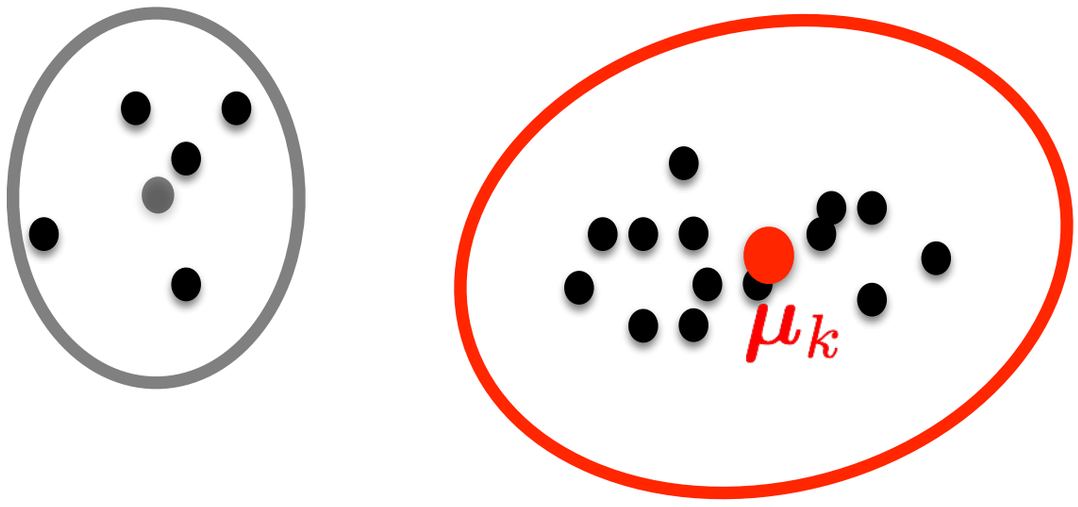

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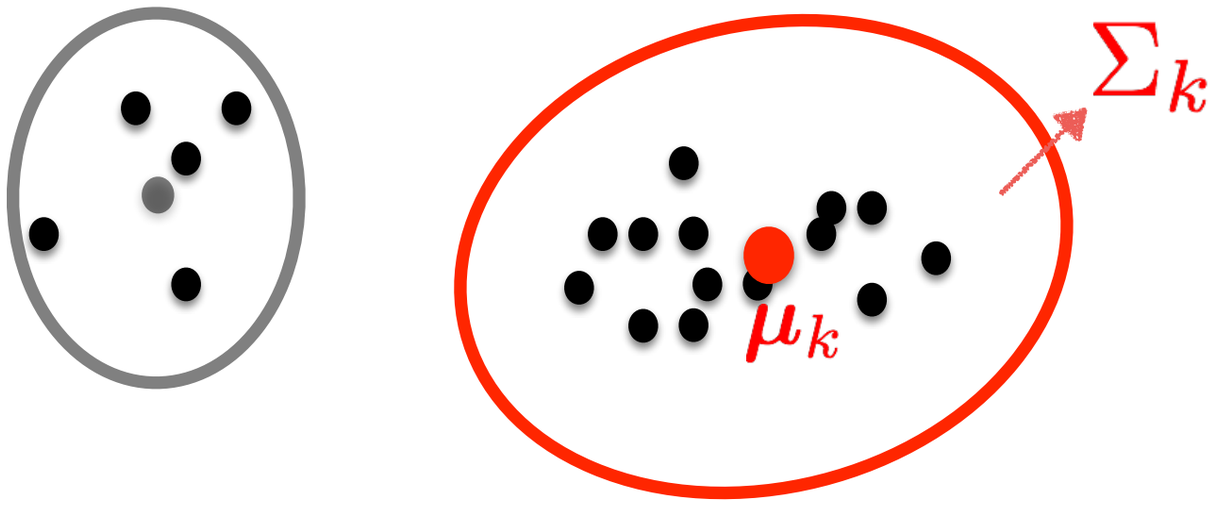

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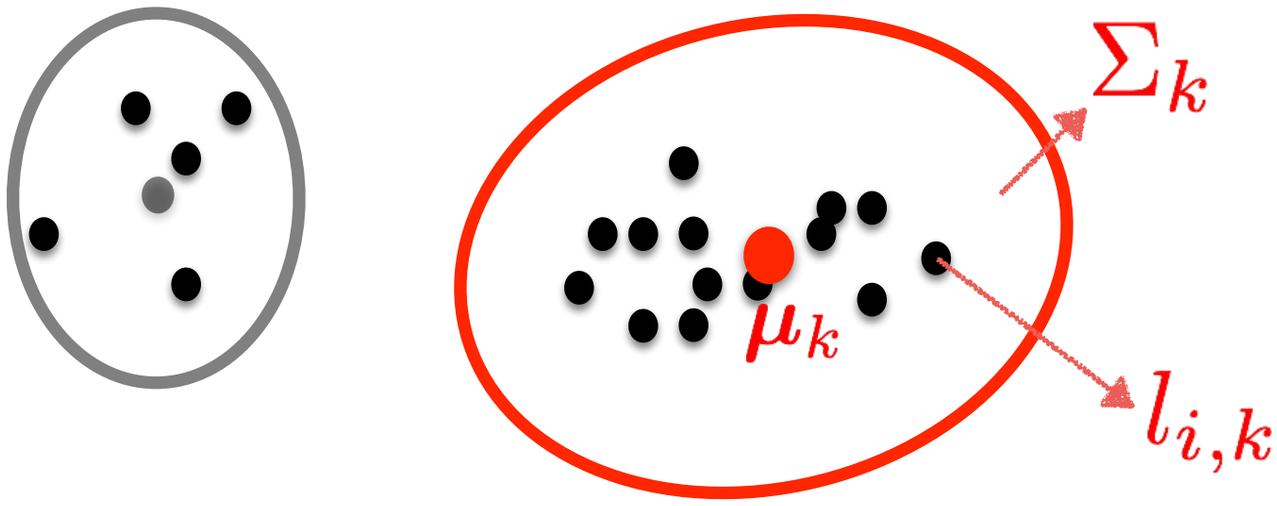

- Assign a Gaussian to learn each cluster
- Each Gaussian is parameterised by $\boldsymbol{m} = \{\boldsymbol{\mu}_k, \Sigma_k\}_{k=1}^{K}$
- Introduce **latent** variables for cluster assignment

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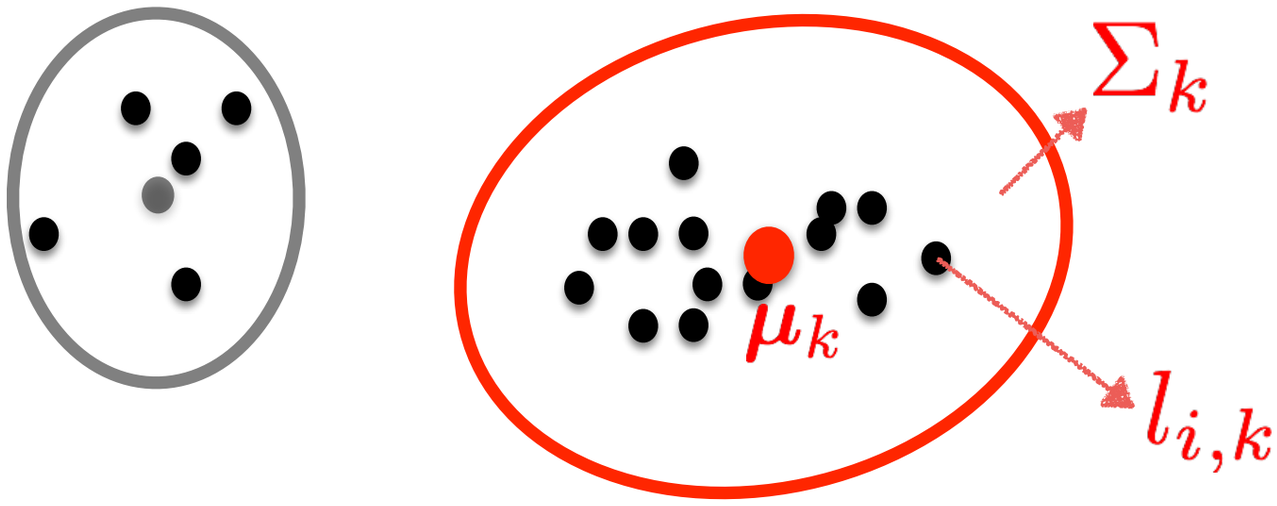

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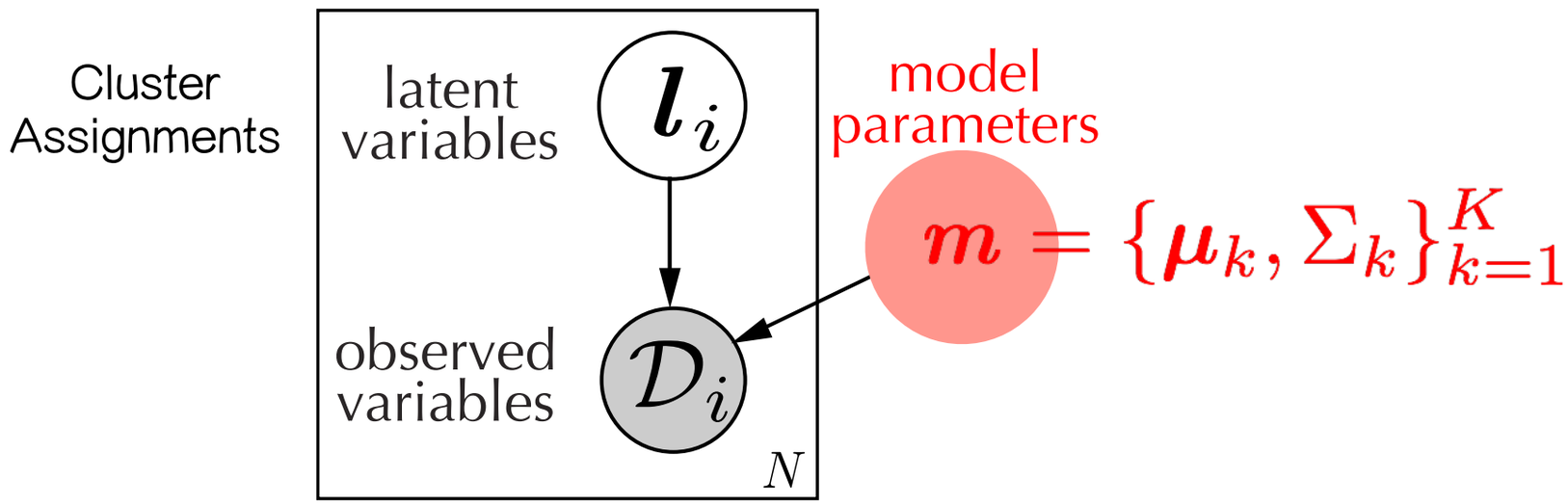
- **Goal:** estimate the parameters

Expectation Maximization



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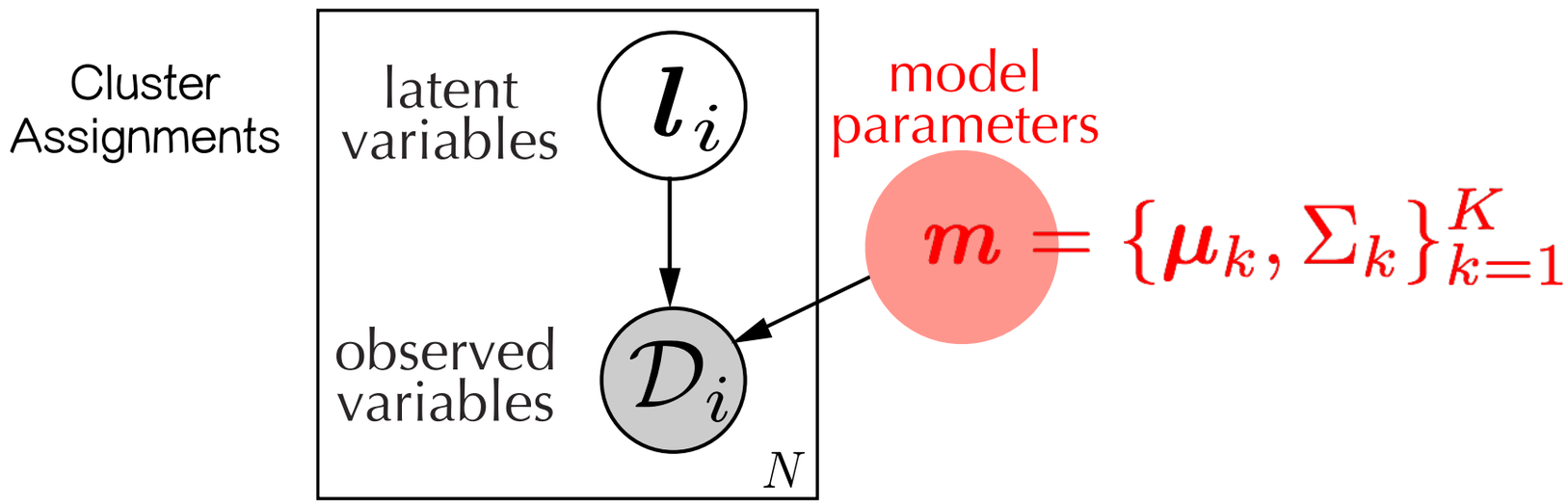

log-likelihood

$$\log p(\mathcal{D}|\mathbf{m}) = \log \int d\mathbf{l}\; p(\mathcal{D}, \mathbf{l}|\mathbf{m})$$

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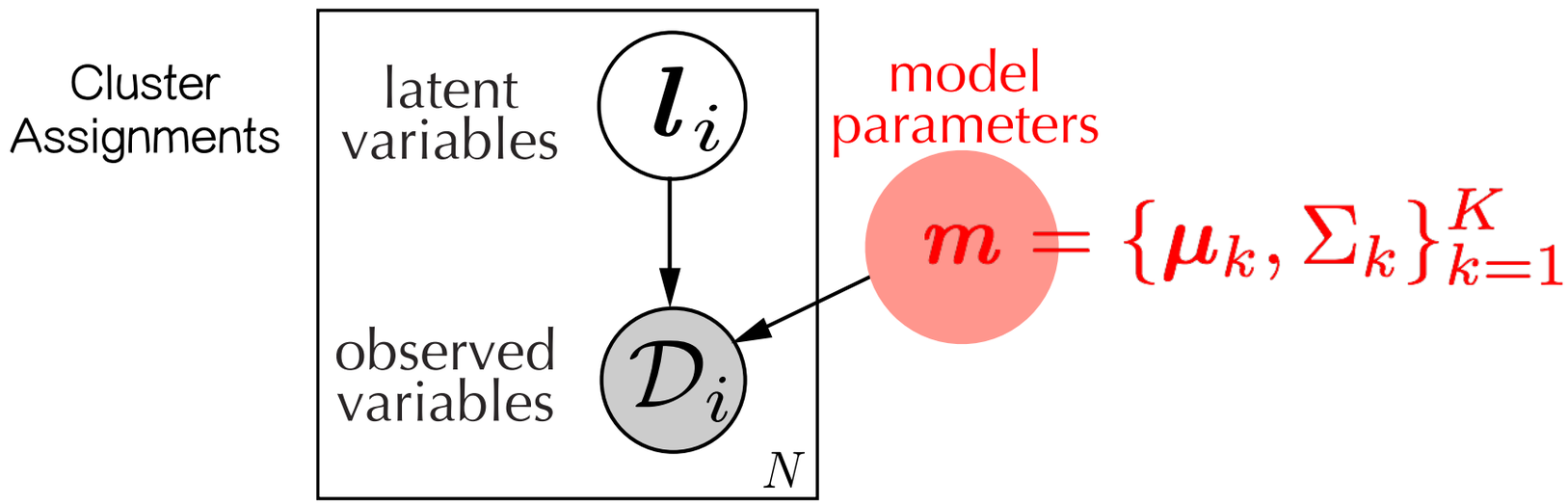

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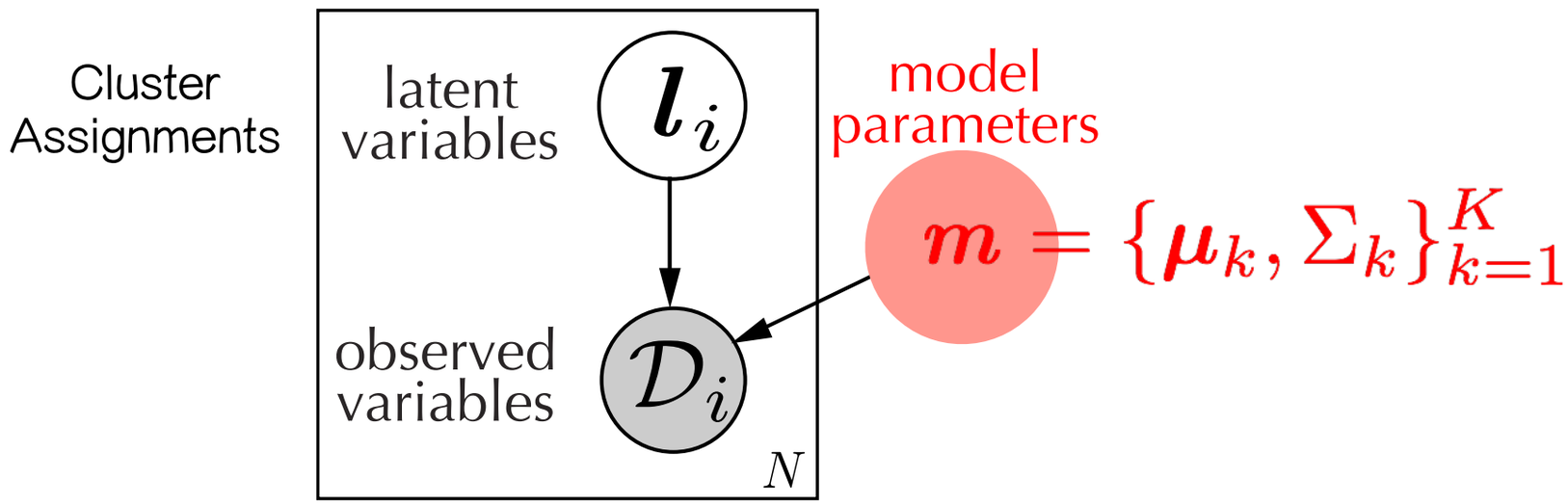

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$\mathcal{F}(q, \mathbf{m})$ Free-energy

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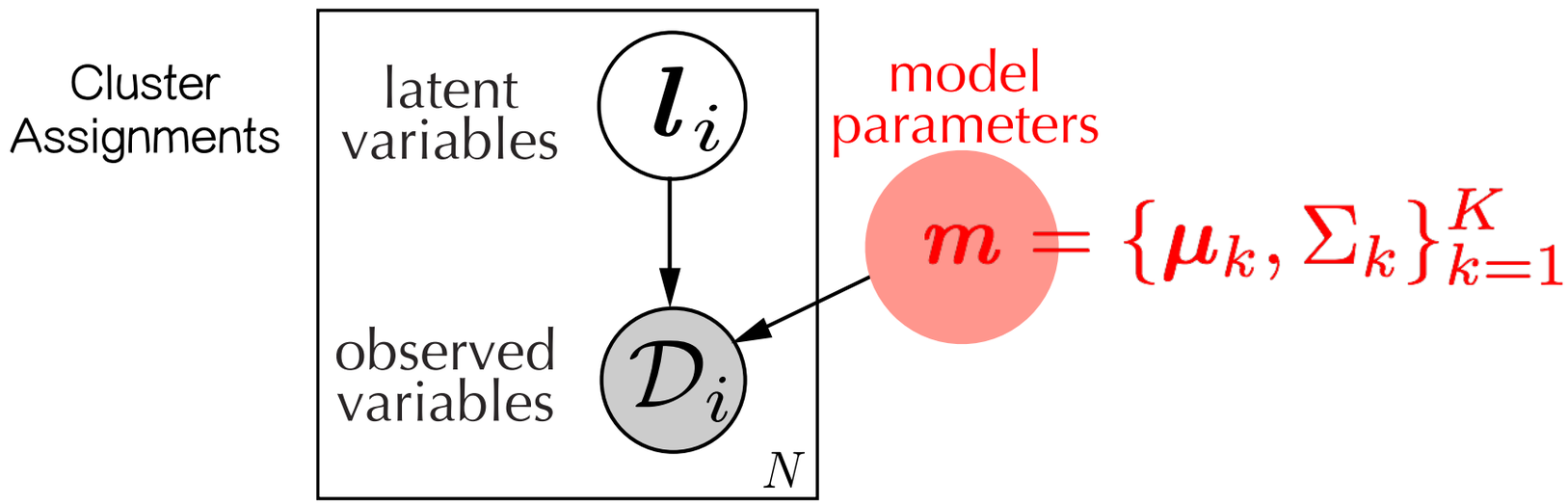

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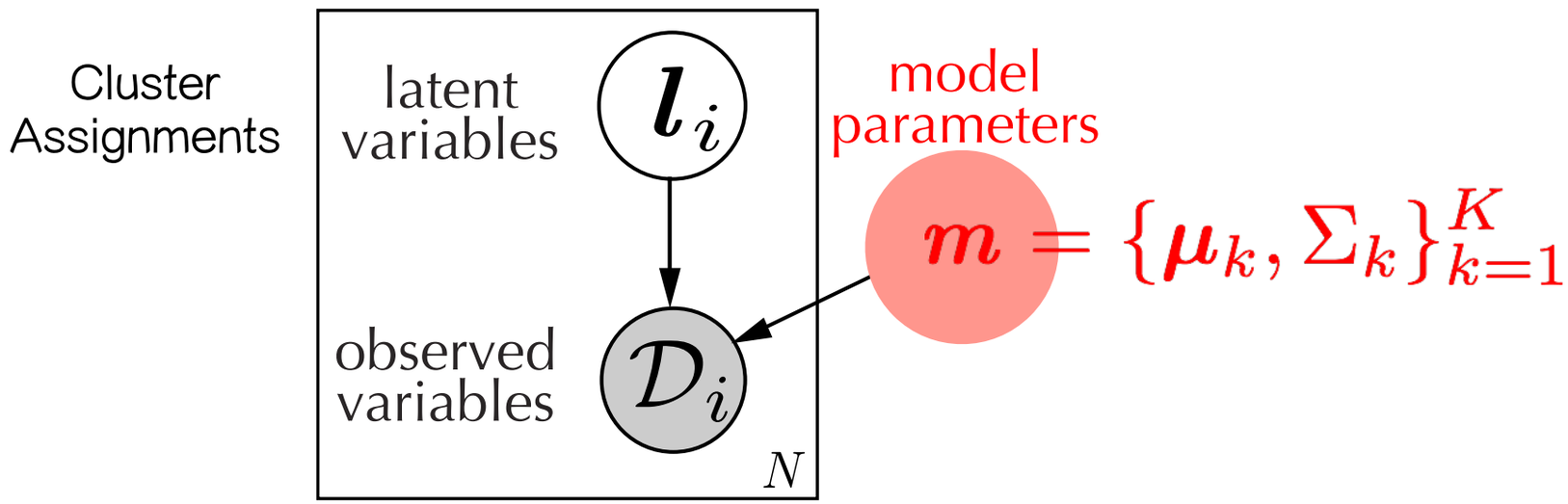

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DP-EM

[Park et al, 2017]

DP-EM

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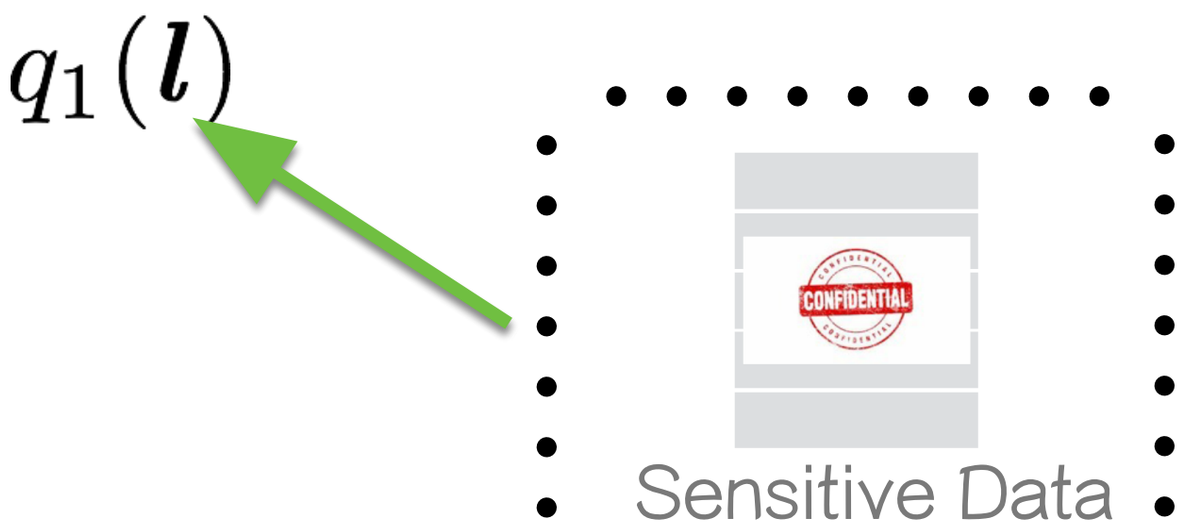

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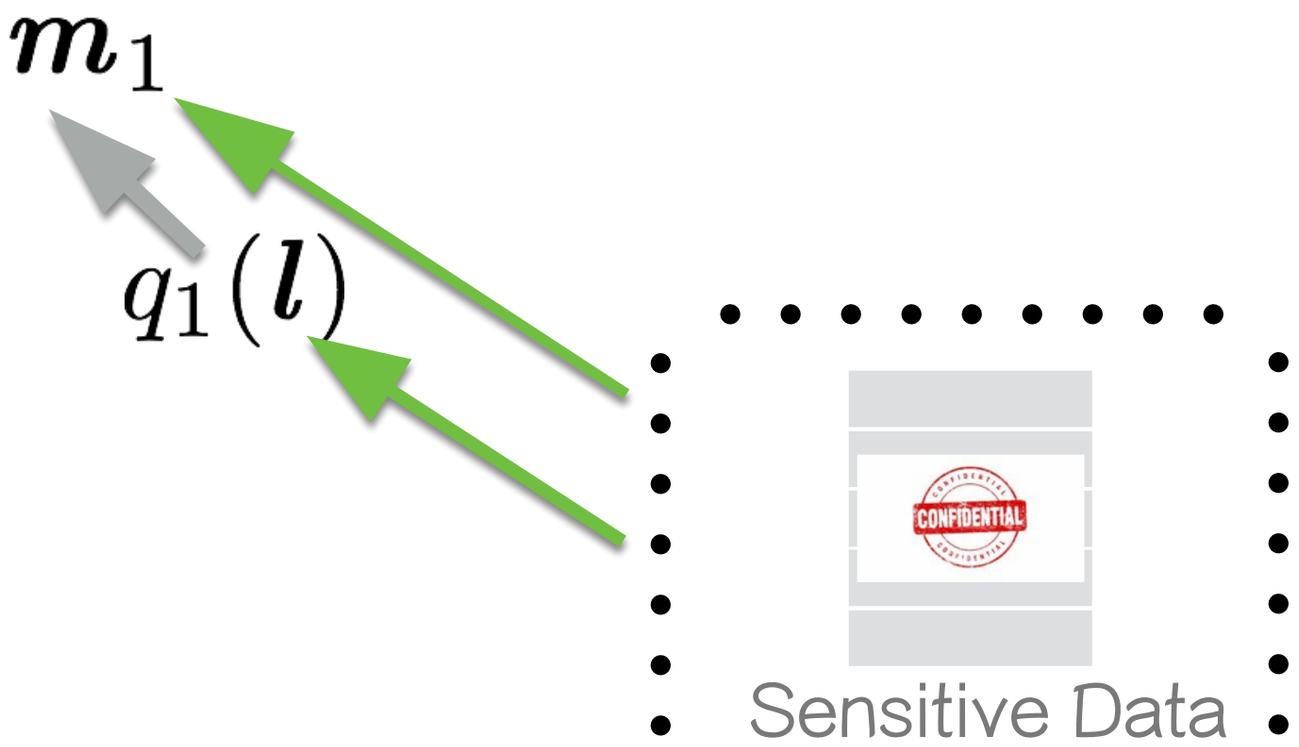

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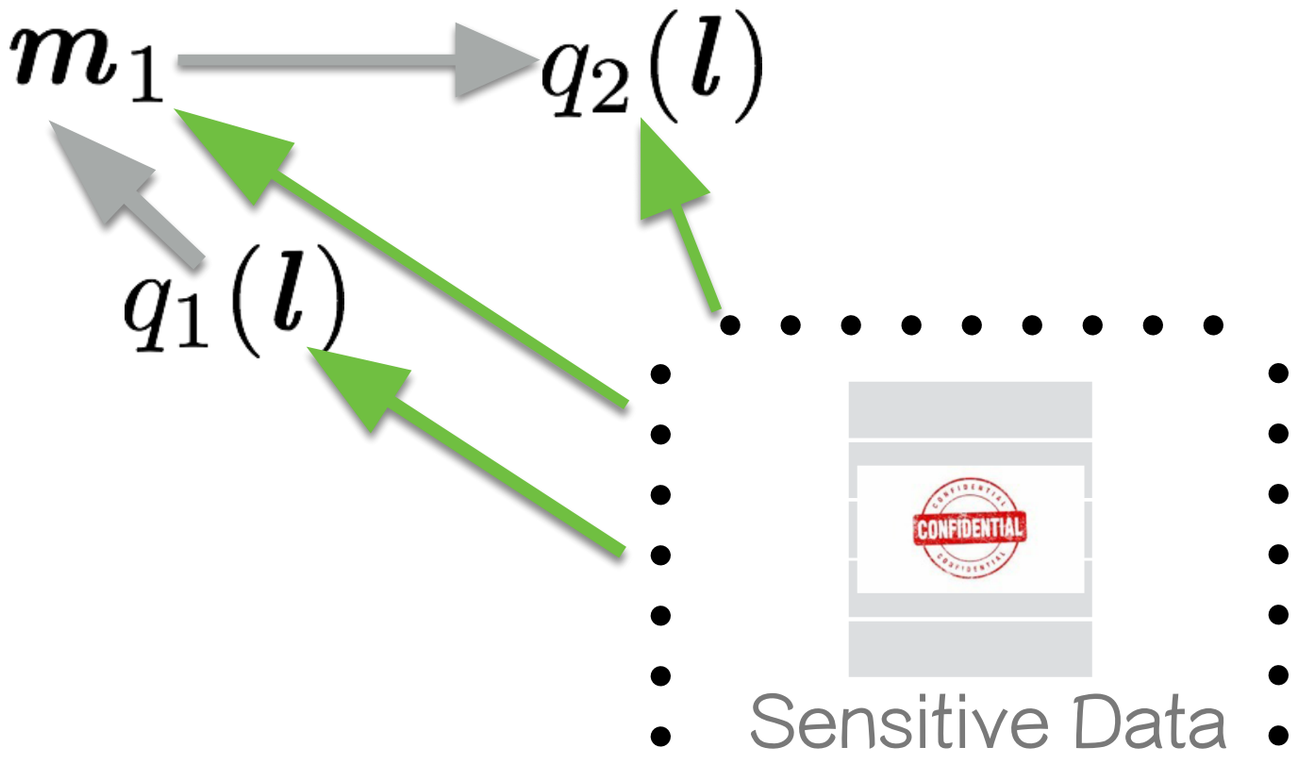

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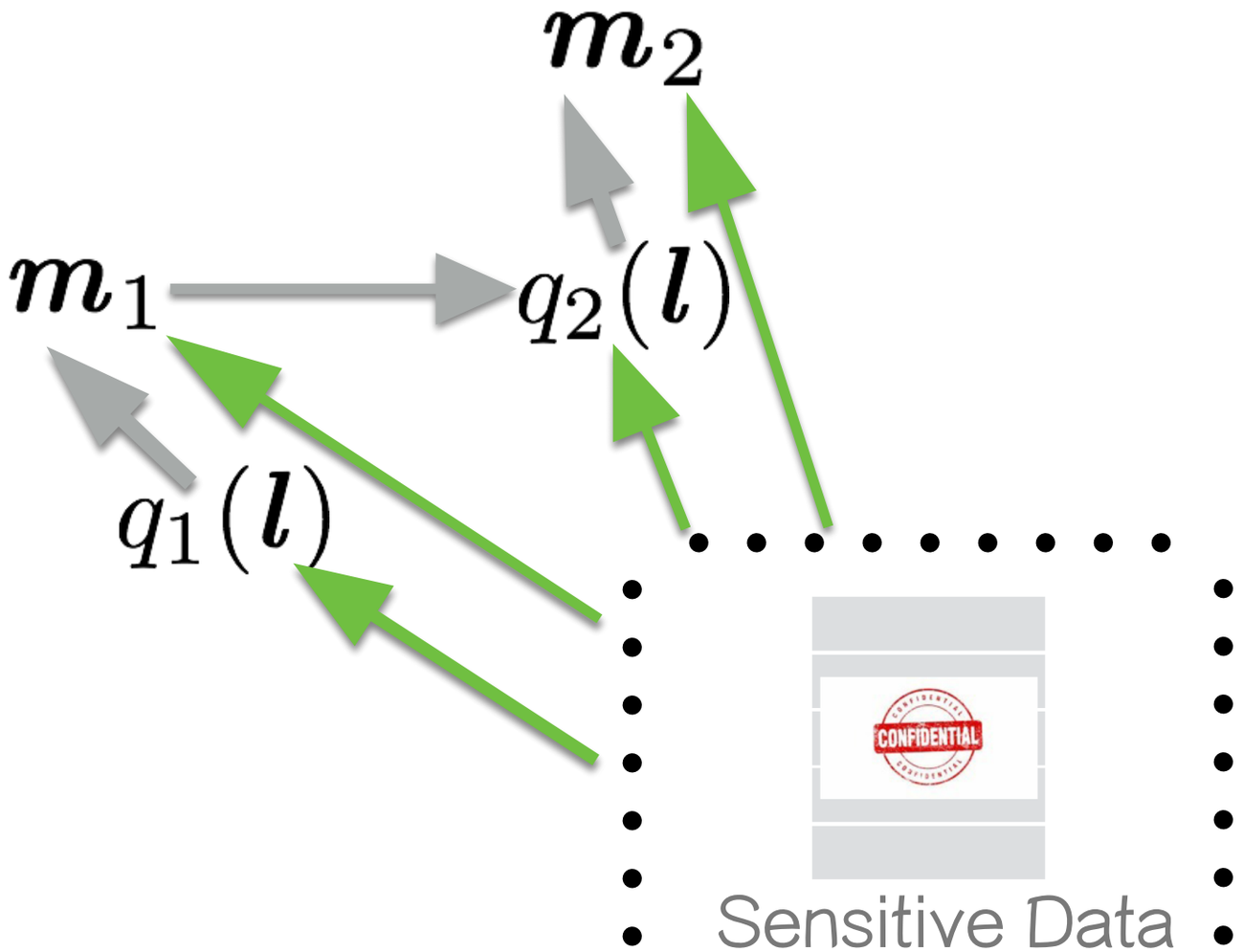

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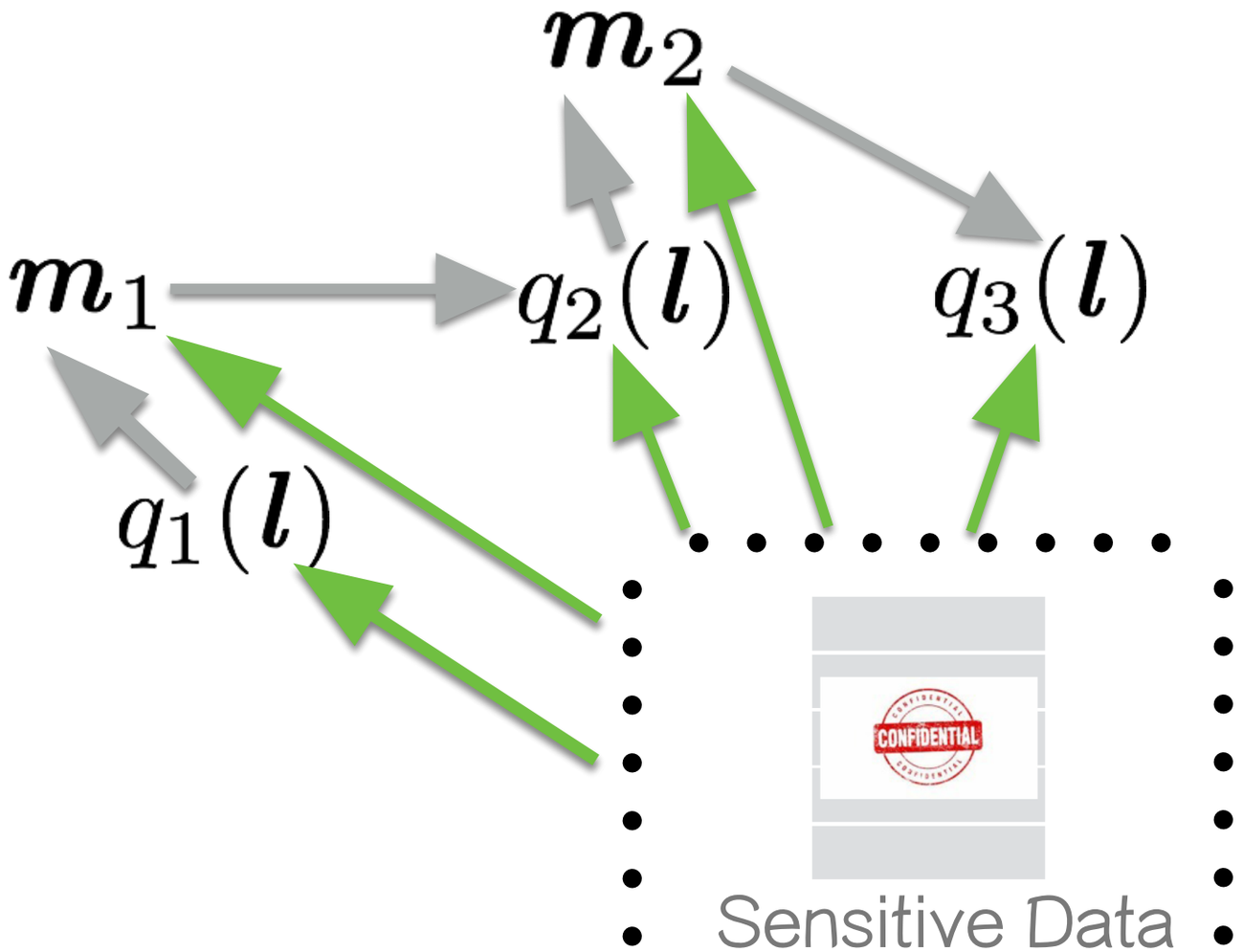

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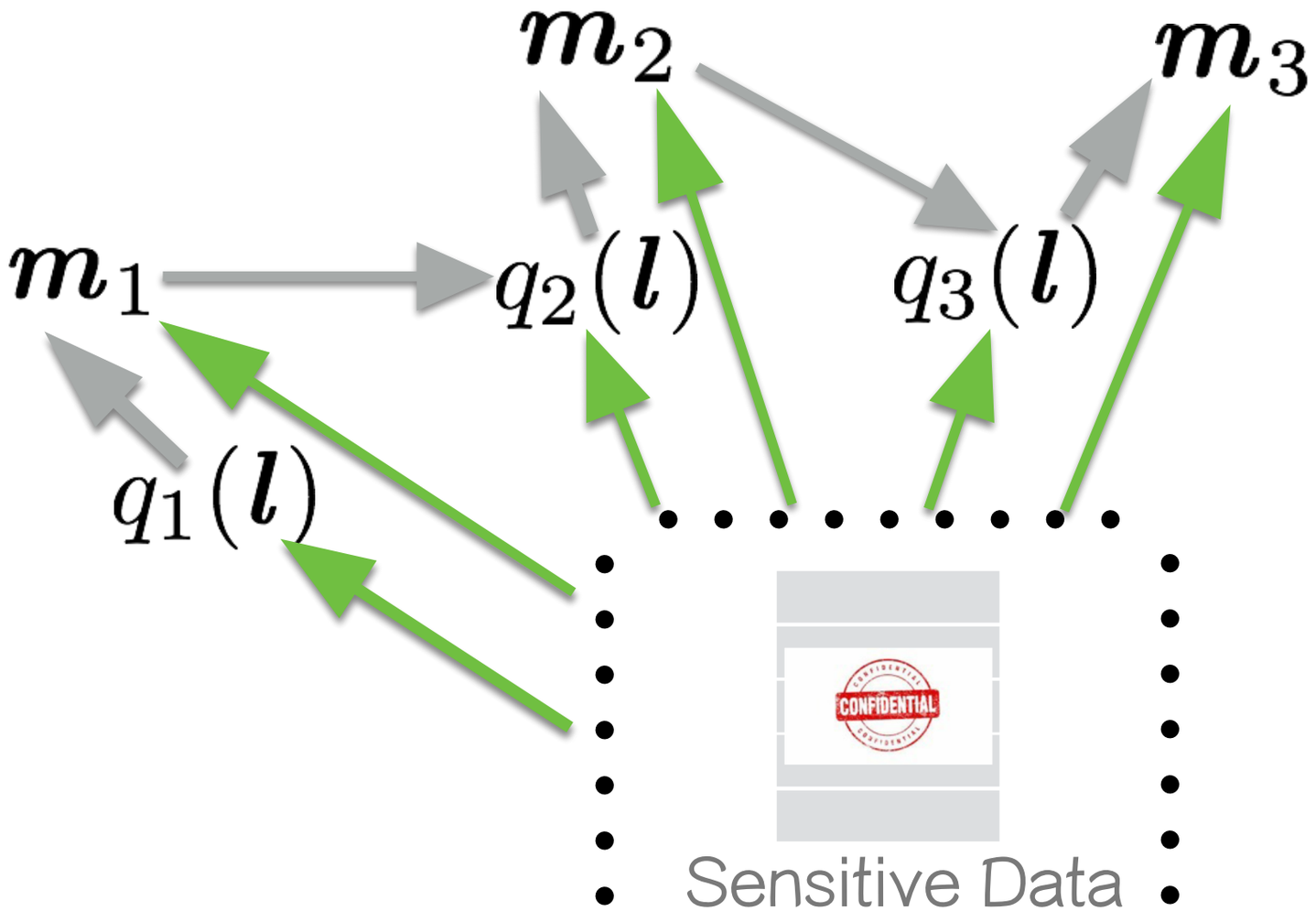

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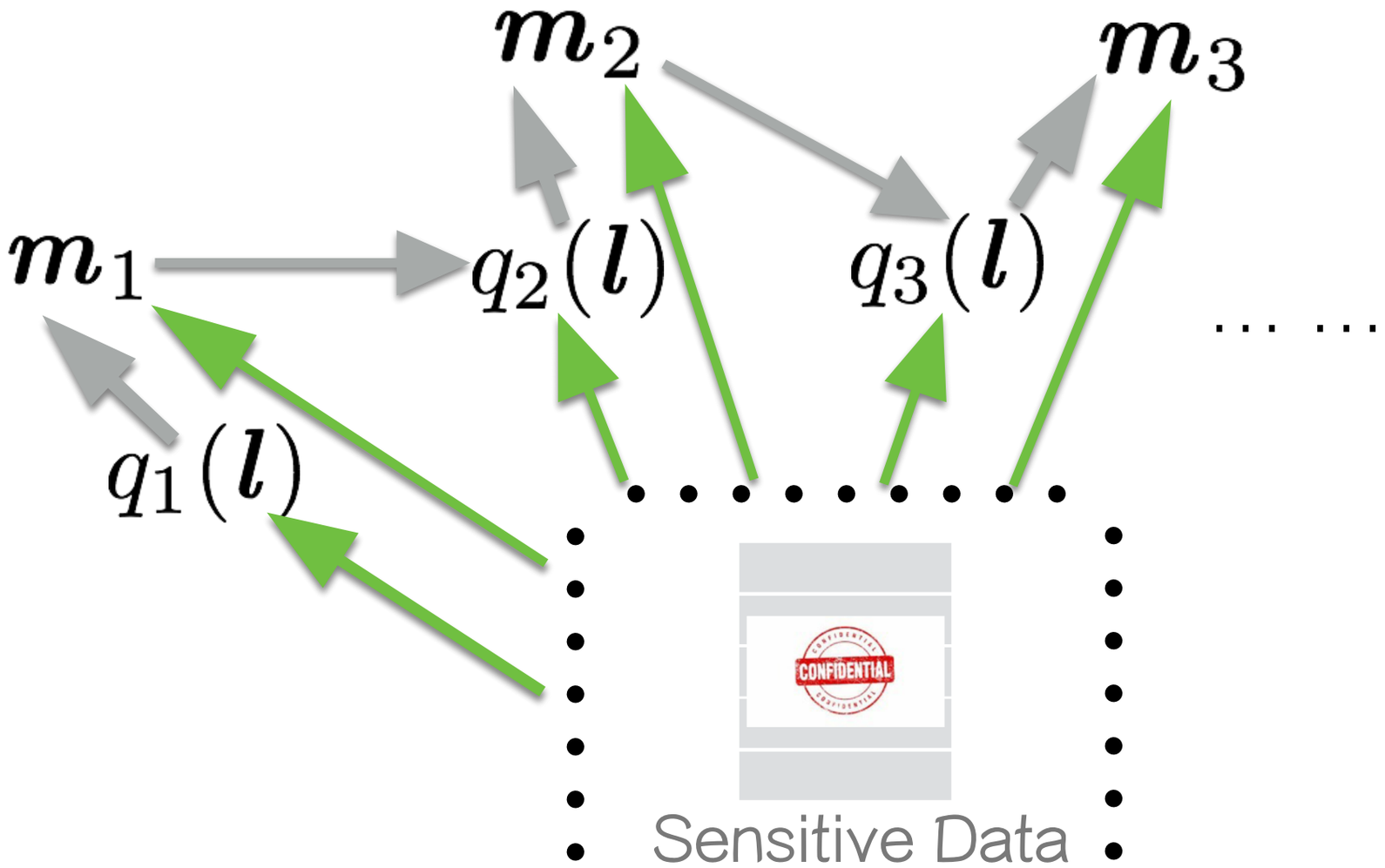

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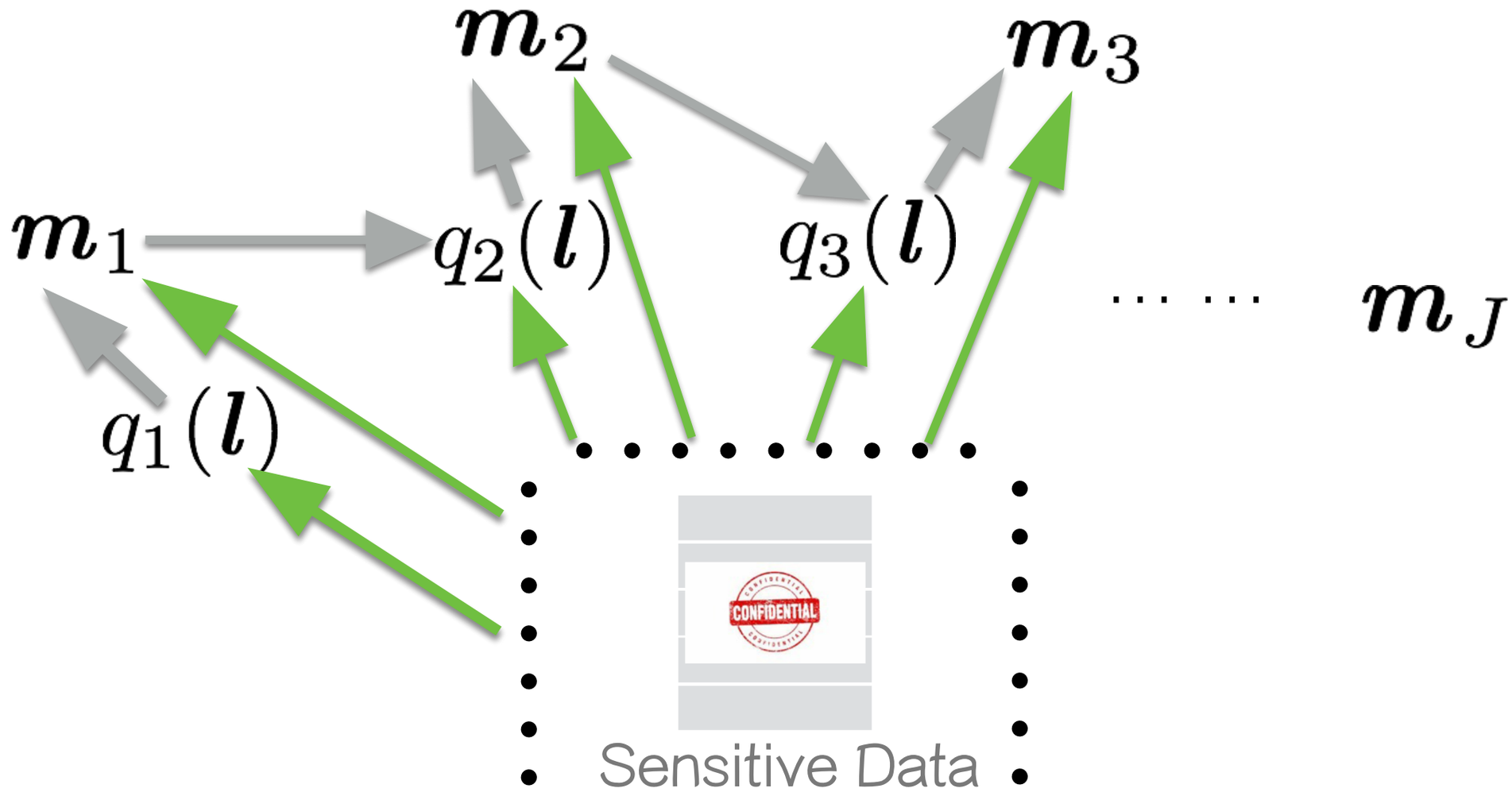

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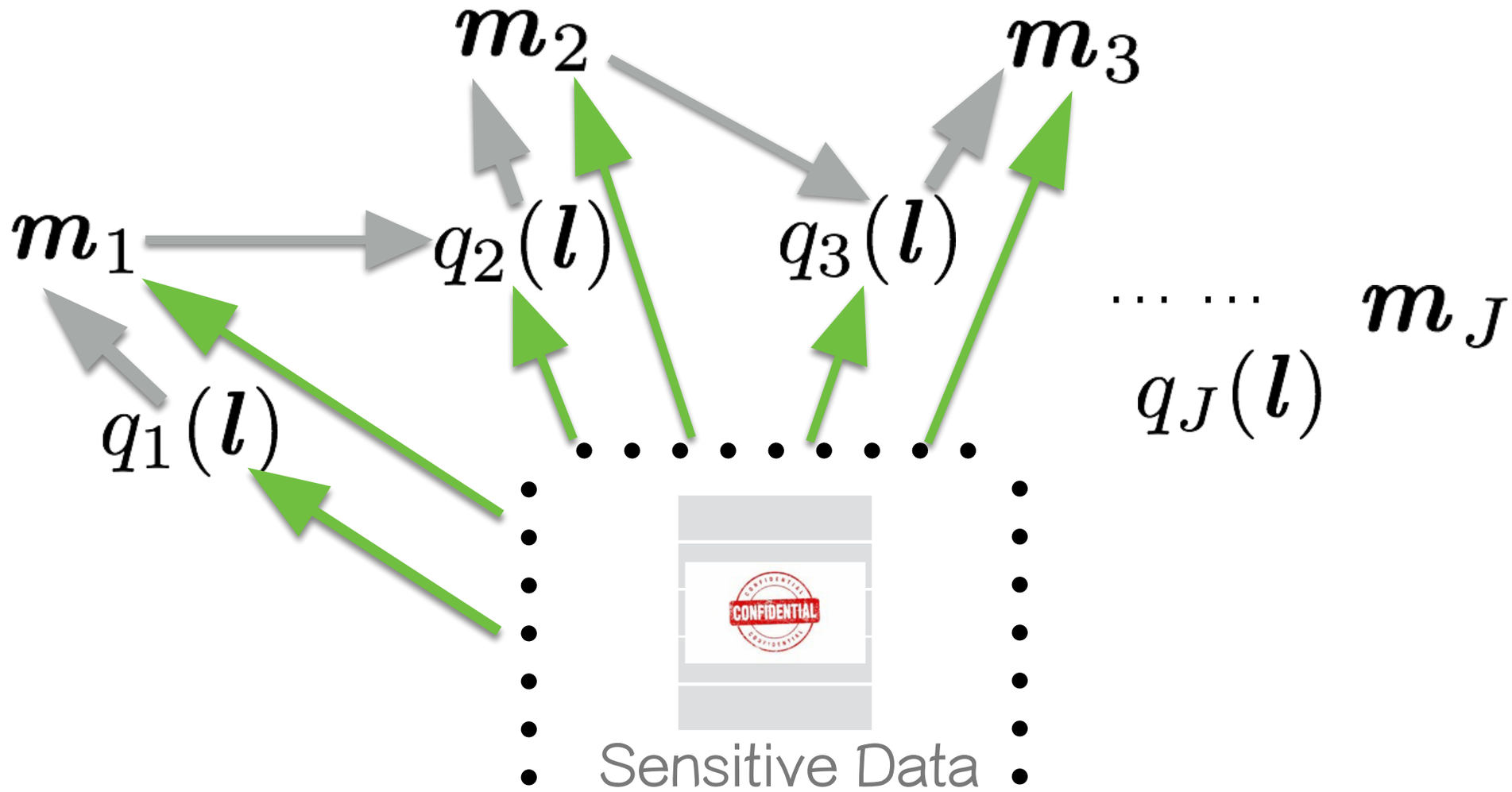

DP-EM

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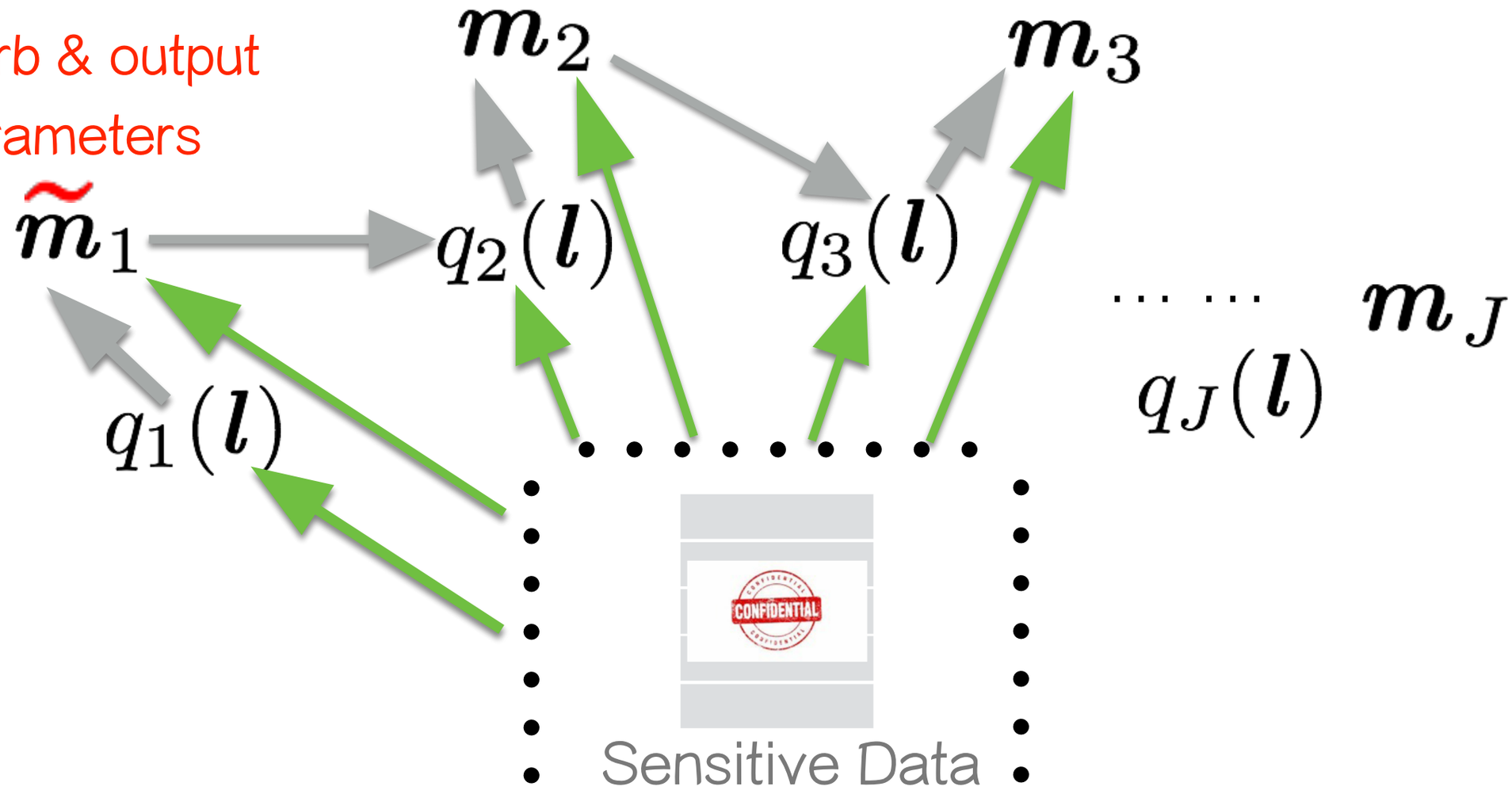
Perturb & output parameters



DP-EM

[Park et al, 2017]

Sensitivity: one-datapoint's worth directly from dataset & indirectly through q(l)

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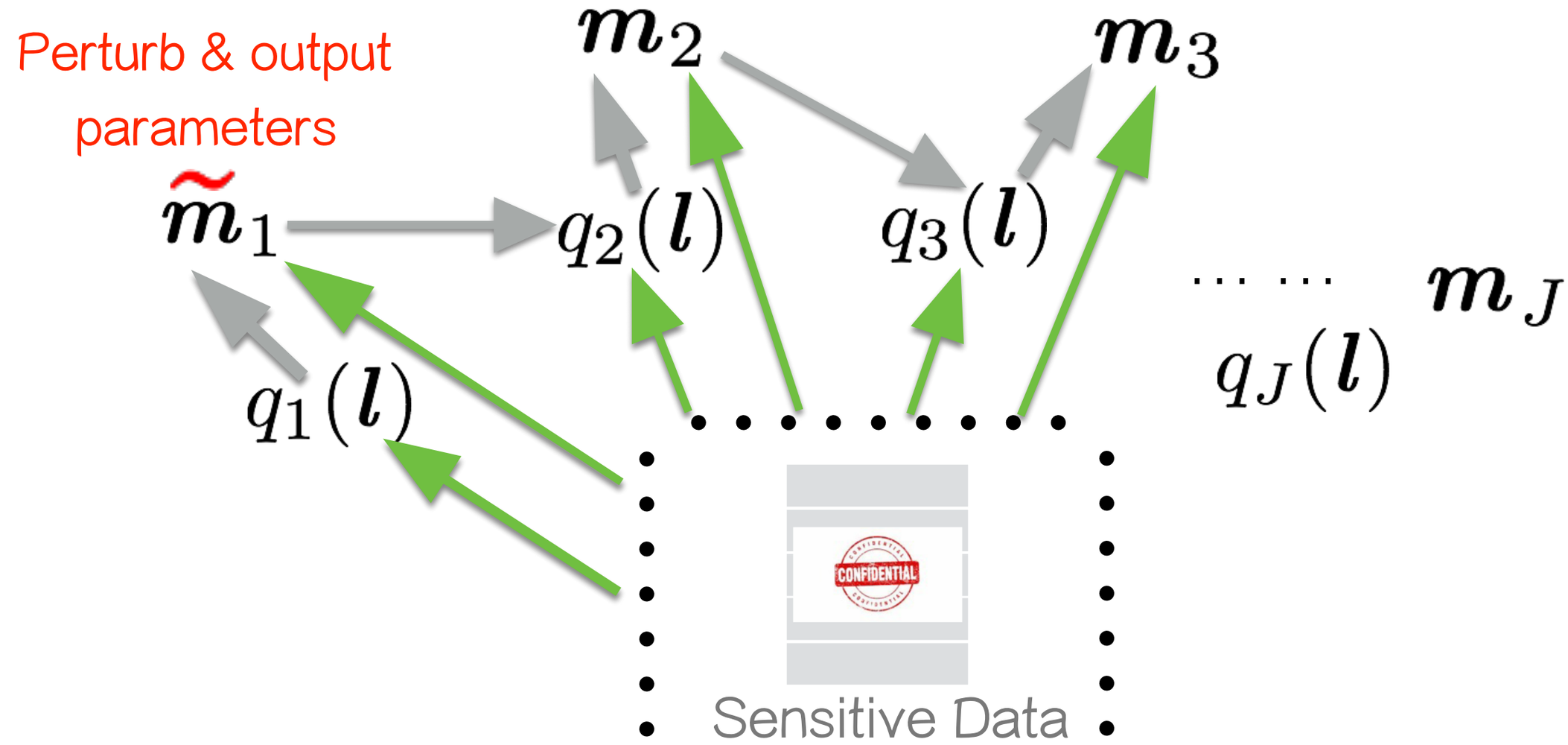

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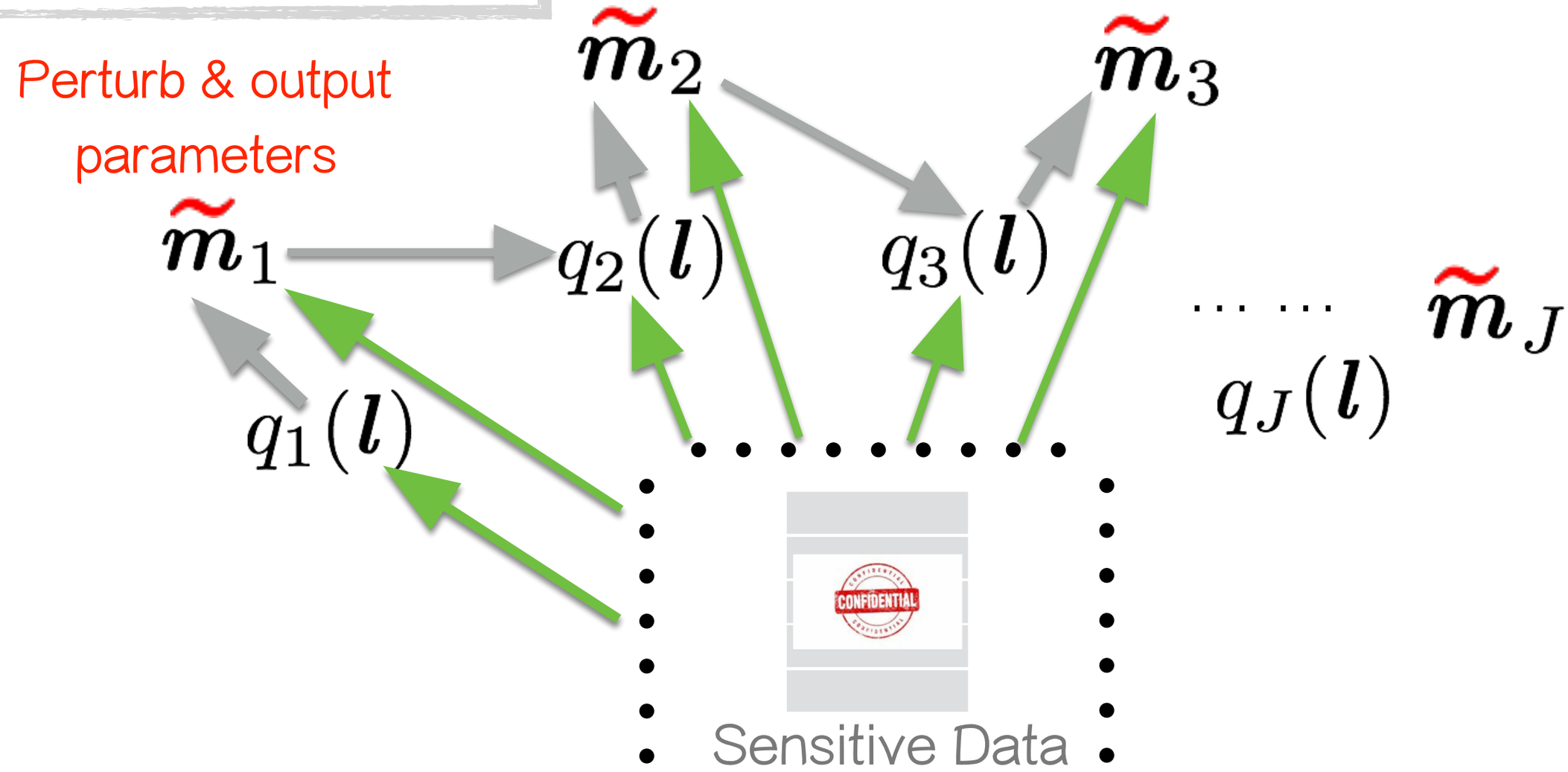

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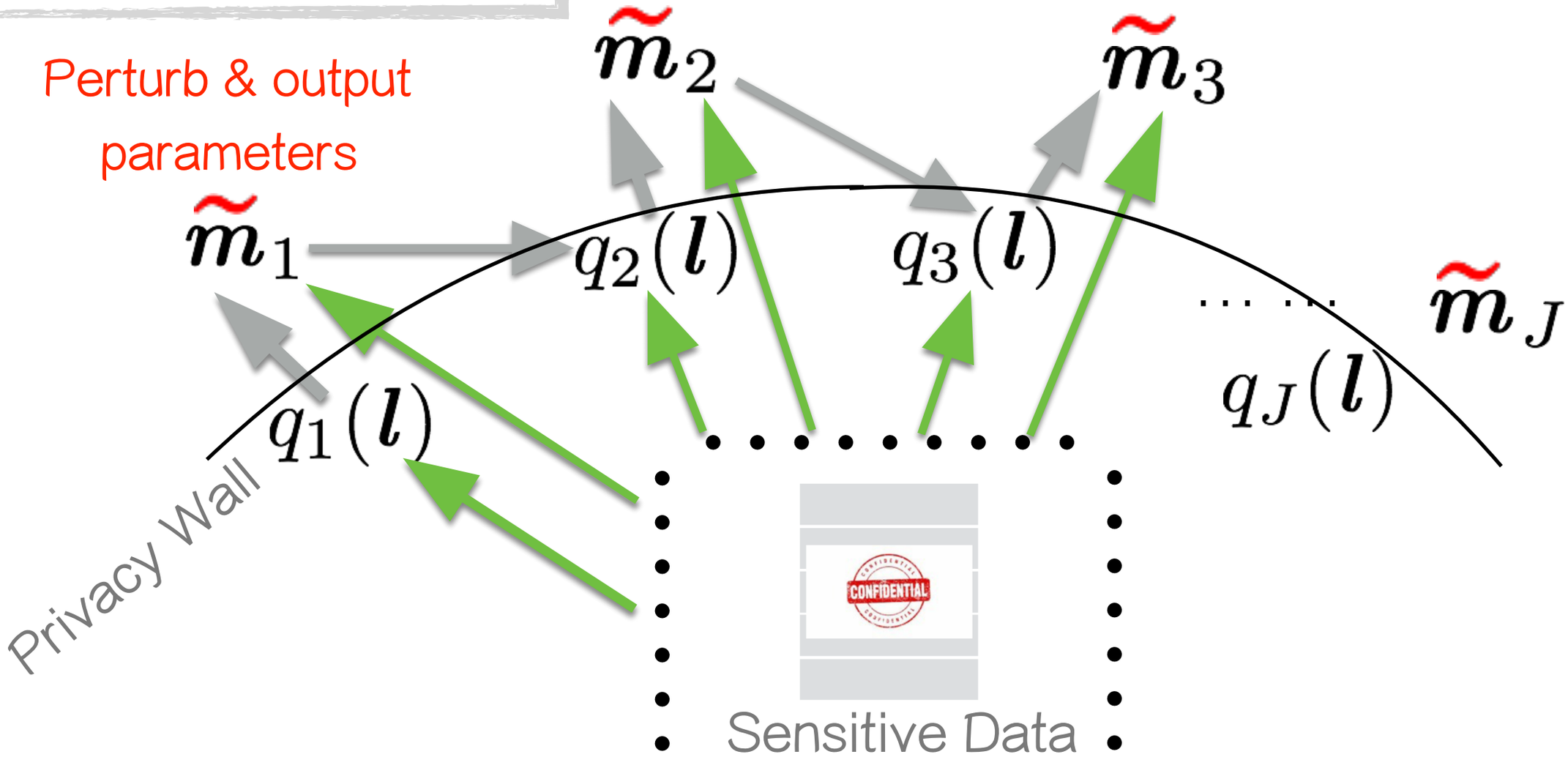

Repetitive access to data, large privacy loss

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Moments accountant

[Abadi et al, 2016]

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$$L^{(o)} = \log \frac{p(A(\mathcal{D}) = o)}{p(A(\mathcal{D}') = o)}$$

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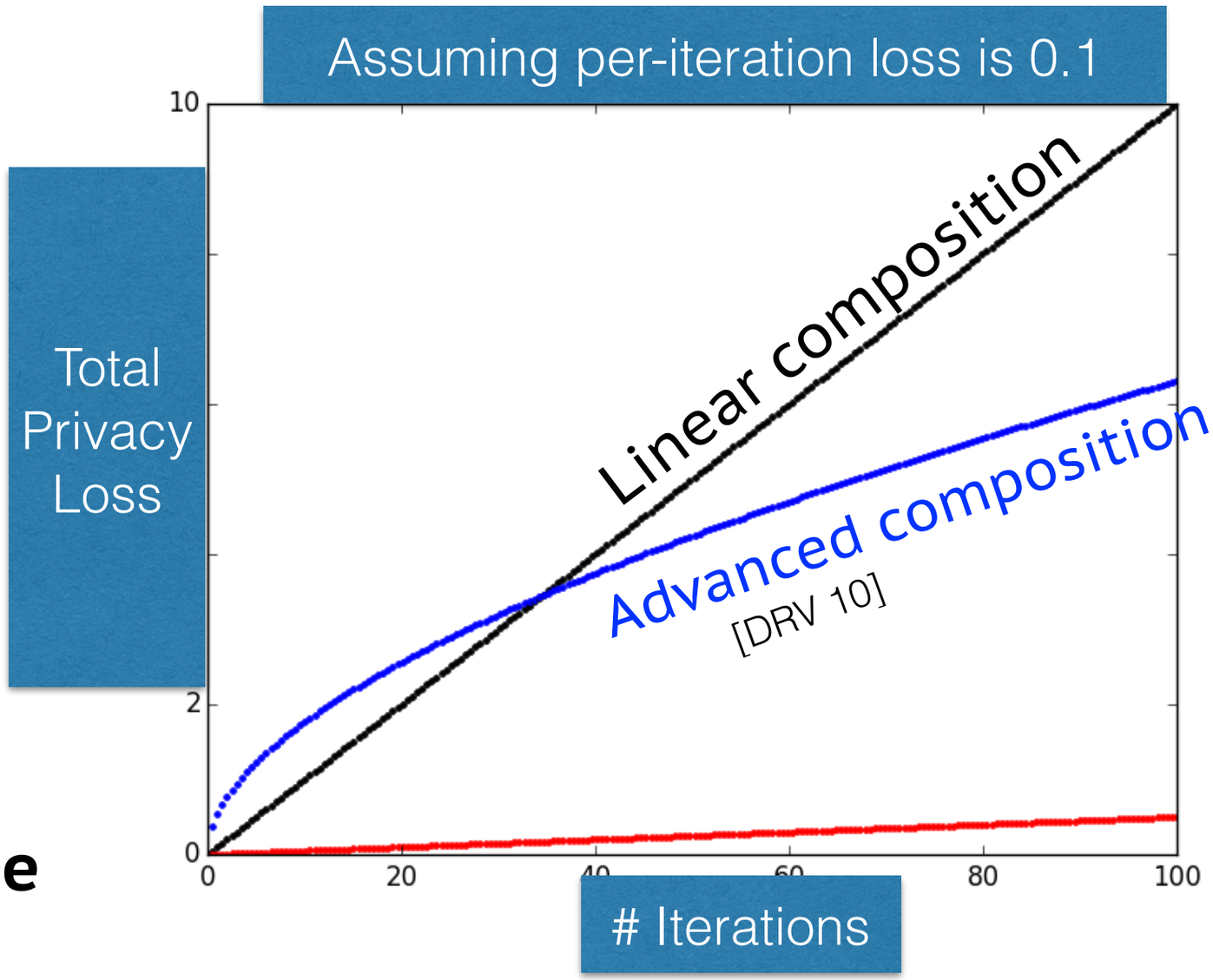

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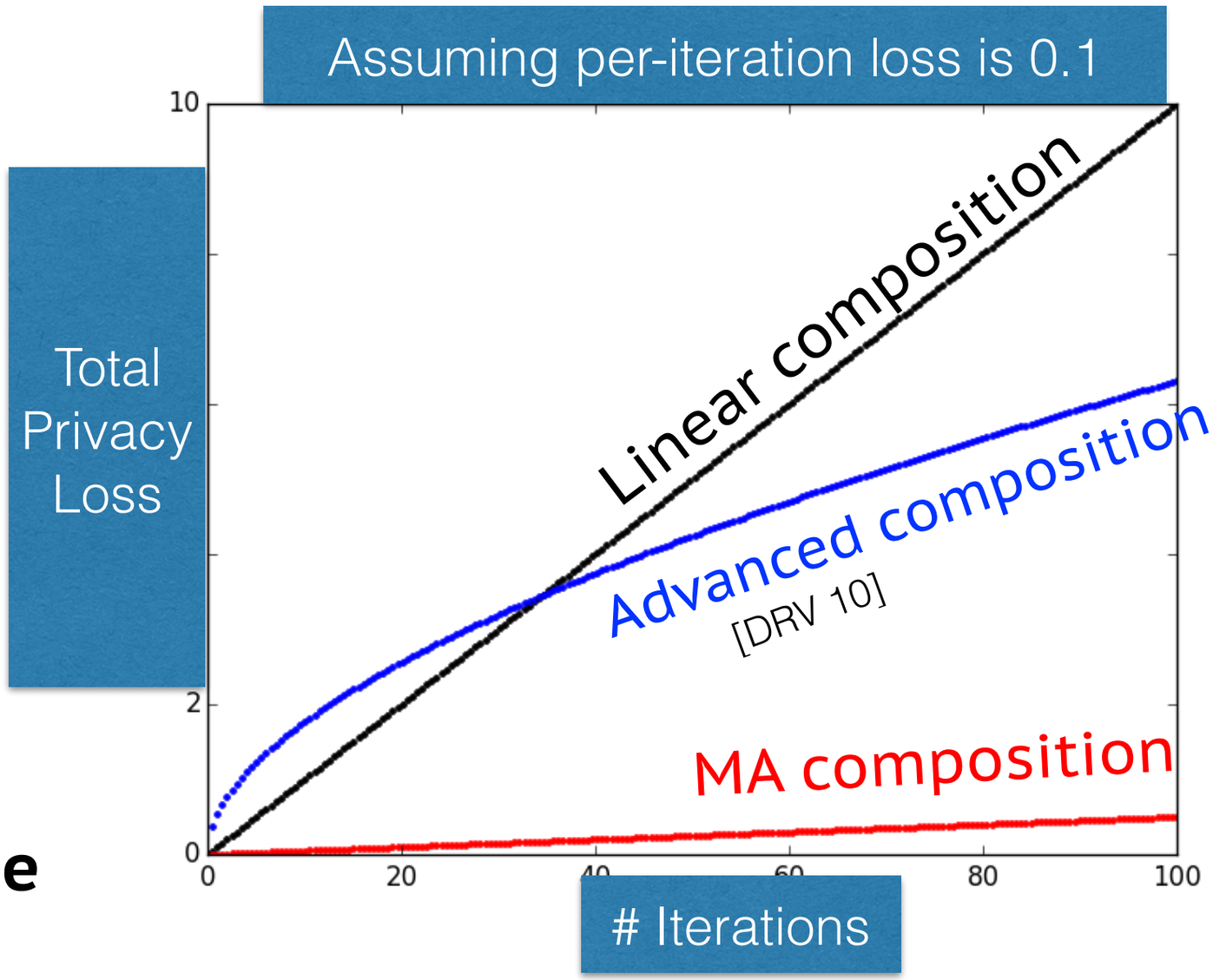
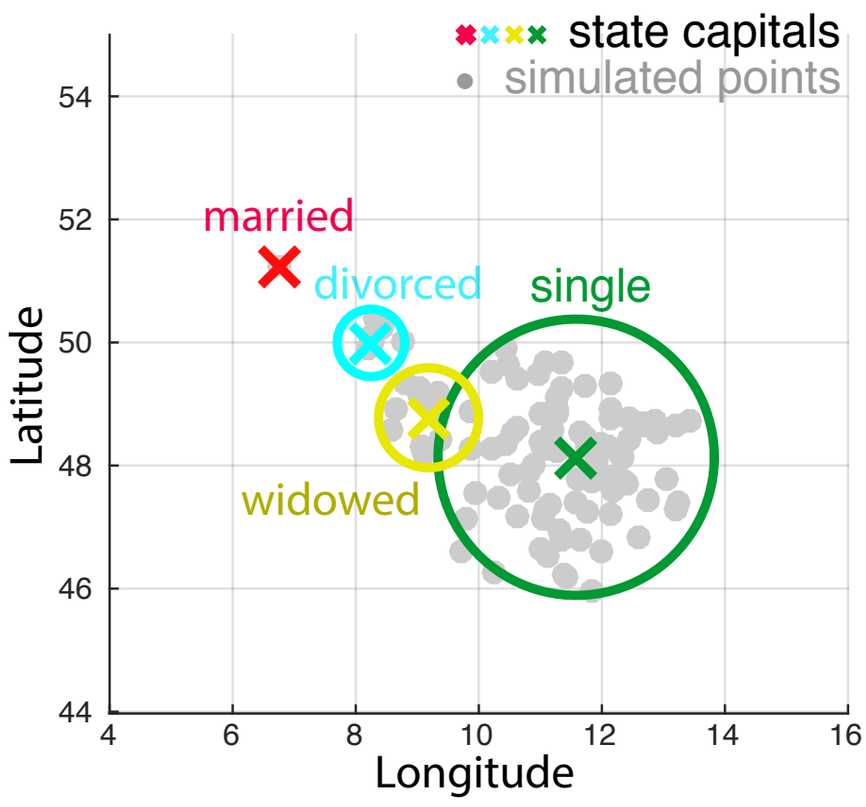


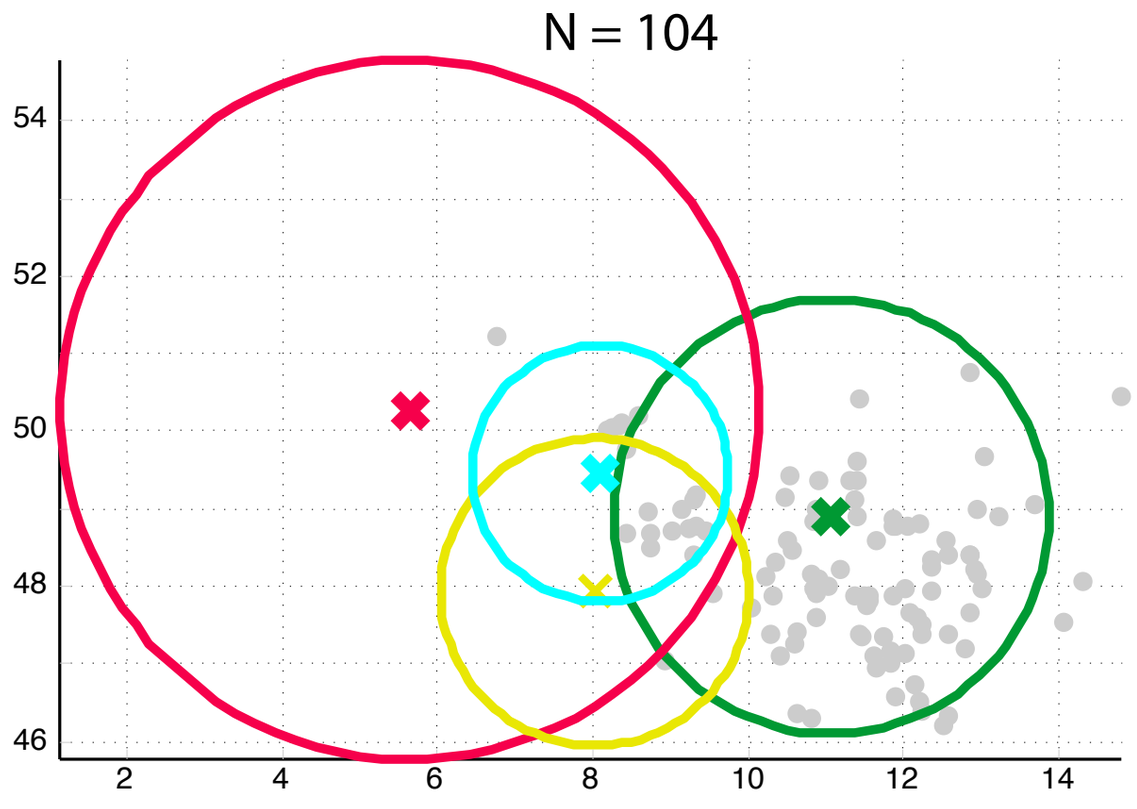
DP-EM: Abortion data

[destatis.de]

Raw data



Privatized MoG using DP-EM

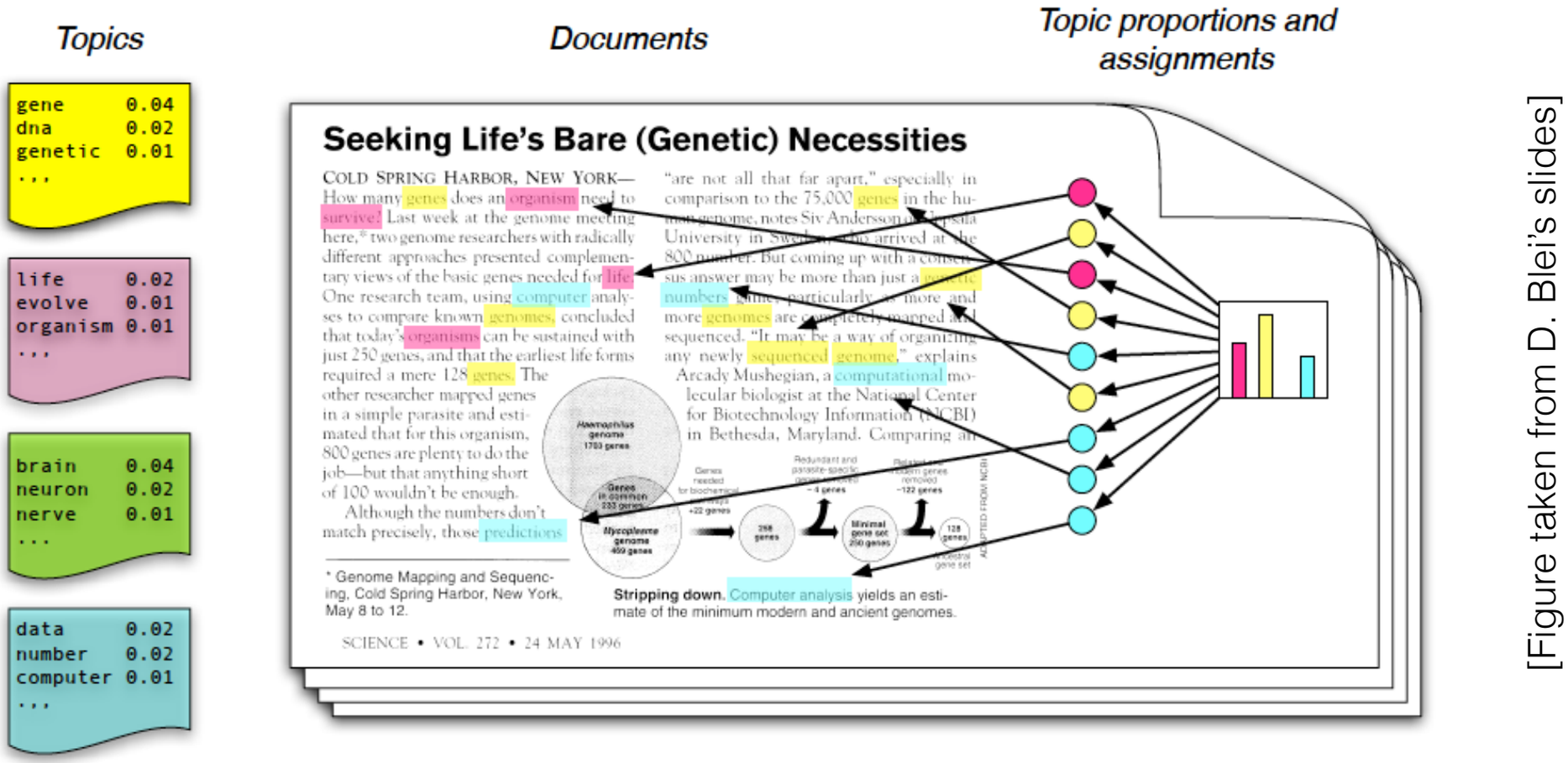


Even for the cluster with a single datapoint (red cluster), one can't accurately identify the geographical location of that individual from outputs of DP-EM

Topic modeling

Topic modeling

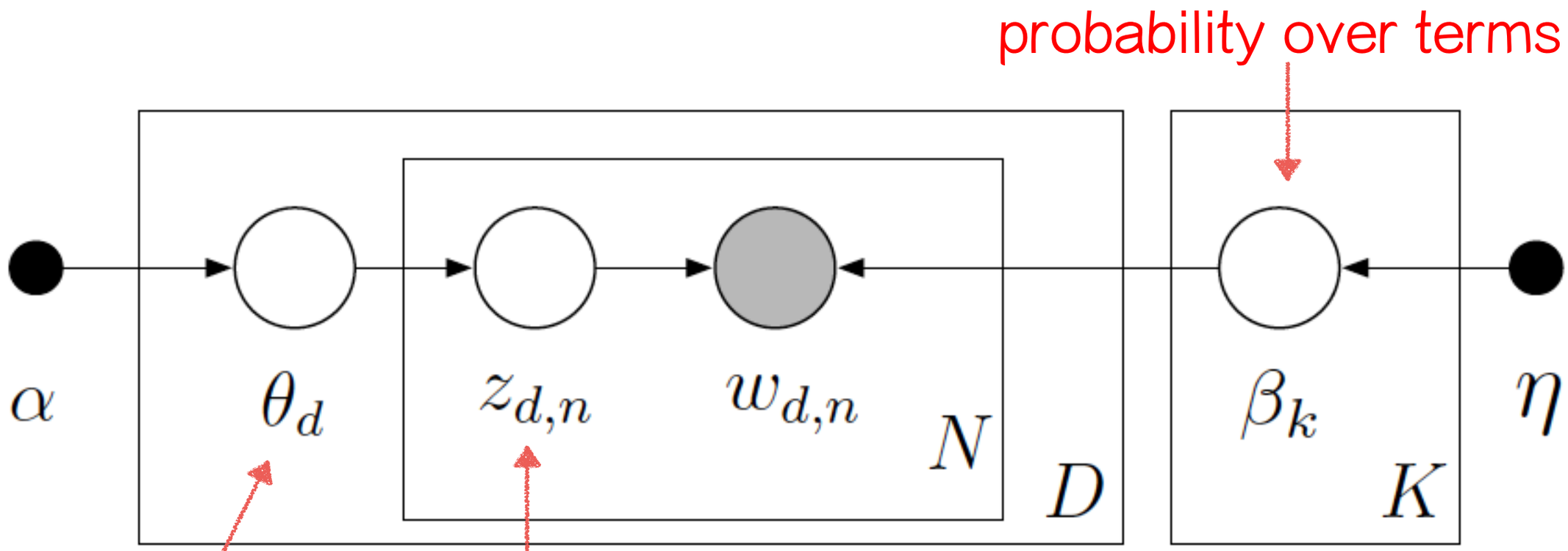
- Given documents, **describe how** documents are organised!



[Figure taken from D. Blei's slides]

Goal : allocate words to topics & assign probability to terms in each topic.

Latent Dirichlet Allocation (LDA)



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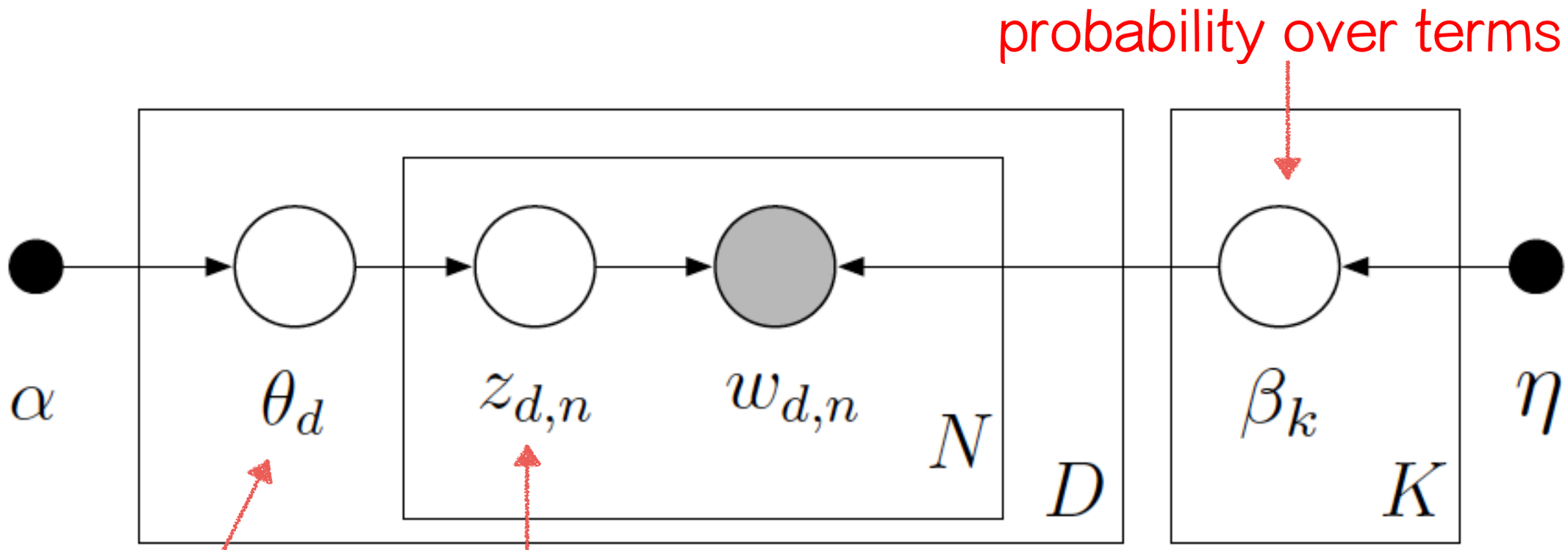


topic proportion of each document

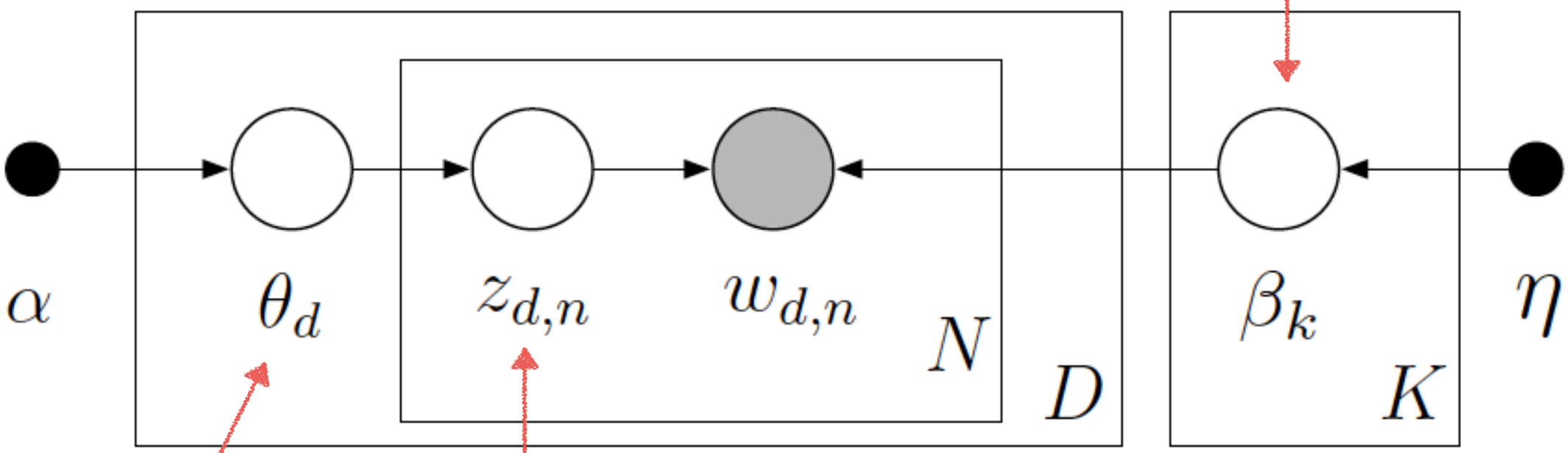
topic assignment of each word

Latent variables

Latent Dirichlet Allocation (LDA)

parameters

probability over terms in voc



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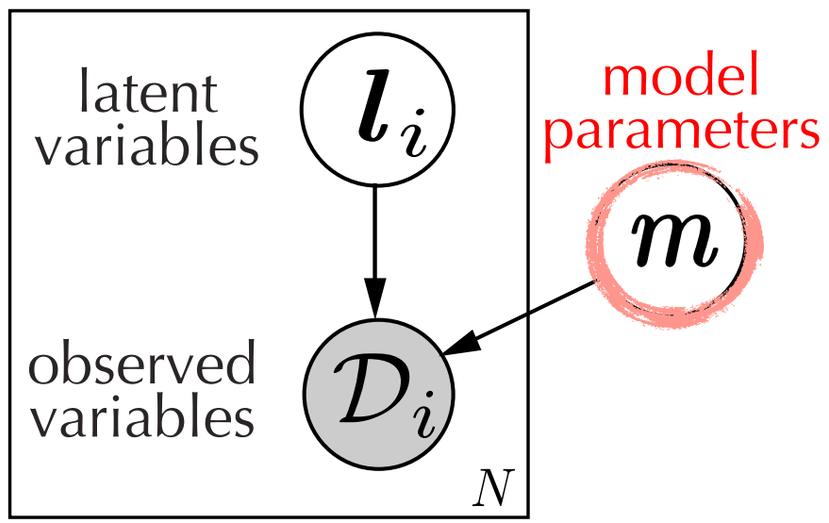
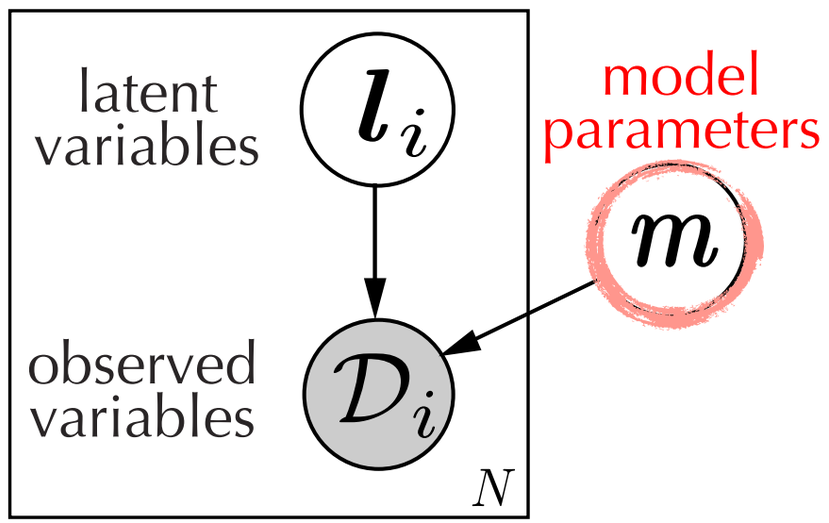
Variational inference

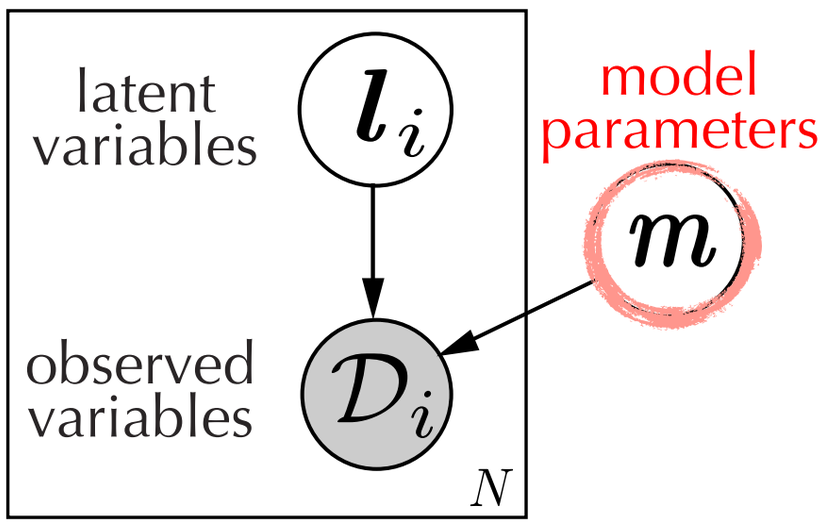


Variational inference



log-marginal-likelihood

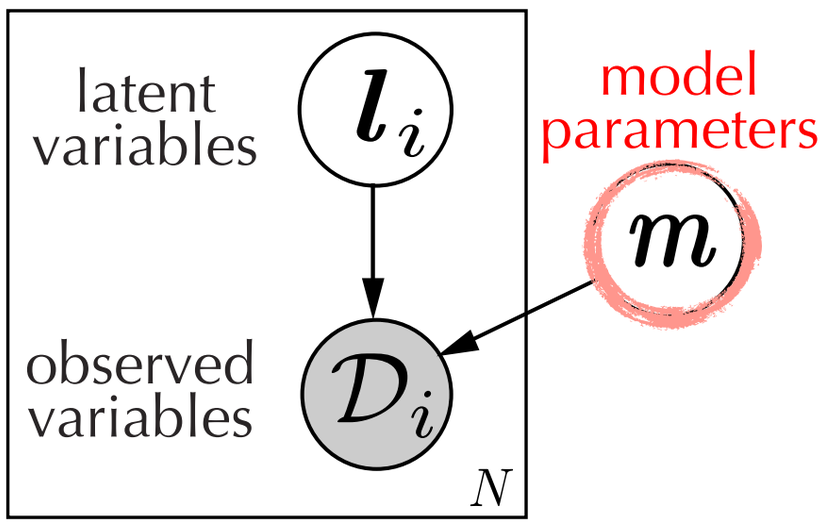
Variational inference



log-marginal-likelihood

$$\log p(\mathcal{D}) \geq \int q(\boldsymbol{l})q(\boldsymbol{m}) \log \frac{p(\mathcal{D}, \boldsymbol{l}|\boldsymbol{m})p(\boldsymbol{m})}{q(\boldsymbol{l})q(\boldsymbol{m})}$$

Variational inference



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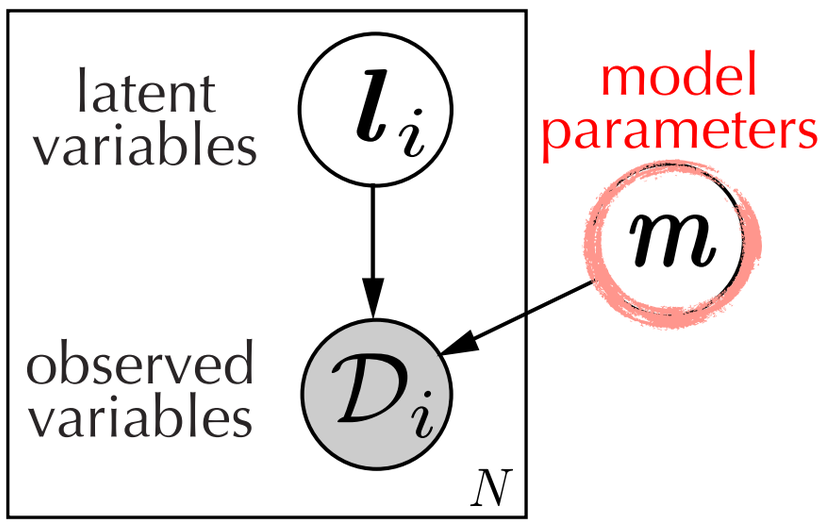
variational posterior
over latent variables

Variational inference



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variational posterior
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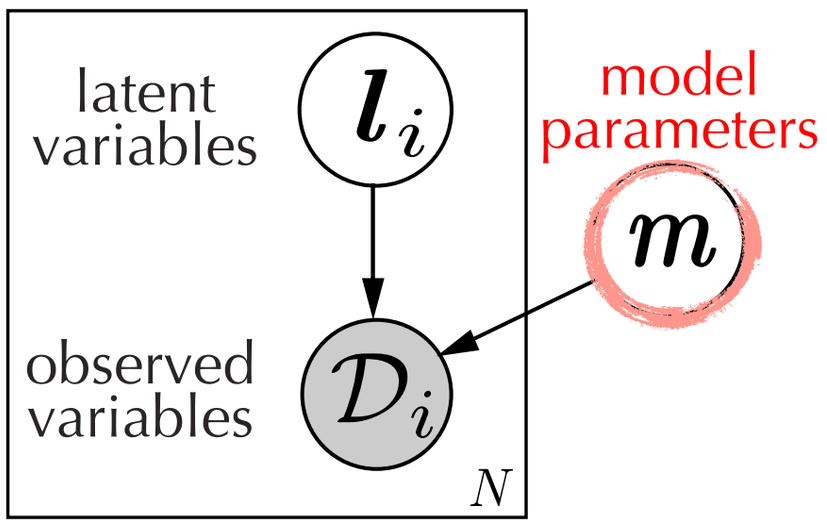
variational posterior
over model params

Variational inference



Variational lower bound

log-marginal-likelihood

$$\log p(\mathcal{D}) \geq \mathcal{L} \int q(\boldsymbol{l})q(\boldsymbol{m}) \log \frac{p(\mathcal{D}, \boldsymbol{l}|\boldsymbol{m})p(\boldsymbol{m})}{q(\boldsymbol{l})q(\boldsymbol{m})}$$

variational posterior
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variational posterior
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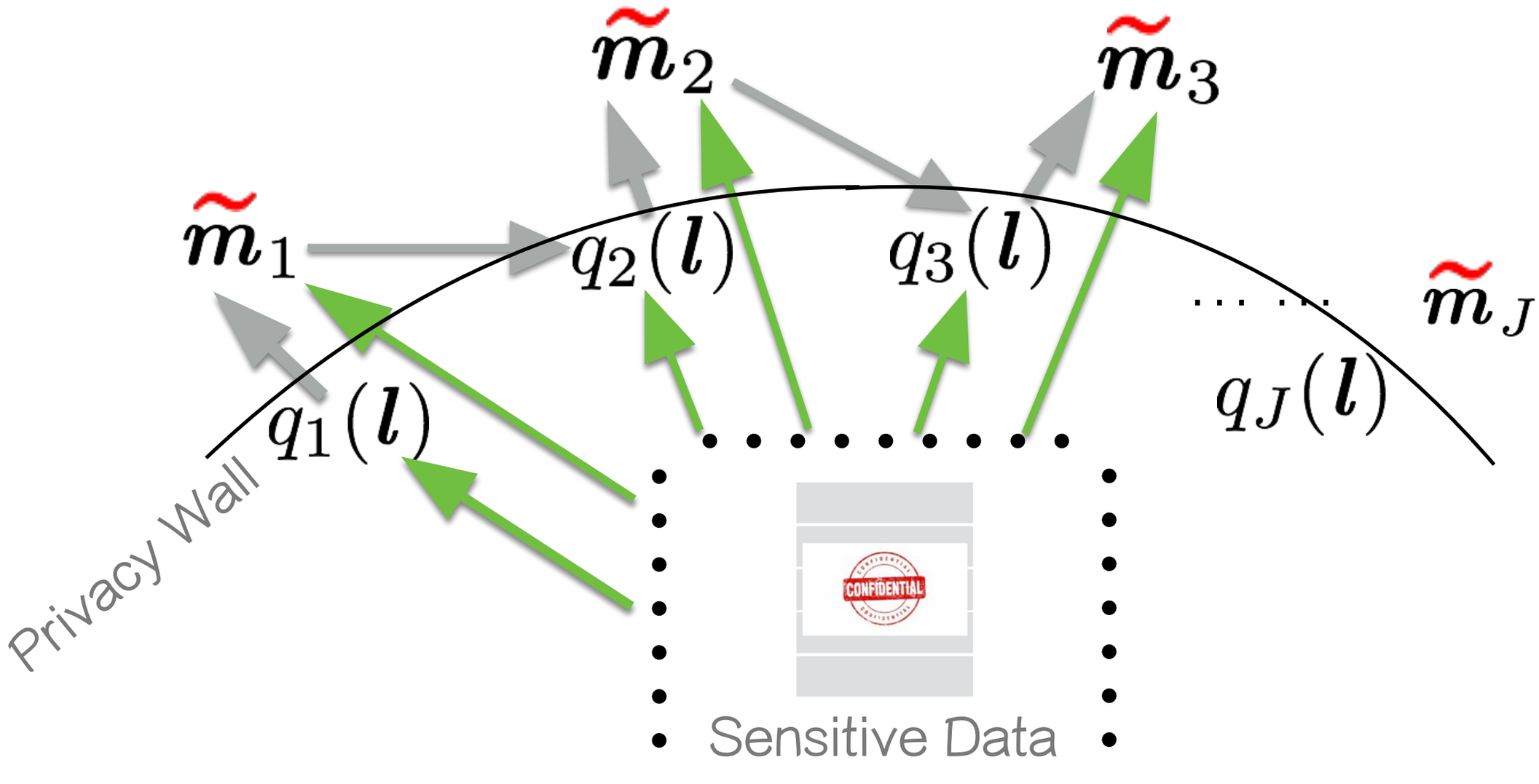
DP-VI

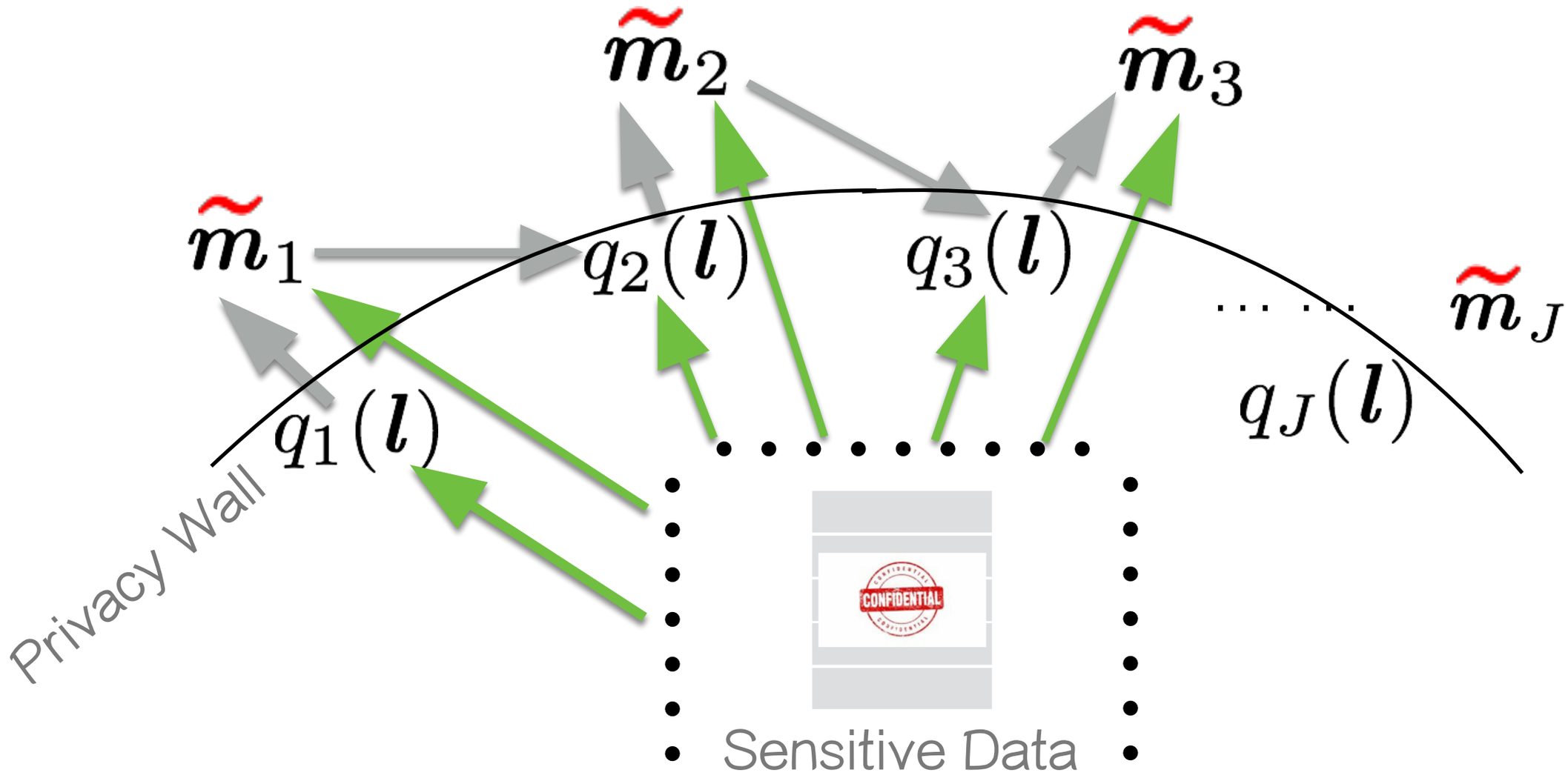
[Park et al, 2019]



DP-VI

[Park et al, 2019]

exponential family: $p(\mathcal{D}_n, \boldsymbol{l}_n|\boldsymbol{m}) \propto \exp(\mathbf{n}(\boldsymbol{m})^\top \mathbf{s}(\mathcal{D}_n, \boldsymbol{l}_n))$



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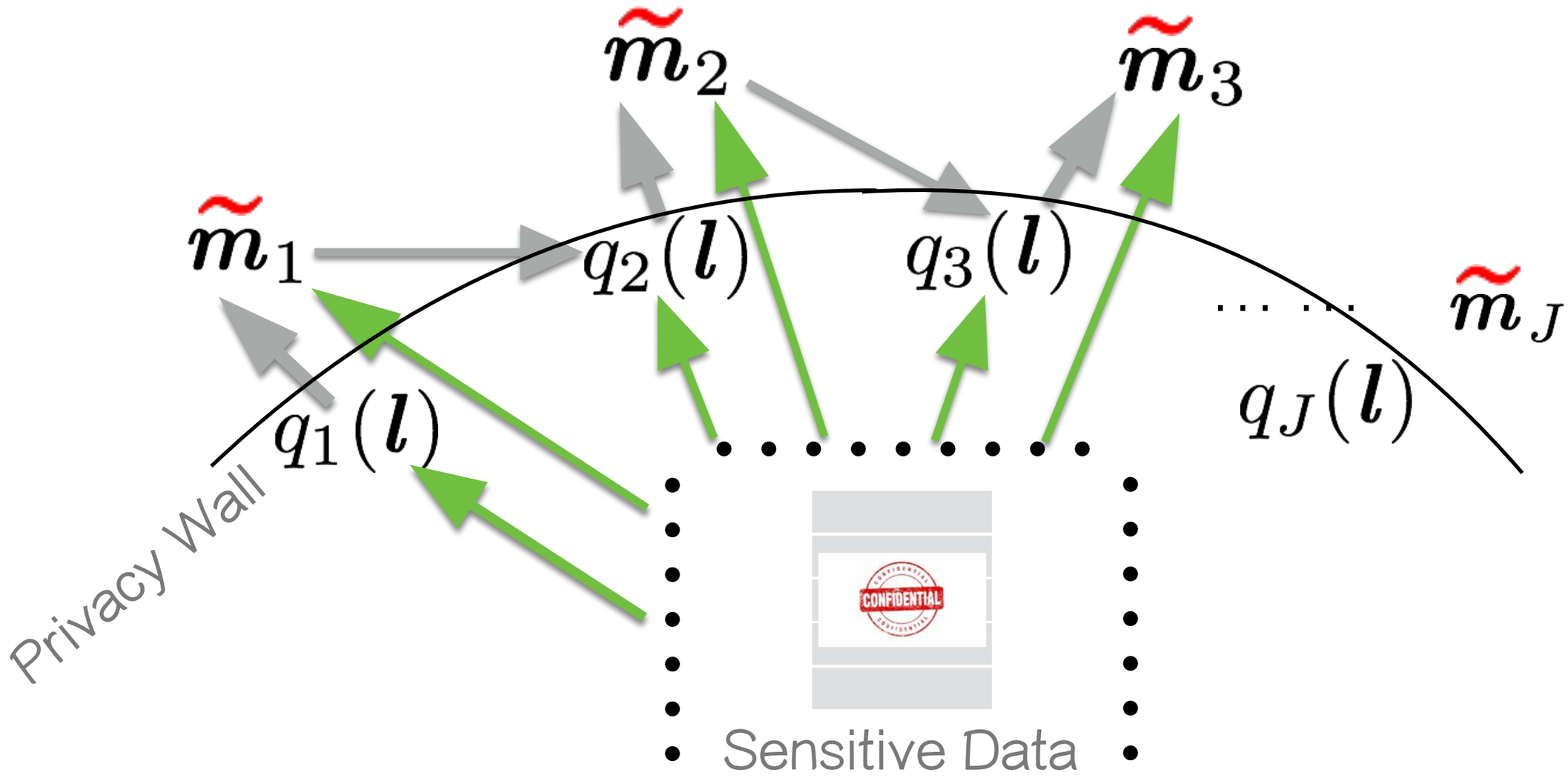
natural params



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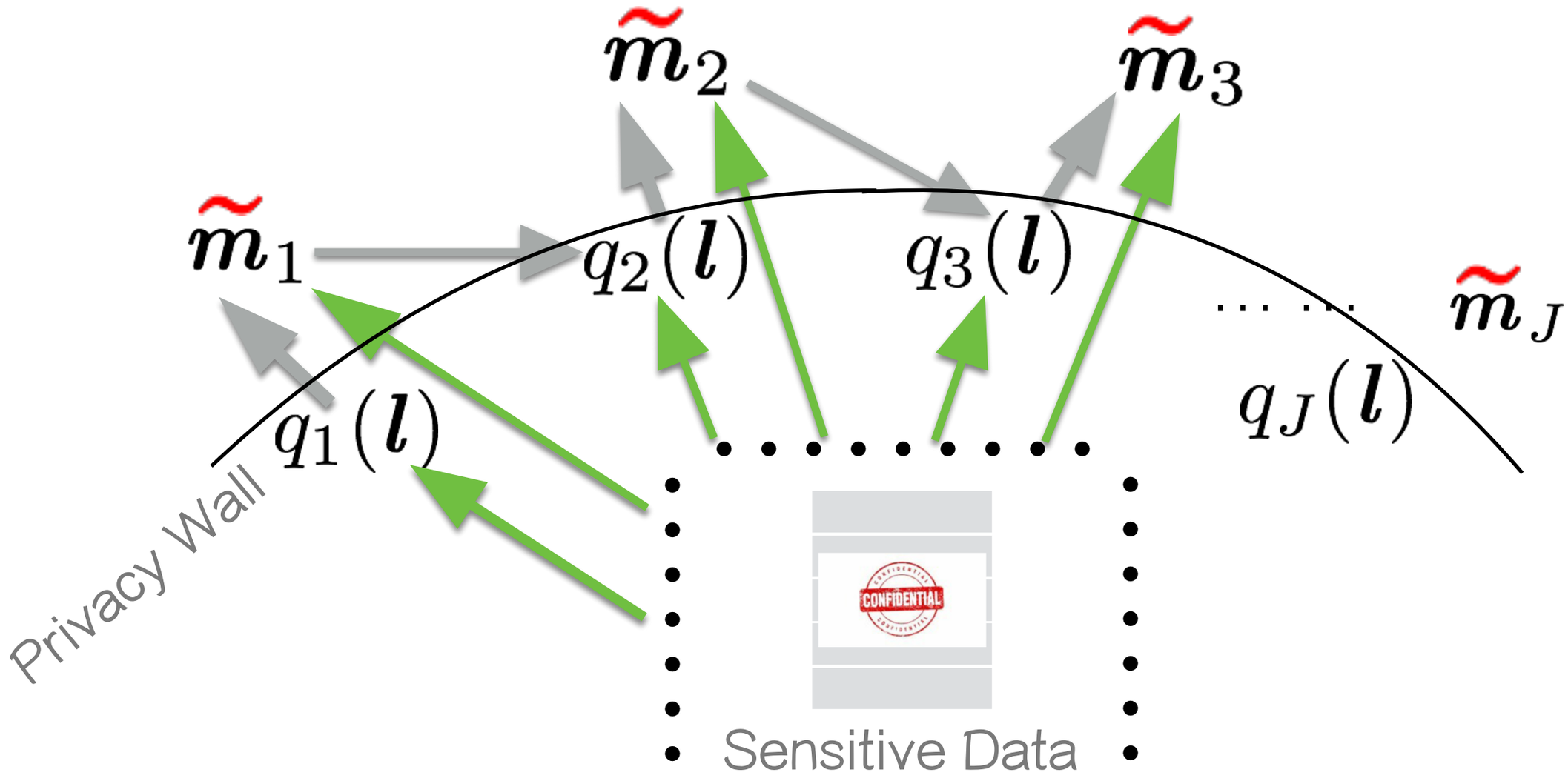
natural params suff stats



DP-VI

[Park et al, 2019]

exponential family: $p(\mathcal{D}_n, \boldsymbol{l}_n|\boldsymbol{m}) \propto \exp(\mathbf{n}(\boldsymbol{m})^\top \mathbf{s}(\mathcal{D}_n, \boldsymbol{l}_n))$

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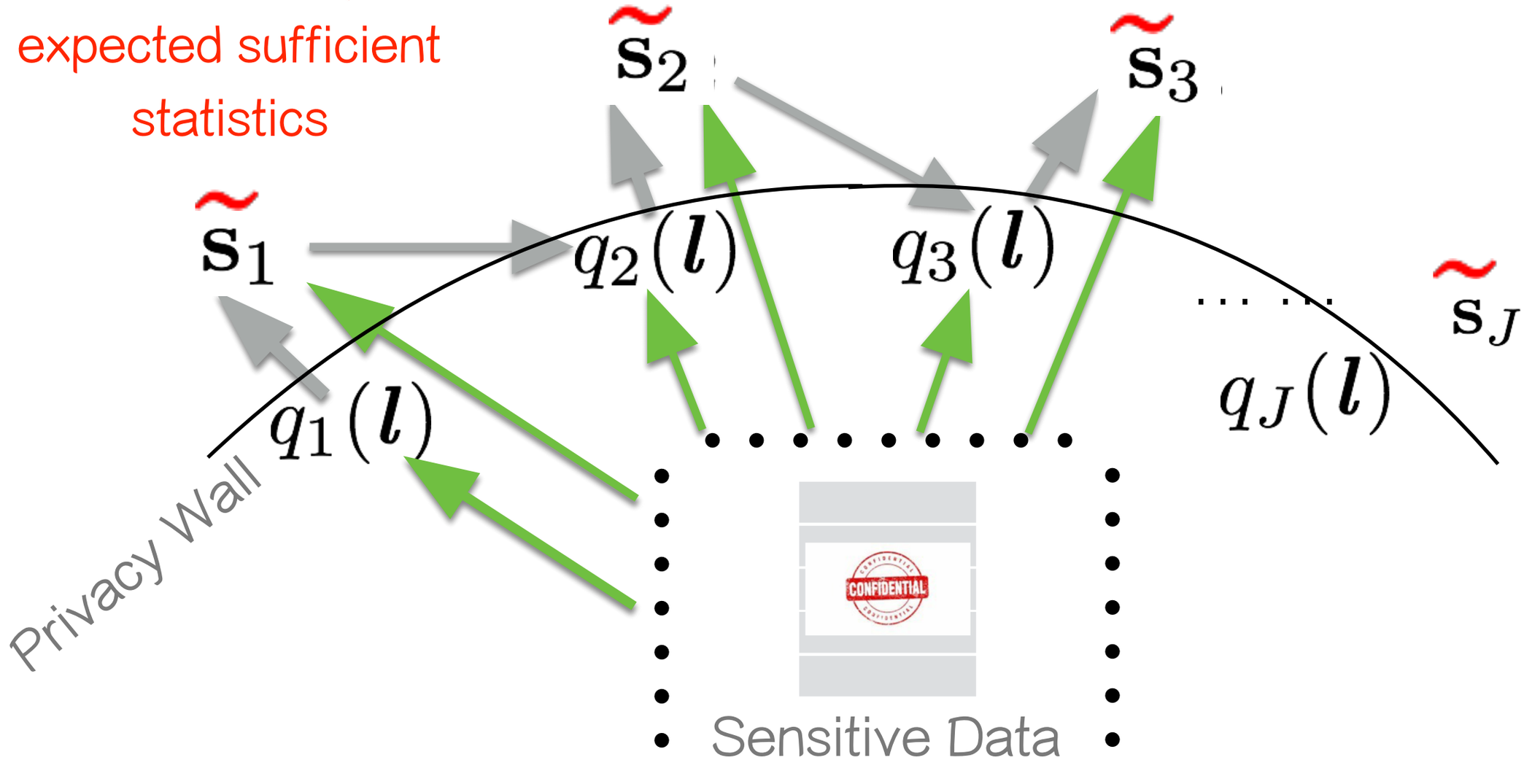
Perturb & output expected sufficient statistics



Large document datasets : stochastic learning

Privacy Amplification Effect due to subsampling

Theorem 1 *(Theorem 1 in (Li et al., 2012)) Any* $(\epsilon_{iter}, \delta_{iter})$*-DP mechanism running on a uniformly sampled subset of data with a sampling ratio* ν *guarantees* $(\log(1+\nu(\exp(\epsilon_{iter})-1)), \nu\delta_{iter})$*-differential privacy.* [Li et al,12]

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sampling rate	total privacy loss
1	1
0,1	0,159
0,01	0,017

Posterior topics by DP-VI

Non-private LDA

topic 3:	
david	0.0667
king	0.0318
god	0.0304
son	0.0197
israel	0.0186
bible	0.0156
hebrew	0.0123
story	0.0102
book	0.0095
adam	0.0092

Private LDA (Moments Accountant)

topic 83:	
david	0.0410
jonathan	0.0199
king	0.0188
samuel	0.0186
israel	0.0112
saul	0.0075
son	0.0068
dan	0.0067
god	0.0053
story	0.0048

Private LDA (Advanced Composition)

topic 73:	
mount	0.0034
display	0.0011
animal	0.0011
equipment	0.0011
cynthia	0.0009
position	0.0008
systems	0.0008
support	0.0008
software	0.0008
heavy	0.0008

DP-VI with MA composition + privacy amplification outputs more coherent topics (red box) than DP-VI with AC (blue box) + privacy amplification

Deep learning

DP-Stochastic gradient descent

[Abadi et al, 2016]

Given a mini-batch,

(A) $\mathbf{g}_t(x_i) \leftarrow \nabla_{\theta_t} \mathcal{L}(\theta_t, x_i)$

(B) $\mathbf{g}_t = \frac{1}{L} \sum_i \mathbf{g}_t(x_i)$

(C) $\theta_{t+1} \leftarrow \theta_t - \eta_t \mathbf{g}_t$

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Each gradient has a limited sensitivity

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Learning rate

(C) $\theta_{t+1} \leftarrow \theta_t - \eta_t \tilde{\mathbf{g}}_t$

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DP parameters

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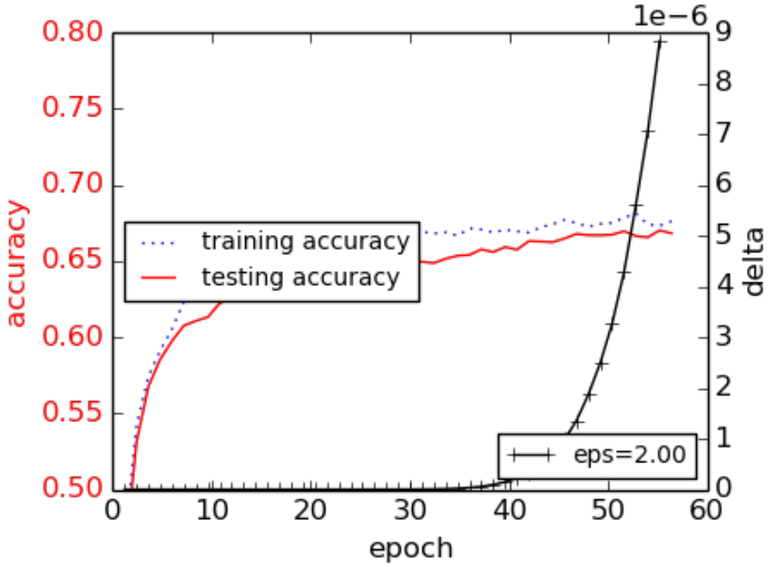
Learning rate

DP parameters

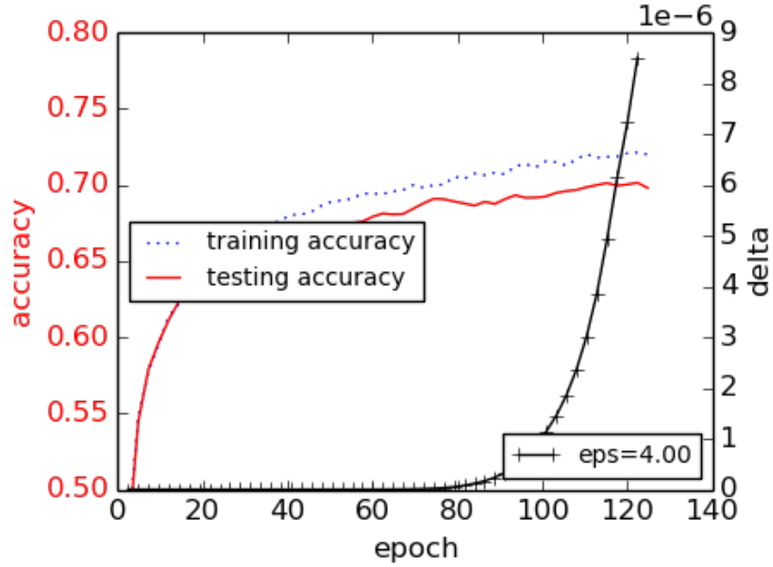
- Moments accountant composition to compute the total privacy loss incurred during training

DP-SGD on CIFAR10 data

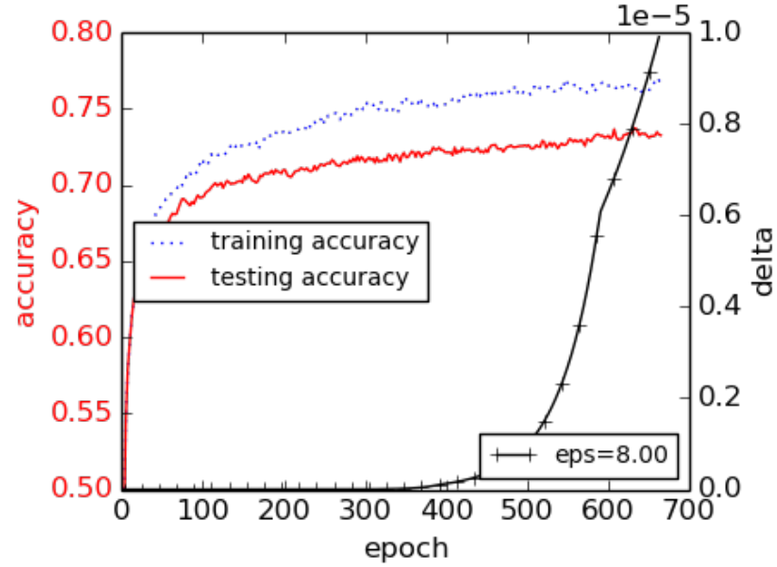
[Abadi et al, 2016]



(1) $\varepsilon = 2$



(2) $\varepsilon = 4$



(3) $\varepsilon = 8$

- DP-SGD with a high level of noise (epsilon=2) provides a less accurate classifier than DP-SGD with a lowe level of noise (epsilon=8)
- The gap between training and test accuracies gets smaller with more additive noise. Noise added for privacy seems helpful for better generalization.

Examples of DP-ML algorithms

- DP-EM for clustering & density estimation

- DP-VI for topic modeling

- DP-SGD for deep learning

DP in industry

DP in machine learning systems

Google's Randomized Aggregatable Privacy-Preserving Ordinal Response (RAPPOR)

- A DP technique for crowdsourcing statistics, e.g., for collecting data about the Google Chrome users.
- Based on Randomised response technique!

DP in machine learning systems

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1. flip a coin
2. if tails, respond truthfully
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4. if heads, "yes". Say "no" otherwise.

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4. if heads, "yes". Say "no" otherwise.

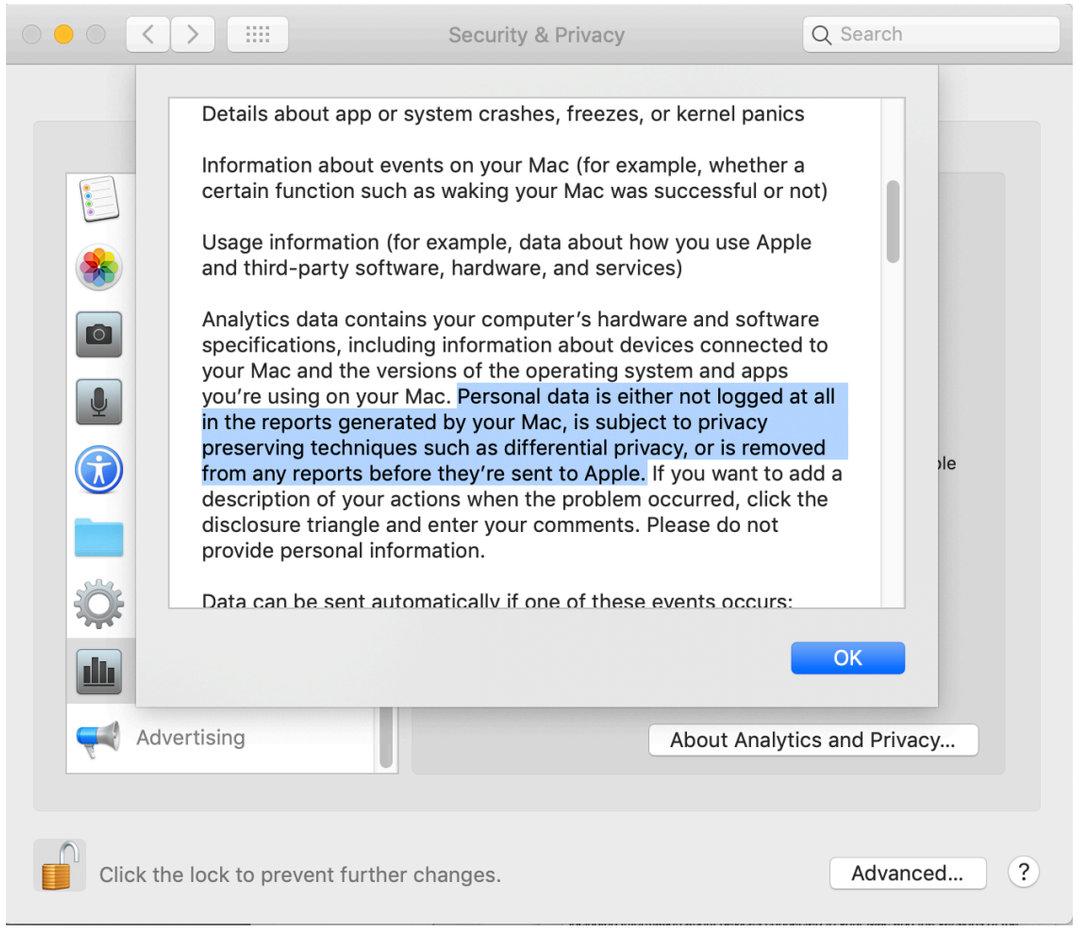
True answer 75% of time

accurate population statistics
while preserving the privacy
of the individual answers!

DP in data collection

Apple Mac OS

- DP techniques are used to send my own personal data collected by iMAC (analytics).



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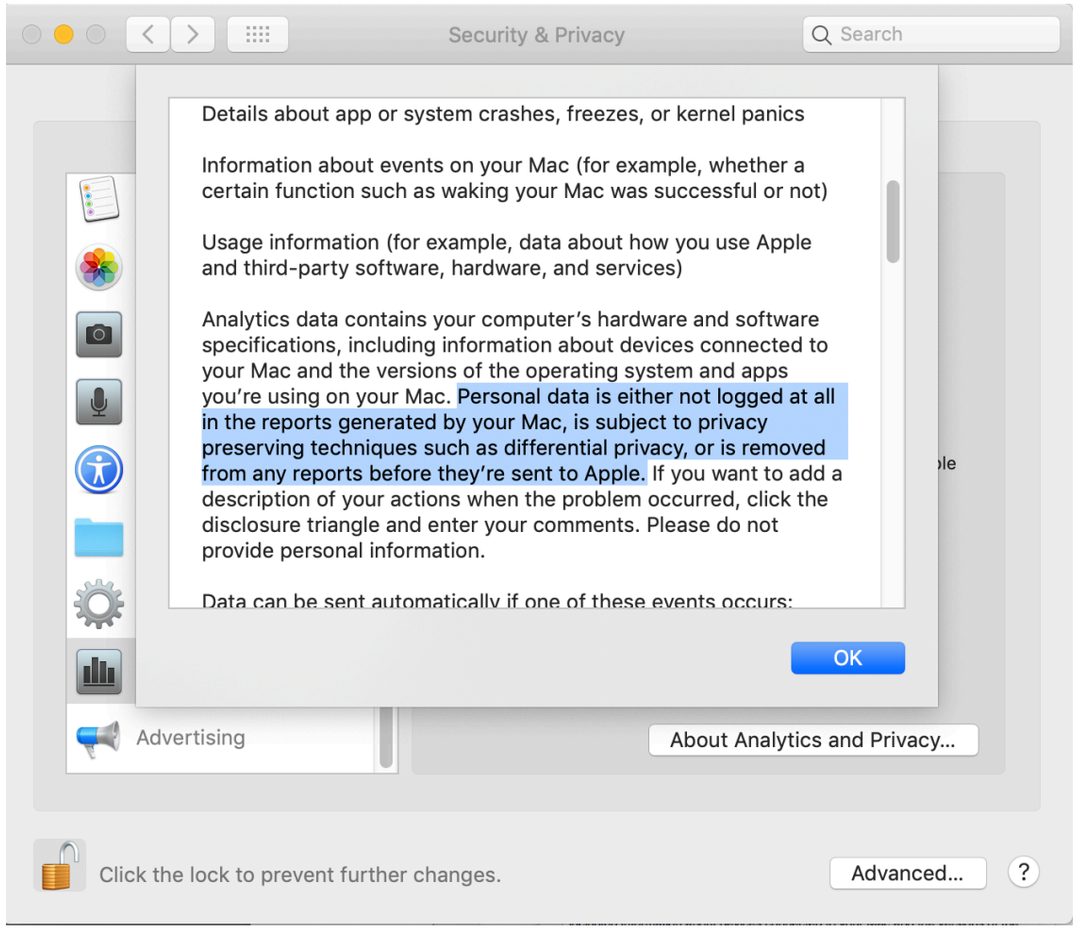

- Specific techniques on a new word and Emoji: OneBitHistogram, CountMedianSketch -> adding noise to data before sending to server!
- Issue: non-transparent & questionable "epsilon" selection [Tang et al. 2017]

Summary

- Privacy is necessary to consider not only for the sake of protection against threats, but also for philanthropic reasons in data sharing.

- Differential privacy seems to dominate the field due to the mathematically provable guarantees.

- Although many progresses have been made in privacy-preserving machine learning, there are still A LOT of work that needs to be done to apply DP in many machine learning/data sharing applications.