Differential privacy and noisy confidentiality concepts for European population statistics

NTTS 2021
Session 'Input and output privacy in official statistics', 11 March 2021

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Unit F2 – Population and migration

Outline

1. Intro: 21st century statistical confidentiality
2. Noisy concepts: bottom-up and top-down
3. Risks: averaging and exploiting constraints
4. Utility: (noise) tail wagging the (statistic) dog
5. Outro: the 2021 EU census picture

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Intro: 21st century statistical confidentiality

20th century lore:

- must protect individuals

SEX \\ POB*	Total	Country	Outside
Total	**42**	**35**	**7**
Male	**22**	17	5
Female	**20**	18	**2**

* Place of birth (POB)

Intro: 21st century statistical confidentiality

20th century lore:

- must protect individuals
- therefore treat small counts

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Intro: 21^{st} century statistical confidentiality

20^{th} century lore:

- must protect individuals
- therefore treat small counts…
- … and ensure consistency…
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- … and ensure consistency…

SEX \\ POB*	Total	Country	Outside
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➔ looks easy, but is generally **neither simple nor efficient**

Intro: 21st century statistical confidentiality

21th century state of the art:

- database reconstruction theorem (Dinur and Nissim, 2003)

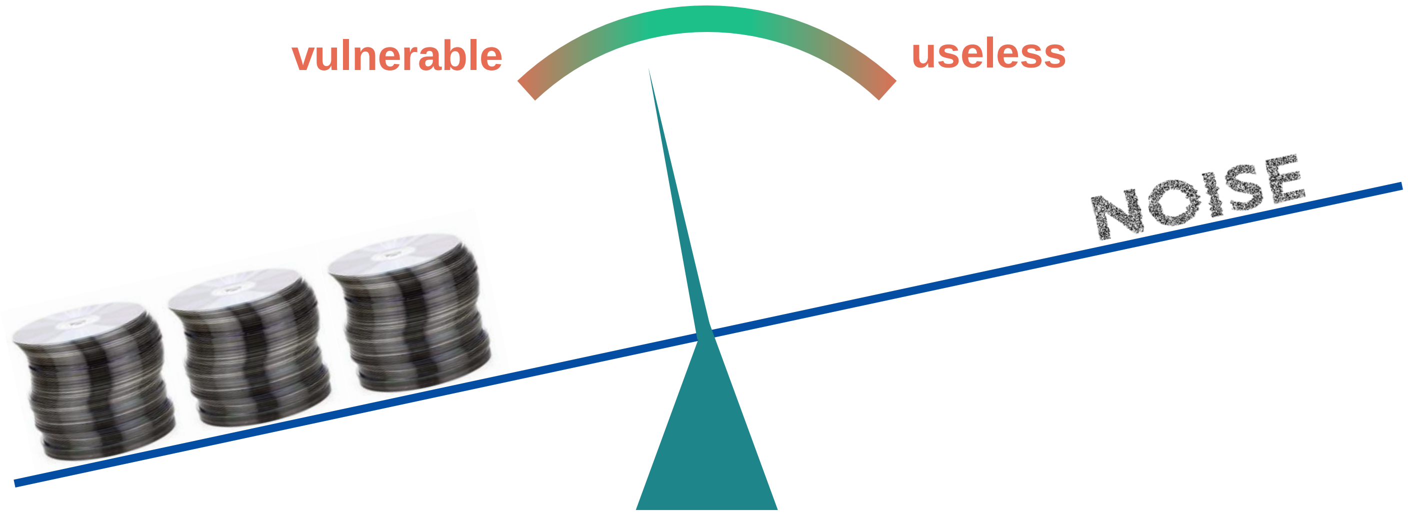
  Too many statistics, published too accurately, allow full & accurate reconstruction of all the input microdata…

  (example e.g. in U.S. Census Bureau, 2018a, 2018b)

Intro: 21st century statistical confidentiality

21th century state of the art:

- database reconstruction theorem (Dinur and Nissim, 2003)



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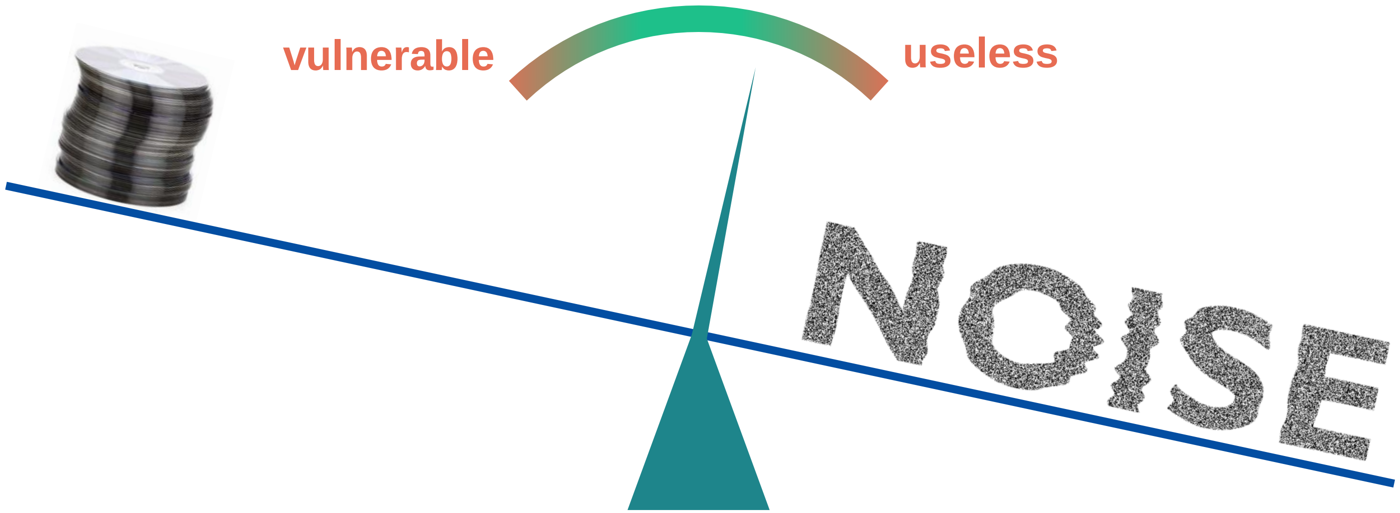

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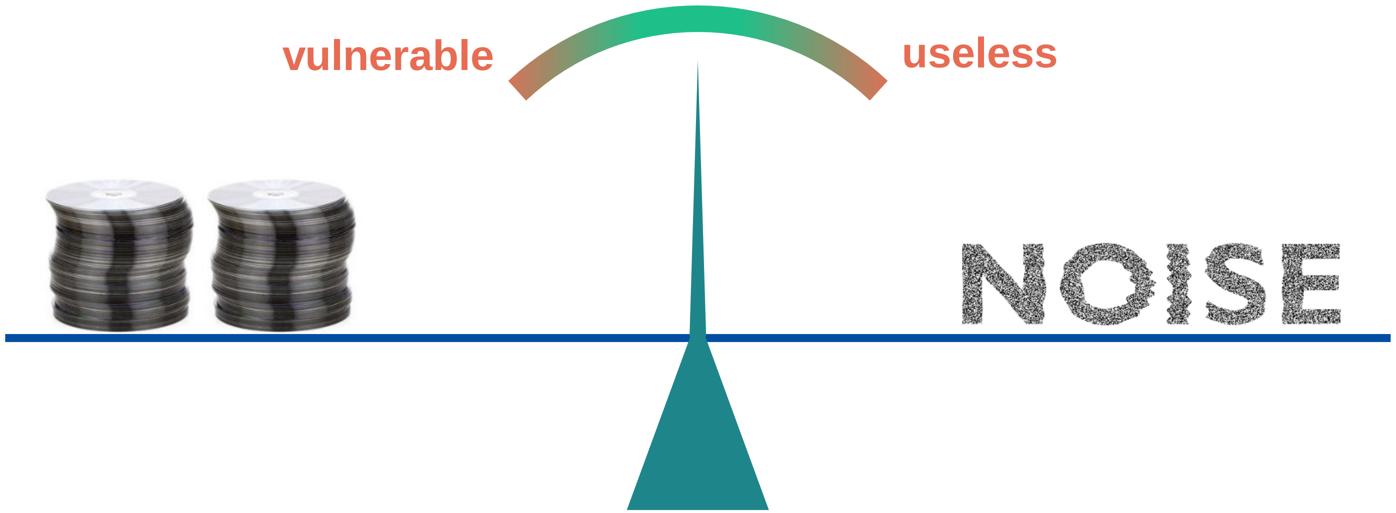

Noisy concepts: bottom-up

Noise in action:

SEX \\ POB	Total	Country	Outside
Total	42	35	7
Male	22	C	C
Female	20	C	C

Noisy concepts: bottom-up

Noise in action: Is this better?

SEX \\ POB	Total	Country	Outside
Total	42	37	7
Male	23	15	4
Female	21	16	3

Noisy concepts: bottom-up

… a closer look at **single statistic** level – e.g. total population in the area:

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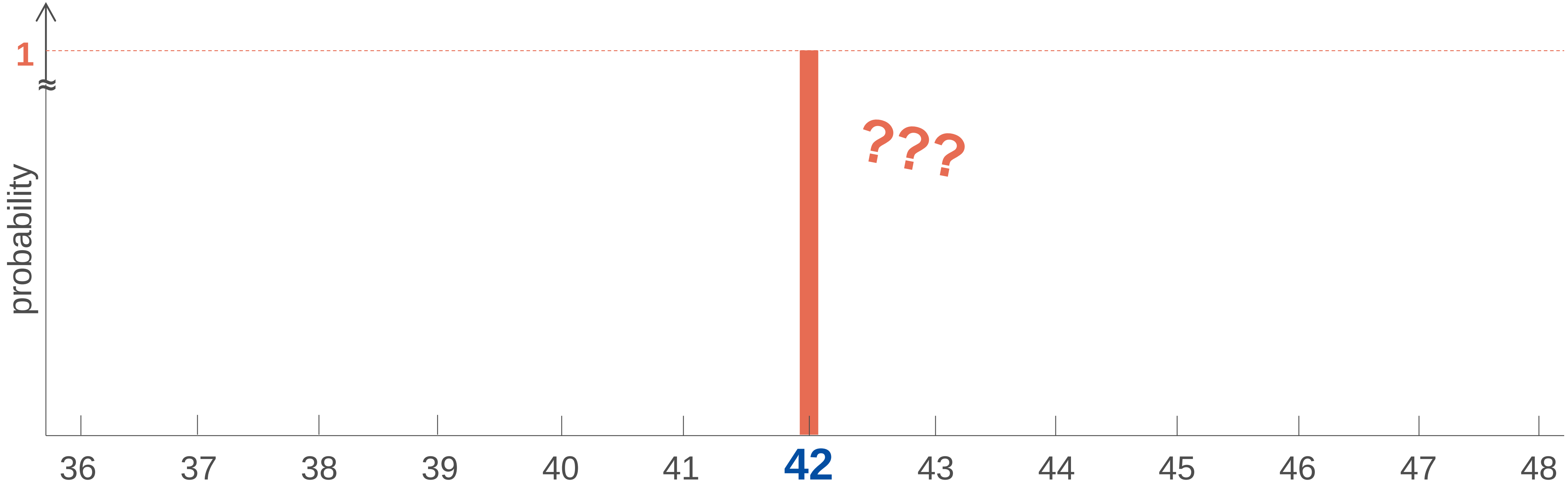

ground truth?

Noisy concepts: bottom-up

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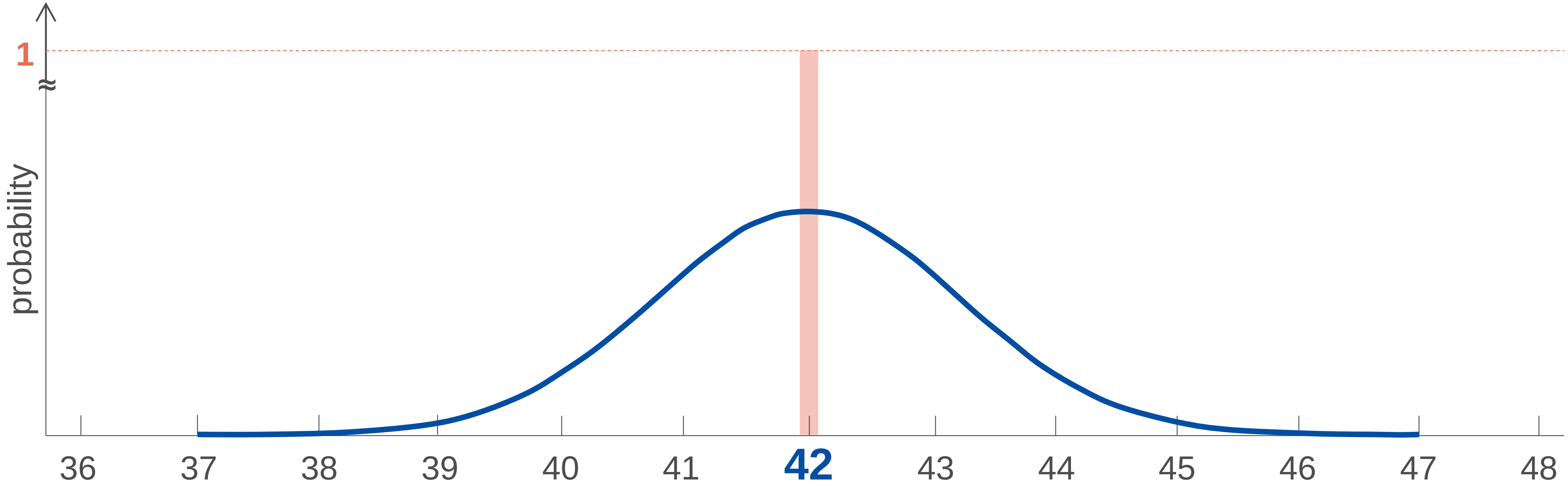

intrinsic uncertainty: ± 2

Noisy concepts: bottom-up

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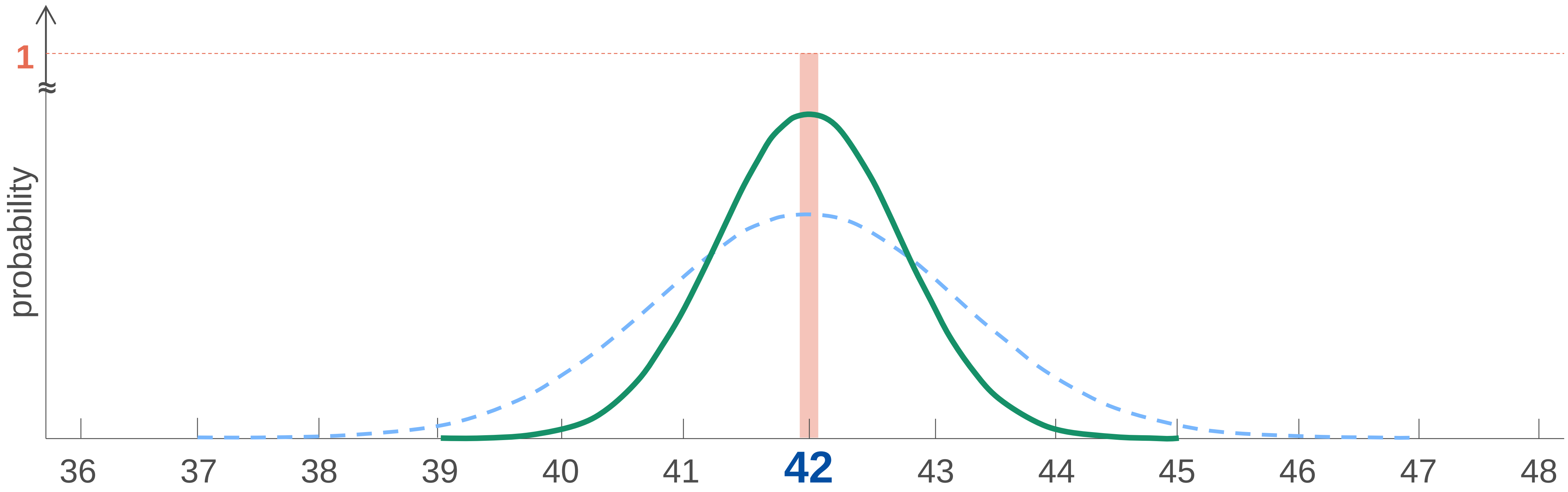

intrinsic uncertainty: ± 2

protective noise added: ± 1

Noisy concepts: bottom-up

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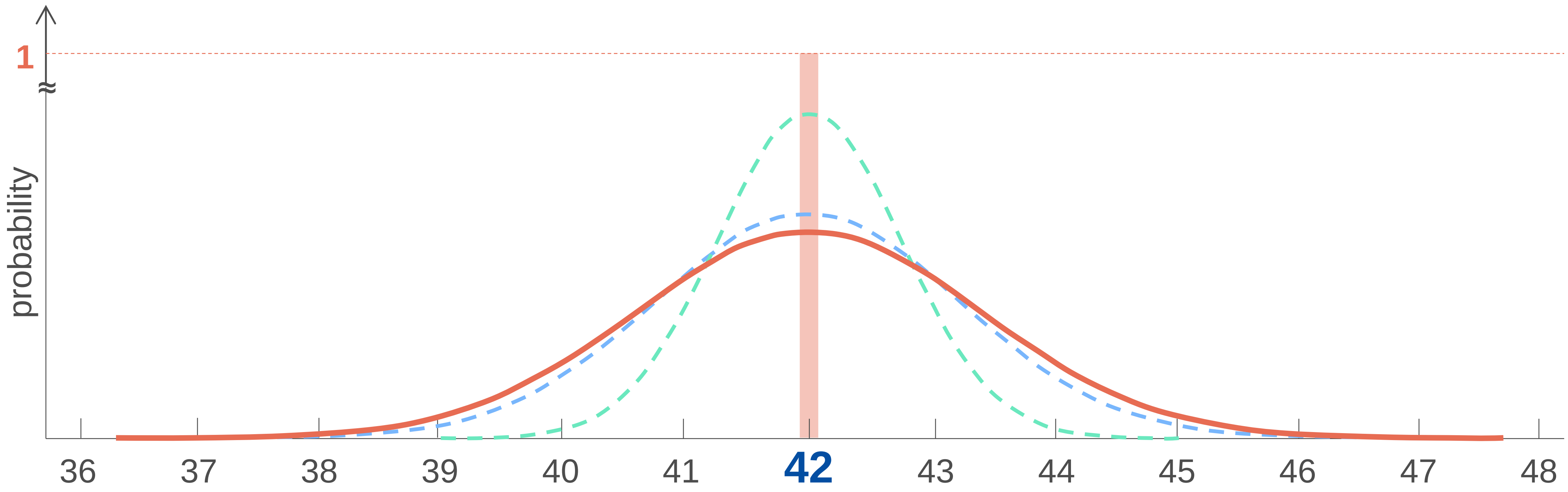

intrinsic uncertainty:	± 2
protective noise added:	± 1
total uncertainty:	**± 2.2**

Noisy concepts: bottom-up

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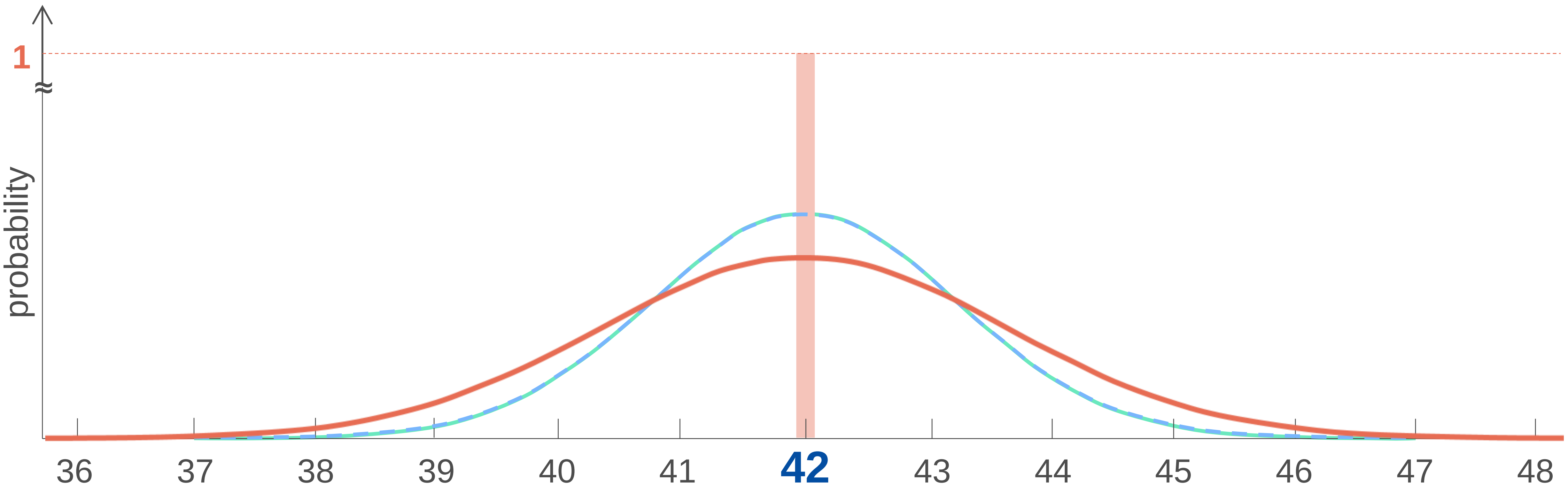

intrinsic uncertainty: ± 2

protective noise added: **± 2**

total uncertainty: ± 2.8

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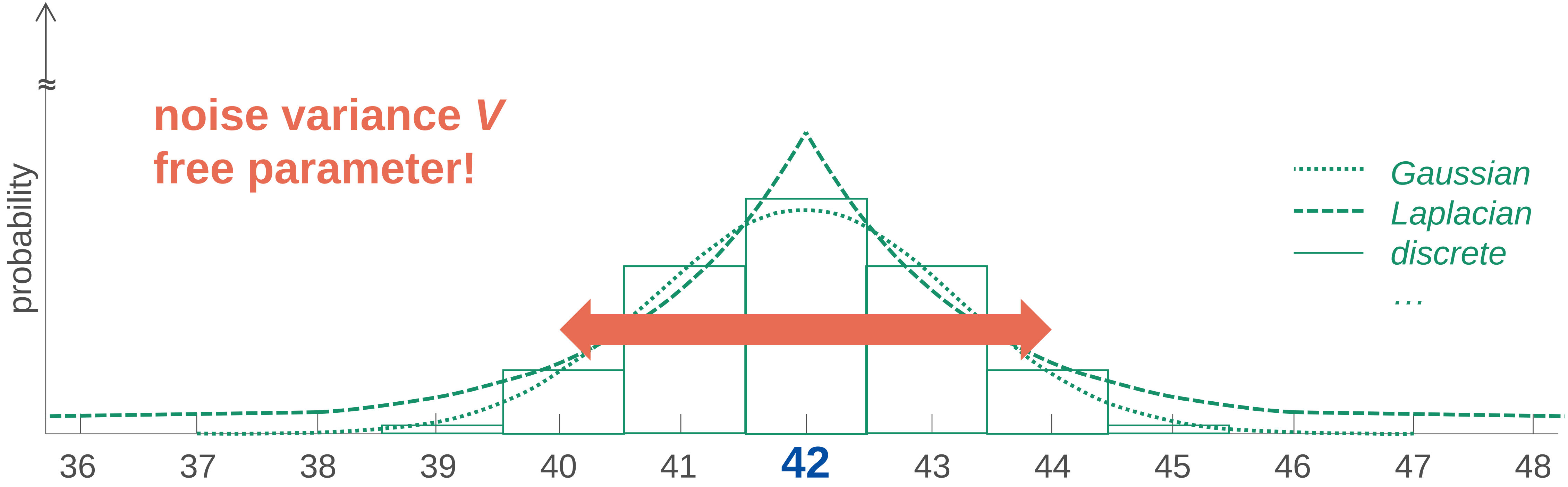
Noisy concepts: bottom-up or *utility-driven*

… a closer look at **single statistic** level – e.g. total population in the area:

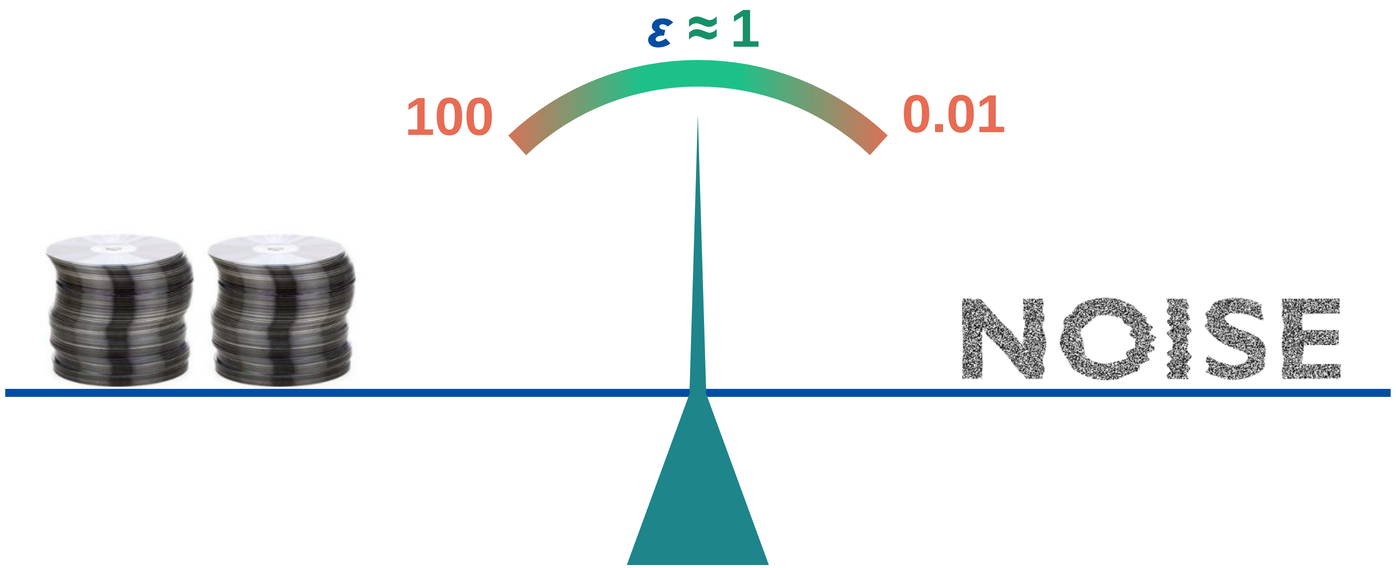


protective noise added: **± 2**

Noisy concepts: top-down

Differential privacy (DP) picture:

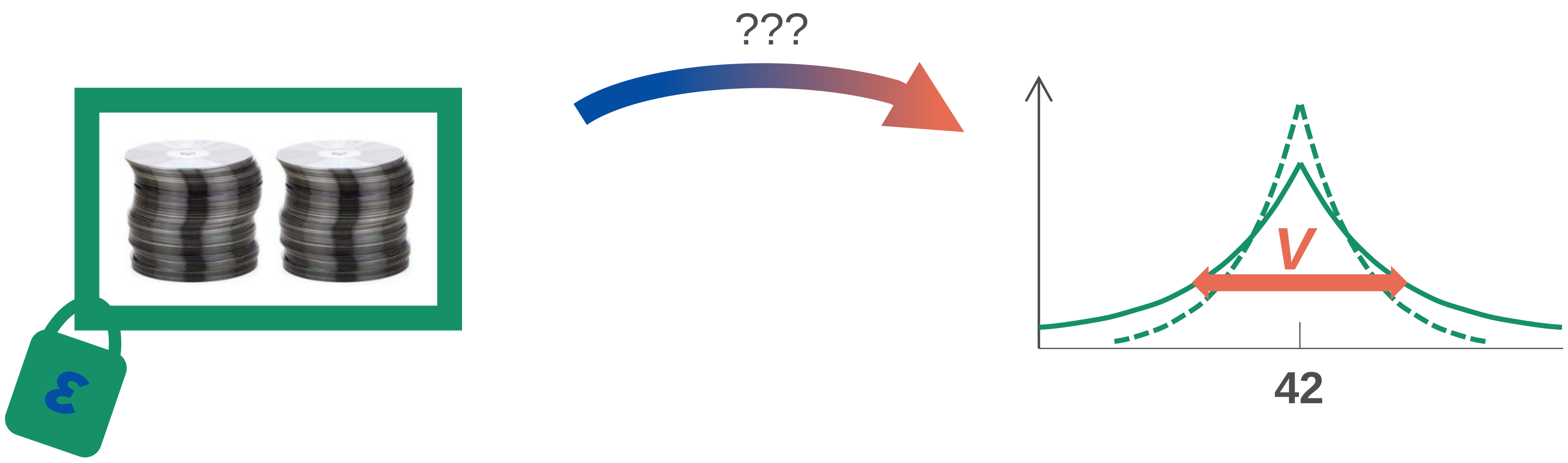
- introducing global privacy budget ε (Dwork et al., 2006)



Noisy concepts: top-down or *risk-driven*

Differential privacy (DP) picture:

- introducing global privacy budget *ε* (Dwork et al., 2006)
- promise: strong global privacy guarantee … but local noise size?



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Noisy concepts: top-down or *risk-driven*

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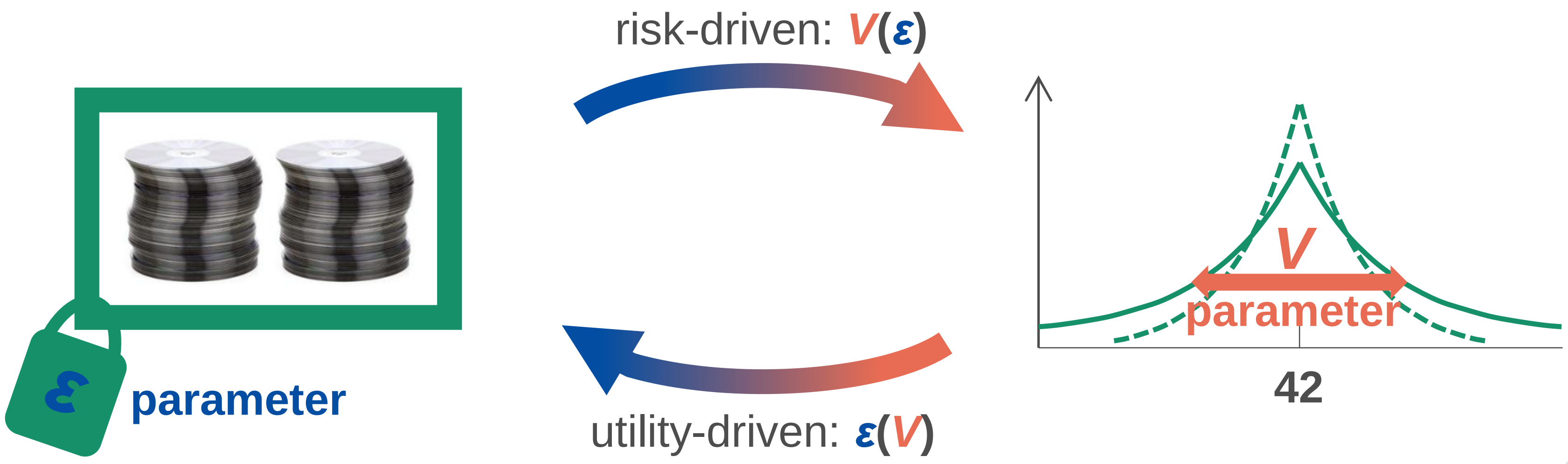

Risks: massive averaging

- How many independent observations t of "total population" are in this table?

  - ❑ $t = 1$
  - ❑ $t = 2$
  - ❑ $t = 3$
  - ❑ $t = 4$

SEX \\ POB	Total	Country	Outside
Total	**42**	**37**	**7**
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each count with noise variance $V = 1$

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each count with noise variance $V = 1$

Risks: massive averaging

- How many independent observations *t* of "total population" are in this table?

  - ❑ ***t* = 1**
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each count with noise variance ***V* = 1**

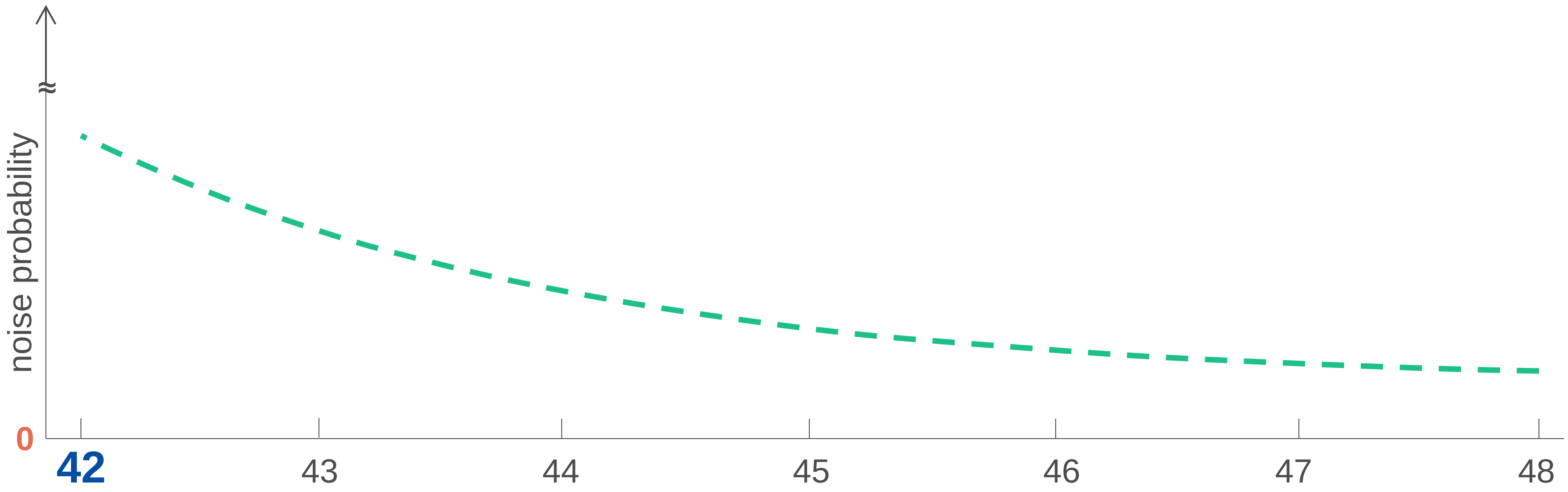
- average variance: $\bar{V} = \frac{k}{t^2} V = \frac{9}{4^2} 1 = 0.\bar{5}$

fixed by output tables

noise parameter

Risks: exploiting table constraints

- Noise distributions – part 2: how long is the **tail**?



Risks: exploiting table constraints

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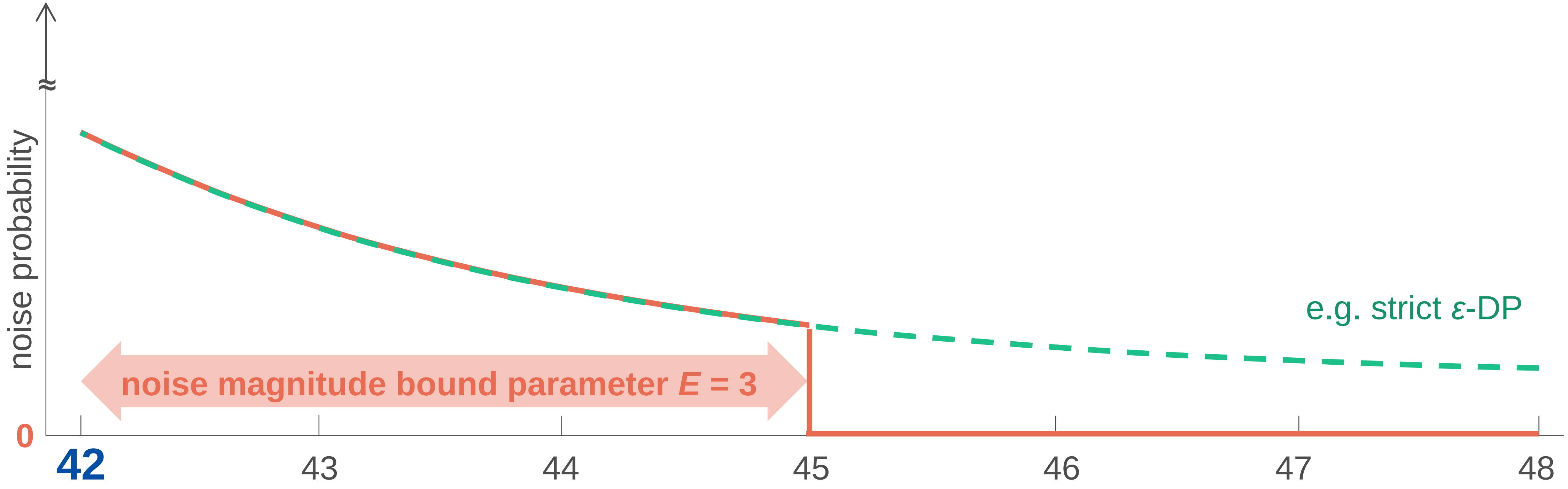

e.g. relaxed (ε,δ)-DP or cell key method (Marley and Leaver, 2011)

… but ~~**strict ε-DP**~~

Risks: exploiting table constraints

- Now would you bet all your money on a guess for the true count of the …
  - ❑ … total population?
  - ❑ … country-born males?
  - ❑ … total females?
  - ❑ … total foreign-born?

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each count with noise variance $V = 1$
and noise bound $E = 2$

- How often does this happen?

$$\#\text{ of constraint } \boldsymbol{n}\text{-tuples in output} \quad \times \quad \Pr(\text{noise} = \pm E)^{n}$$

fixed by output tables

fixed by noise parameters V and E

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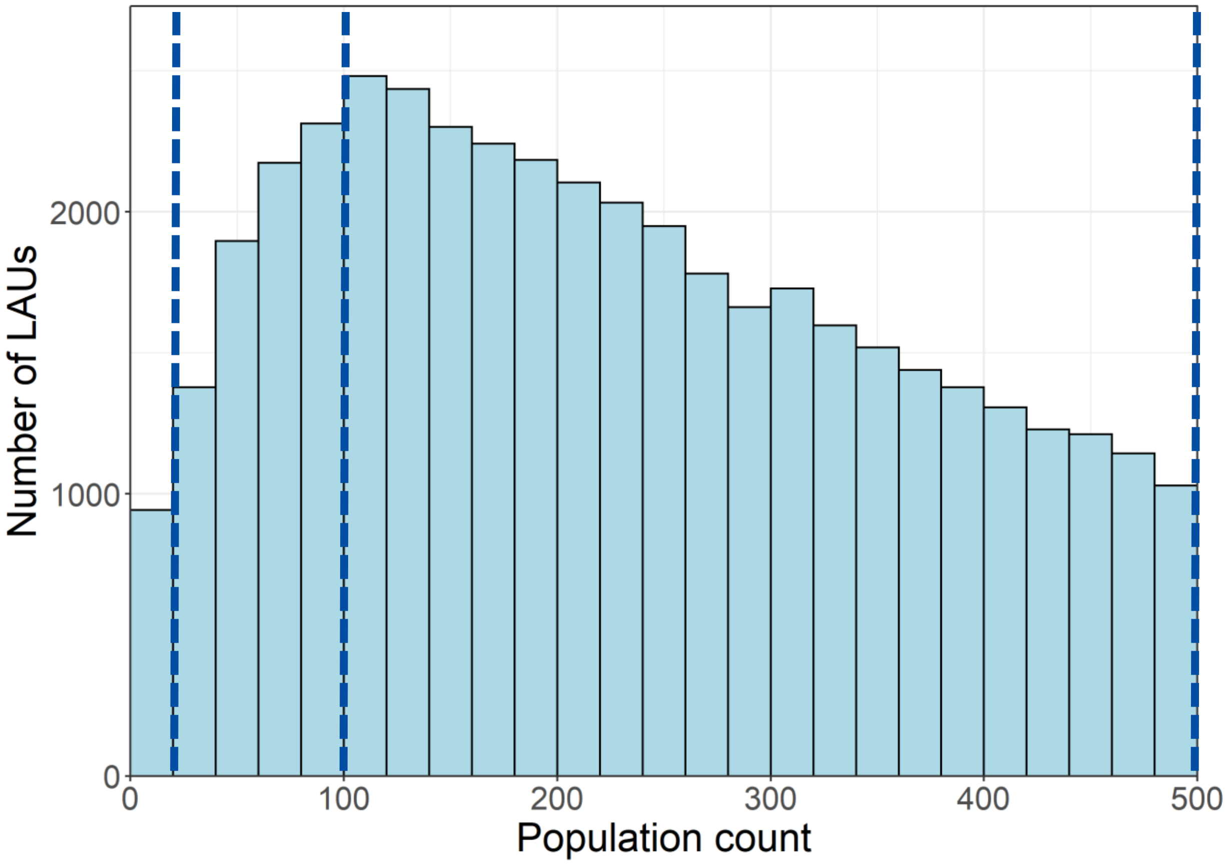
Utility: (noise) tail wagging the (statistic) dog

- 2021 EU census: ca. 110 000 **L**ocal **A**dministrative **U**nits (~ municipalities), of which
  - 43 395 with <500 people
  - 8 502 with <100 people
  - 866 with <20 people
- Could we accept here e.g. Pr(|noise|>100) = 0.1% or more?

❑ **Yes** ❑ **No**



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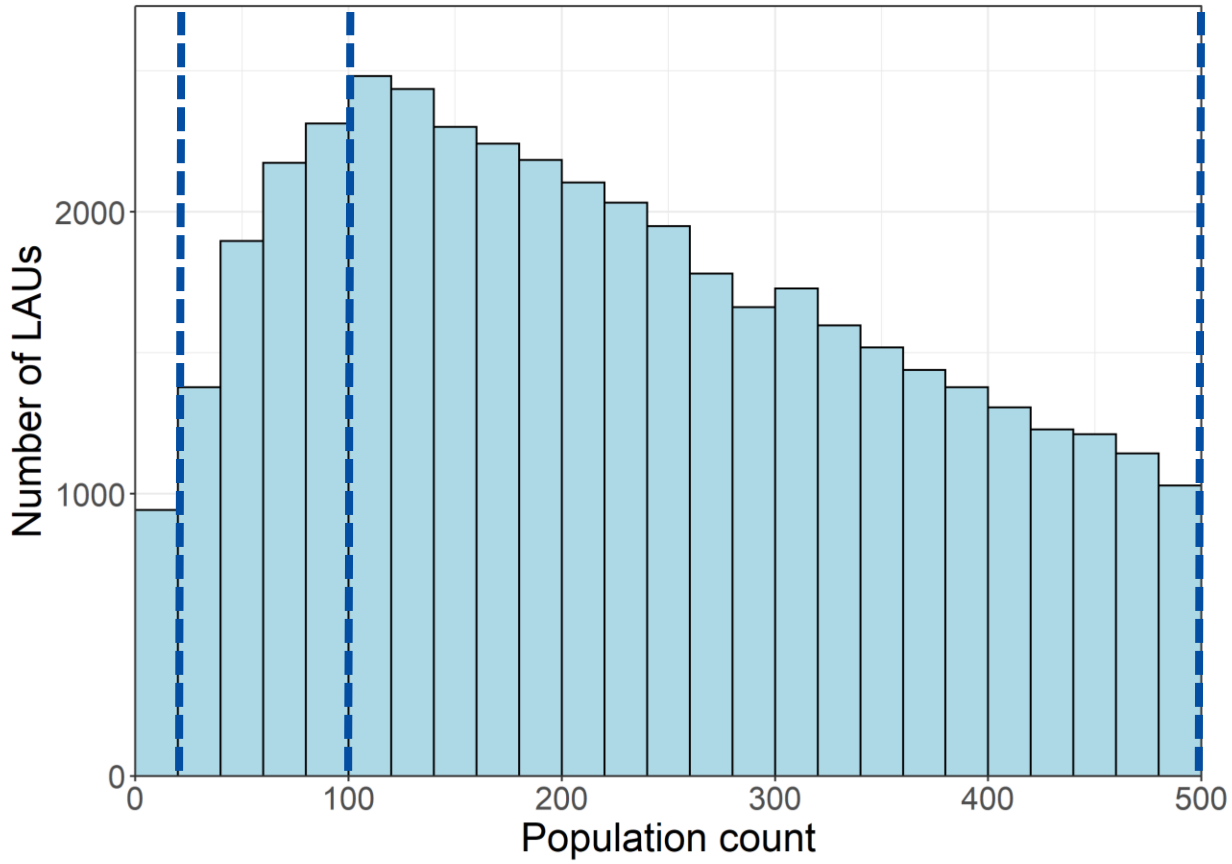

Utility: (noise) tail wagging the (statistic) dog

- mainly a problem of **strict ε-DP** approaches

  Recall: *Noise magnitude bound parameter **E**, "cutting off" the tail, is **forbidden** in strict ε-DP*

- E.g. 2020 test setup of [U.S. Census Bureau (2019)]() with moderate global $\varepsilon = 1$

source: [Wikipedia]()

source: [Google Maps]()

	2011 census	strict ε-DP
Total	**30**	**-17**
Male	20	-1
Female	15	-9

Cidamón, La Rioja, Spain
ES230_26048

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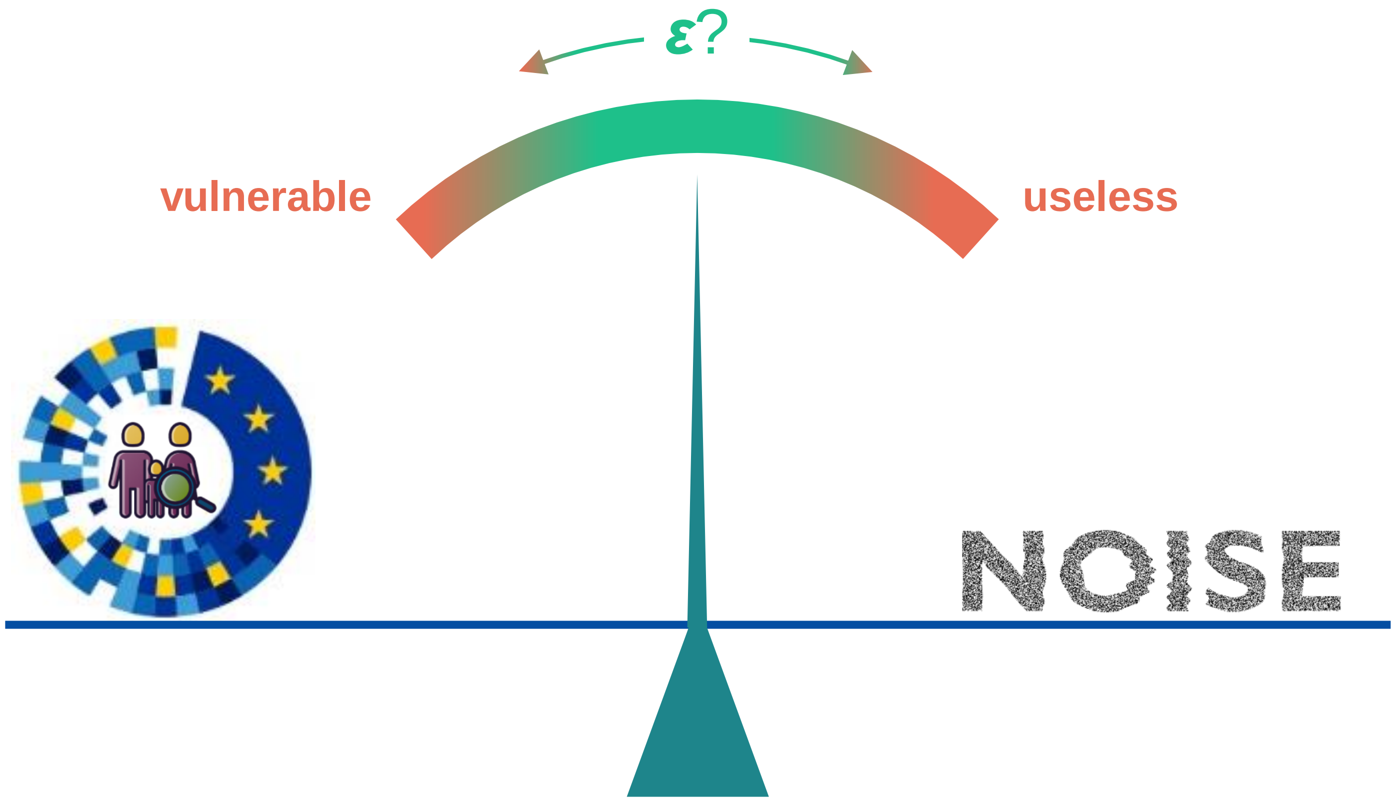
Outro: the 2021 EU census picture

- risk + utility constraints on strict ε-DP setup for whole 2021 EU census output



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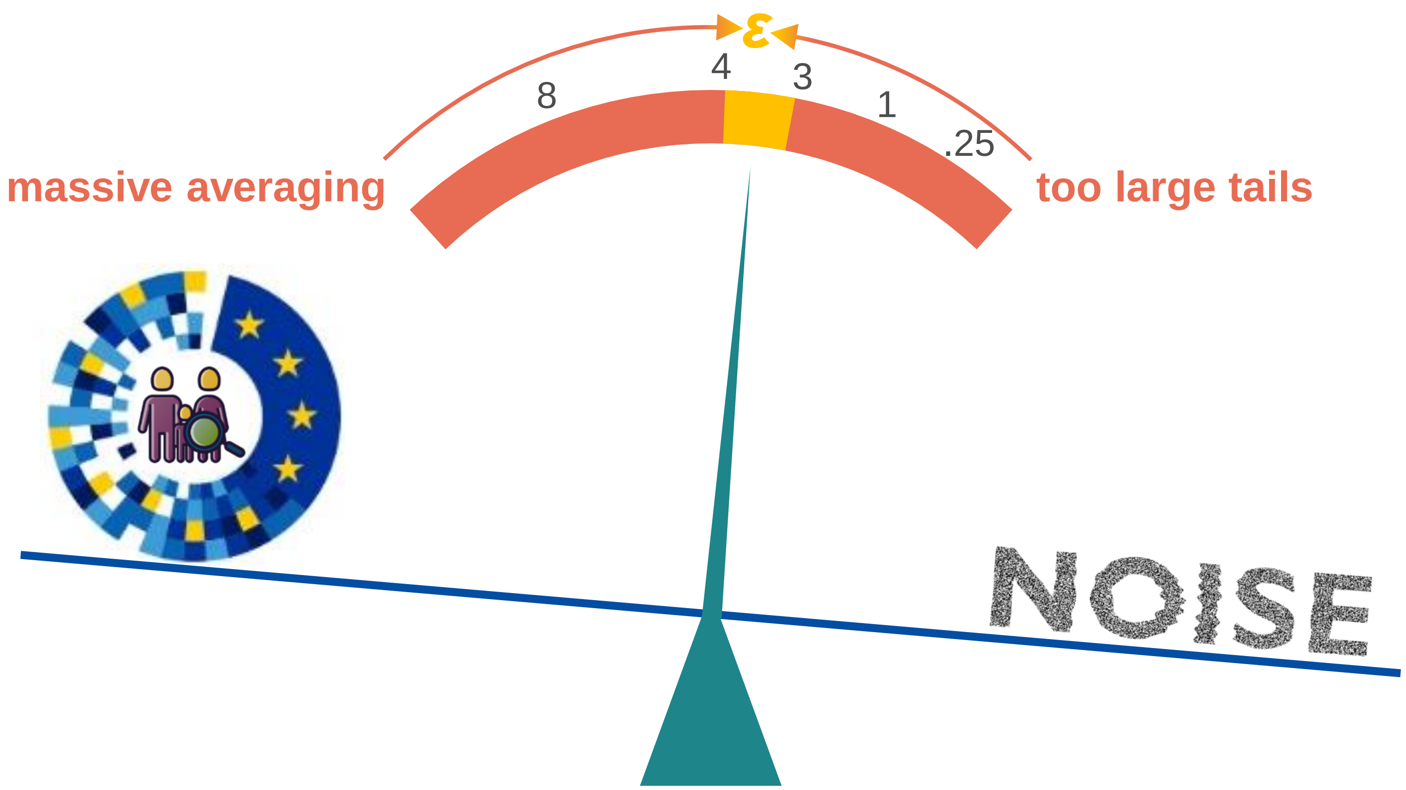
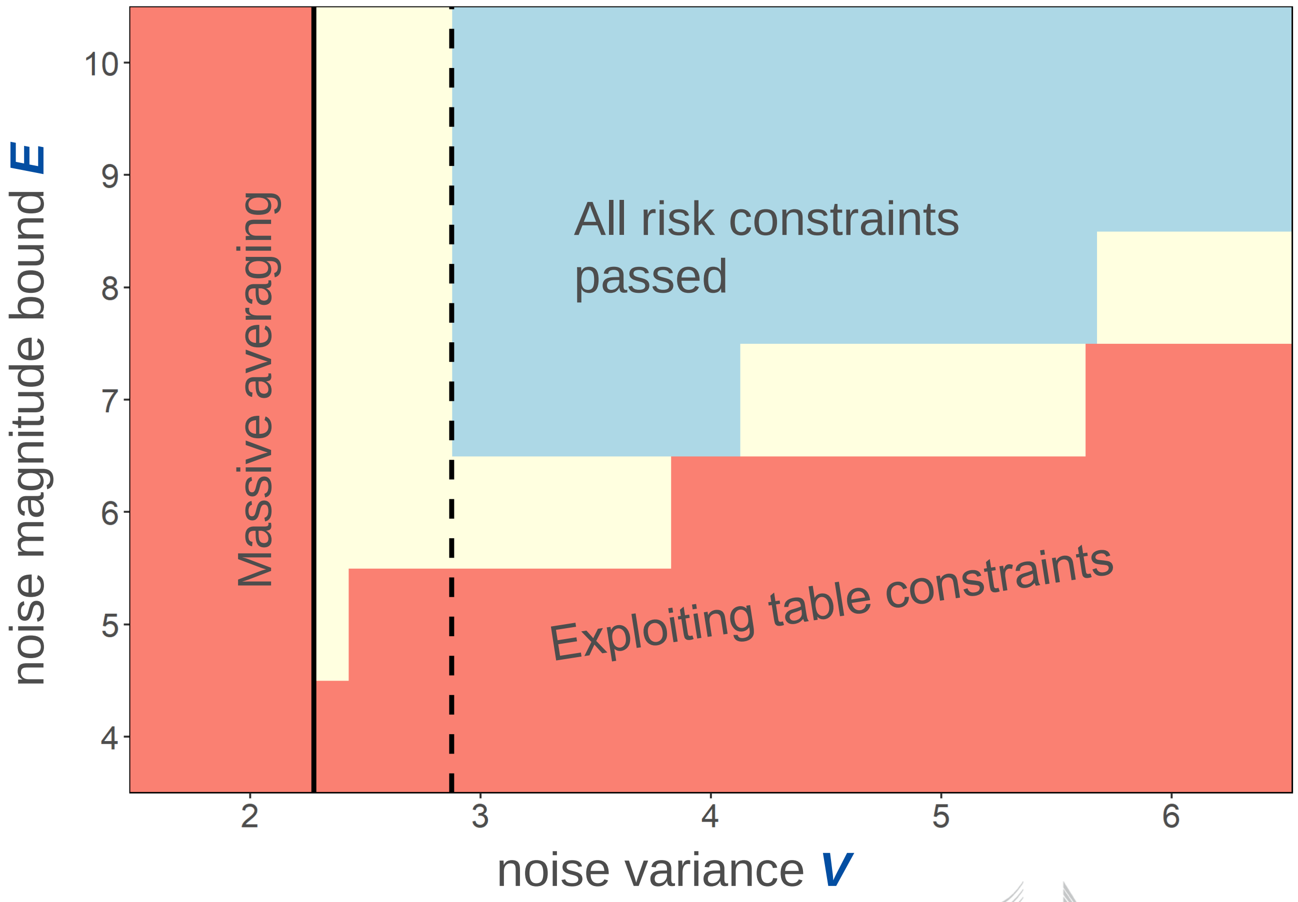


Outro: the 2021 EU census picture

- whole 2021 EU census output
- risk constraints on bottom-up parameter space ***V* – *E***
- utility controlled directly by ***V*** and ***E*** (utility-driven)
- e.g. cell key method recommended for 2021 EU census ([ESSnet, 2017, 2019](#))



Thank you

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