fn make_scalar_integer_laplace

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Proves soundness of make_scalar_integer_laplace in mod.rs at commit f5bb719 (outdated¹). The function on the resulting measurement takes in a data set x (a single integer), and returns a sample from the Discrete Laplace Distribution centered at x, with a fixed noise scale.

1 Hoare Triple

Preconditions

Compiler-verified

- Argument input_domain, of type AtomDomain<T>
- Argument input_metric, of type AbsoluteDistance<T>
- Argument scale, of type f64
- Generic T must have trait Integer and support saturating cast from IBig (for postprocessing a noisy big integer back to T)
- IBig must be constructable from T (to convert the data into a big integer)

Human-verified

None

Pseudocode

```
def make_scalar_integer_laplace(
      input_domain: AtomDomain[T], input_metric: AbsoluteDistance[T], scale: f64
3):
      if scale.is_sign_negative():
          raise ValueError("scale must not be negative")
      # conversion to rational will fail if scale is null
      r_scale = RBig.try_from(scale)
      if scale == 0.0:
11
          def function(x: T):
              return x
12
13
          def function(x: T):
14
              release = IBig.from_(x) + sample_discrete_laplace(r_scale)
16
              # postprocessing
              return T.saturating_cast(release)
17
```

¹See new changes with git diff f5bb719..77ce8ef4 rust/src/measurements/laplace/integer/mod.rs

```
return Measurement(
input_domain=input_domain,
function=function,
input_metric=input_metric,
output_measure=MaxDivergence(),
privacy_map=laplace_puredp_map(scale, relaxation=0.0),
)
```

Postcondition

Theorem 1.1. For every setting of the input parameters (input_domain, input_metric, scale, T) to make_scalar_integer_laplace such that the given preconditions hold,

make_scalar_integer_laplace raises an exception (at compile time or run time) or returns a valid measurement. A valid measurement has the following property:

1. (Privacy guarantee). For every pair of elements x, x' in input_domain and for every pair (d_{in}, d_{out}) , where d_in has the associated type for input_metric and d_out has the associated type for output_measure, if x, x' are d_in-close under input_metric, privacy_map(d_in) does not raise an exception, and privacy_map(d_in) \leq d_out, then function(x), function(x') are d_out-close under output_measure.

2 Proof

Proof. (Privacy guarantee.)

sample_integer_laplace can only fail due to lack of system entropy. This is usually related to the computer's physical environment and not the dataset. The rest of this proof is conditioned on the assumption that this function does not raise an exception.

Let x and x' be datasets that are d_in-close with respect to input_metric. Here, the metric is AbsoluteDistance<T>.

By the postcondition of sample_integer_laplace, the output of the function follows the Discrete Laplace Distribution with scale scale.

$$\begin{aligned} & \max_{x \sim x'} D_{\infty}(M(x), M(x')) \\ &= \max_{x \sim x'} \max_{z \in supp(M(\cdot))} \ln \left(\frac{\Pr\left[M(x) = z\right]}{\Pr\left[M(x') = z\right]} \right) & \text{substitute } D_{\infty} \\ &= \max_{x \sim x'} \max_{z \in \mathbb{Z}} \ln \left(\frac{\Pr\left[\operatorname{DLap}(x, b) = z\right]}{\Pr\left[\operatorname{DLap}(x', b) = z\right]} \right) & \text{where } b \text{ is the noise scale} \\ &= \max_{x \sim x'} \max_{z \in \mathbb{Z}} \ln \left(\frac{\exp^{1/b} - 1}{\exp^{1/b} + 1} \exp\left(-\frac{|x - z|}{b}\right)}{\exp^{1/b} - 1} \exp\left(-\frac{|x' - z|}{b}\right) \right) & \text{use PMF of Discrete Laplace} \\ &= \max_{x \sim x'} \max_{z \in \mathbb{Z}} \ln \left(\frac{\exp\left(-\frac{|x - z|}{b}\right)}{\exp\left(-\frac{|x' - z|}{b}\right)} \right) & \text{exp and In cancel} \\ &= \max_{x \sim x'} \max_{z \in \mathbb{Z}} \frac{|x' - z| - |x - z|}{b} & \text{by reverse triangle inequality} \\ &= \frac{d_{in}}{b} & \text{by definition of absolute distance} \end{aligned}$$

This bound satisfies the postcondition of laplace_puredp_map. The saturating conversion to T is a post-processing step.

Therefore it has been shown that for every pair of elements $x, x' \in \text{input_domain}$ and every $d_{Abs}(x, x') \leq d_{in}$ with $d_{in} \geq 0$, if x, x' are d_{in} -close then function(x), function(x') are $privacy_map(d_{in})$ -close under output_measure (the Max-Divergence).