fn make_gaussian

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> This proof resides in **"contrib"** because it has not completed the vetting process.

Proves soundness of the implementation of `make_gaussian` in `mod.rs` at commit f5bb719 (outdated[1]). Perturbative noise mechanisms may be parameterized along many different axes:

- domain: scalar or vector

- domain dtype: i8, i16, i32, i64, u8, u16, u32, u64, f32, f64, UBig, IBig, RBig

- metric: absolute distance, l1 distance, modular distance

- metric dtype: i8, i16, i32, i64, u8, u16, u32, u64, f32, f64, UBig, IBig, RBig

- measure: max divergence, zero concentrated divergence

- distribution: laplace, gaussian

All parameterizations reduce to a single core mechanism that perturbs a vector of signed big integers with noise sampled from the appropriate discrete distribution.

The implementation of this function constructs a random variable denoting the noise distribution to add, and then dispatches to the `MakeNoise<DI, MI, MO>` trait which constructs the core mechanism and wraps it in pre-processing transformations and post-processors to match the desired parameterization.

1 Hoare Triple

Precondition

Compiler-Verified

- generic `DI` implements trait `NoiseDomain`

- generic `MI` implements trait `Metric`

- generic `MO` implements trait `Measure`

- type `DI_Atom_RV2` (the random variable associated with the atom data type) implements trait `MakeNoise<DI, MI, MO>` This trait bound constrains the choice of input domain, input metric and output measure to those that can form valid measurements.

- type `(DI, MI)` implements trait `MetricSpace`

User-Verified

None

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[1]See new changes with `git diff f5bb719..69324fc rust/src/measurements/noise/distribution/gaussian/mod.rs`

Pseudocode

```
1  def make_gaussian(
2      input_domain: DI,
3      input_metric: MI,
4      scale: f64,
5      k: Option[i32],
6  ) -> Measurement[DI, DI_Carrier, MI, MO]:
7      return DiscreteGaussian(scale, k).make_noise((input_domain, input_metric))
```

Postcondition

Theorem 1.1. For every setting of the input parameters (`input_domain, input_metric, scale, k, DI, MI, MO`) to `make_gaussian` such that the given preconditions hold, `make_gaussian` raises an error (at compile time or run time) or returns a valid measurement. A valid measurement has the following properties:

1. (Data-independent runtime errors). For every pair of members x and x' in `input_domain`, `invoke`(x) and `invoke`(x') either both return the same error or neither return an error.

2. (Privacy guarantee). For every pair of members x and x' in `input_domain` and for every pair $(\mathtt{d\_in}, \mathtt{d\_out})$, 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 error, and `privacy_map(d_in) = d_out`, then `function`(x), `function`(x') are `d_out`-close under `output_measure`.

Proof. We first construct a random variable `DiscreteGaussian` representing the desired noise distribution. Since `MakeNoise.make_noise` has no preconditions, the postcondition follows, which matches the postcondition for this function. $\square$