

CompositionMeasure for ZeroConcentratedDivergence

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This proof resides in “**contrib**” because it has not completed the vetting process.

Proves soundness of the implementation of **CompositionMeasure** for **ZeroConcentratedDivergence** in **mod.rs** at **commit f5bb719** (outdated¹).

1 Hoare Triple

Precondition

Compiler-Verified

Types matching pseudocode.

Caller-Verified

None

Pseudocode

```
1 class CompositionMeasure(ZeroConcentratedDivergence):
2     def composability( #
3         self, adaptivity: Adaptivity
4     ) -> Composability:
5         match adaptivity:
6             case Adaptivity.FullyAdaptive:
7                 return Composability.Sequential
8             case _:
9                 return Composability.Concurrent
10
11     def compose(self, d_mids: Vec[Self_Distance]) -> Self_Distance:
12         d_out = 0.0
13         for d_mid in d_mids:
14             d_out = d_out.inf_add(d_mid)
15         return d_out
```

Postcondition

Theorem 1.1. `composability` returns `Ok(out)` if the composition of a vector of privacy parameters `d_mids` is bounded above by `self.compose(d_mids)` under `adaptivity` `adaptivity` and `out-composability`. Otherwise returns an error.

Definition 1.2 (Definition of **ZeroConcentratedDivergence**). For any two distributions Y, Y' and any non-negative d , Y, Y' are d -close under the zero-concentrated divergence measure if, for every possible choice of $\alpha \in (1, \infty)$,

¹See new changes with `git diff f5bb719..1fb97a7 rust/src/combinators/sequential_composition/mod.rs`

$$D_\alpha(Y, Y') = \frac{1}{1-\alpha} \mathbb{E}_{x \sim Y'} \left[\ln \left(\frac{\Pr[Y = x]}{\Pr[Y' = x]} \right)^\alpha \right] \leq d \cdot \alpha. \quad (1)$$

Lemma 1.3. 1. $\mathcal{F}(\rho_1, \rho_2, \dots; \rho) = \mathbb{I}(\sum_i \rho_i \leq \rho)$ is a valid ρ -zCDP IM-filter.

2. $\mathcal{G}(\rho_1, \dots, \rho_k) = \sum_{i=1}^k \rho_i$ is a valid ρ -zCDP IM-privacy loss accumulator.

Proof. For any fixed choice of $\alpha > 1$, we have that $\mathcal{F}(\rho_1, \rho_2, \dots; \rho) = \mathbb{I}(\sum_i \epsilon_i / \alpha \leq \epsilon / \alpha)$, by 1.2, which by Theorem 1.22[VW21] is a valid (α, ϵ) -RDP IM-filter.

Similarly, for any fixed choice of $\alpha > 1$, we have that $\mathcal{G}(\rho_1, \dots, \rho_k) = \sum_i \epsilon_i / \alpha \leq \epsilon / \alpha$, by 1.2, which by Theorem 1.22[VW21] is a valid (α, ϵ) -RDP IM-privacy loss accumulator. \square

Proof. By the postcondition of **InfAdd** we have that $\sum_i \mathbf{d_mids}_i \leq \mathbf{compose}(\mathbf{d_mids})$.

| Adaptivity | Sequential | Concurrent |
|----------------|------------------|--------------------|
| Non-Adaptive | Lemma 1.7[BS16] | Corollary 1[Lyu22] |
| Adaptive | Lemma 1.7[BS16] | Corollary 1[Lyu22] |
| Fully-Adaptive | Remark 4.4[FZ22] | 1.3 |

This table is reflected in the implementation of **composability** on line 2.

\square

References

- [BS16] Mark Bun and Thomas Steinke. Concentrated differential privacy: Simplifications, extensions, and lower bounds, 2016.
- [FZ22] Vitaly Feldman and Tijana Zrnic. Individual privacy accounting via a renyi filter, 2022.
- [Lyu22] Xin Lyu. Composition theorems for interactive differential privacy, 2022.
- [VW21] Salil Vadhan and Tianhao Wang. Concurrent composition of differential privacy, 2021.