



The University of Vermont

Evaluating the Usability of Differential Privacy Tools with Data Practitioners

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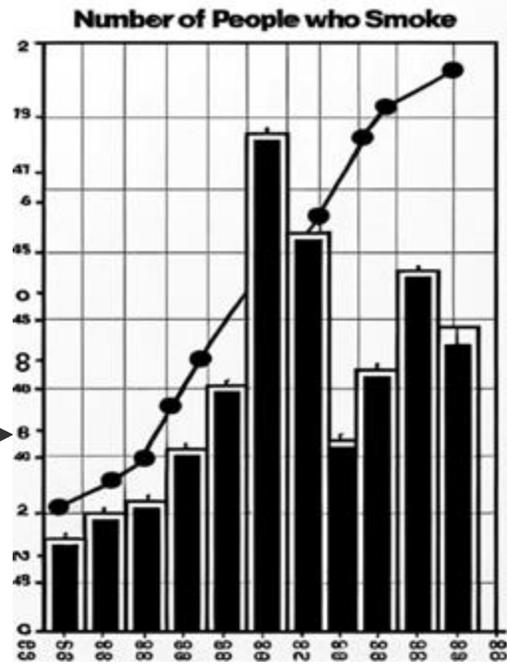
GOALS

- Understand usability issues in differential privacy.
- Make recommendations for improving usability

Let's see a chart of the number of people who smoke versus the number of people with cancer

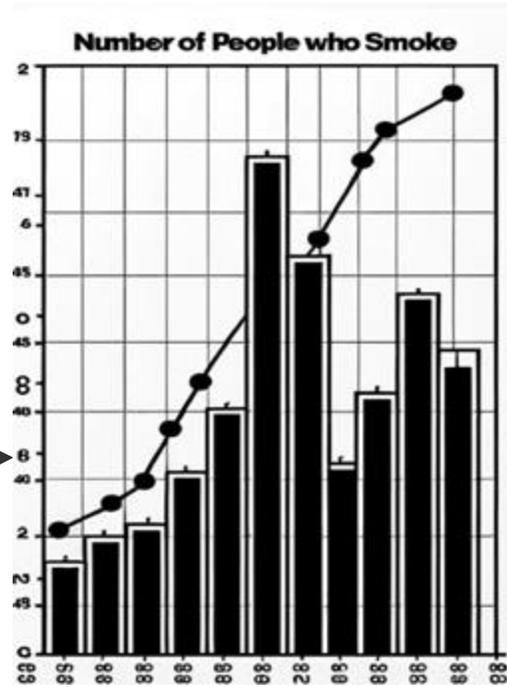


Oh no, the results could accidentally reveal that John has cancer!



Sensitive Query
Result
**Smoking Causes
Cancer**

Differential Privacy is the solution!

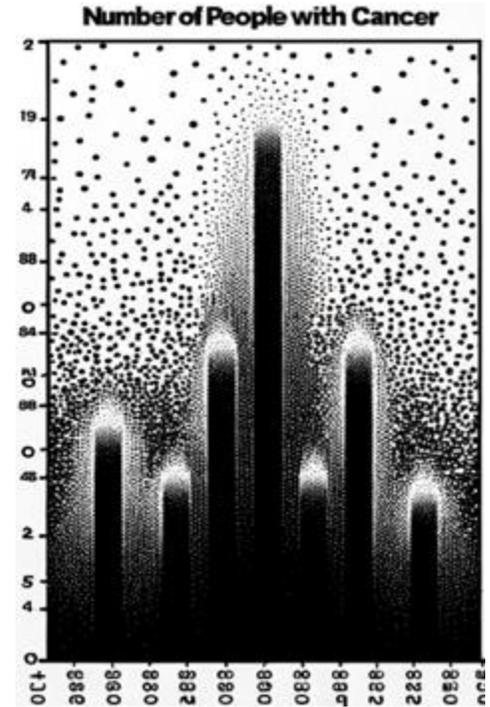


Sensitive Query
Result
Smoking Causes Cancer

+



Calibrated
Random
Noise



Differentially Private Result
Smoking Causes Cancer

DP is Challenging to Implement and Error Prone



- It's **hard to understand** DP terms and concepts especially for non-experts.
- There are **many tools out there**; it's hard to choose the right one.
- Even after using a tool, **it's easy to make mistakes & interpreting results is hard**. Are the results correct? what do they mean? how do you use them?
- Existing tool **effectiveness** and **ease of use are unclear**, possibly slowing DP adoption.

Goal: Compare usability of open-source DP tools for data scientist"

Research Questions

RQ1: How effectively can DP tools help data practitioners understand DP concepts?

(**DP Understanding**)

RQ2: How effectively can DP tools help data practitioners implement DP solutions?

(**DP Implementation**)

RQ3: How satisfied are data practitioners with DP tools for their DP implementation?

(**User Satisfaction**)

Selected DP Tools



Tumult Analytics

IBM/differential-privacy-library



Diffprivlib: The IBM Differential Privacy Library

11 Contributors 113 Used by 743 Stars 194 Forks



DiffPrivLib



PipelineDP



OpenDP

Selected DP Tools



Tumult Analytics

Selection Criteria

1. Open source
2. Python-based
3. Aim for accessibility for non-experts
4. Comprehensive Documentation
5. Support Usability Tasks
6. No server requirements

IBM/differential-privacy-



rary

194
Forks



PipelineDP

PipelineDP



OpenDP

OpenDP

Study Design



- Distributed **eligibility survey** alongside recruitment ads.
- Assessed Python and **DP knowledge**.
- **24 data practitioners**, including 12 DP novices & 12 experts
- **Between-subjects design** - each participant to one of the four DP tools
- **DP Experts** - answered 3/4 DP questions correctly

Study Design

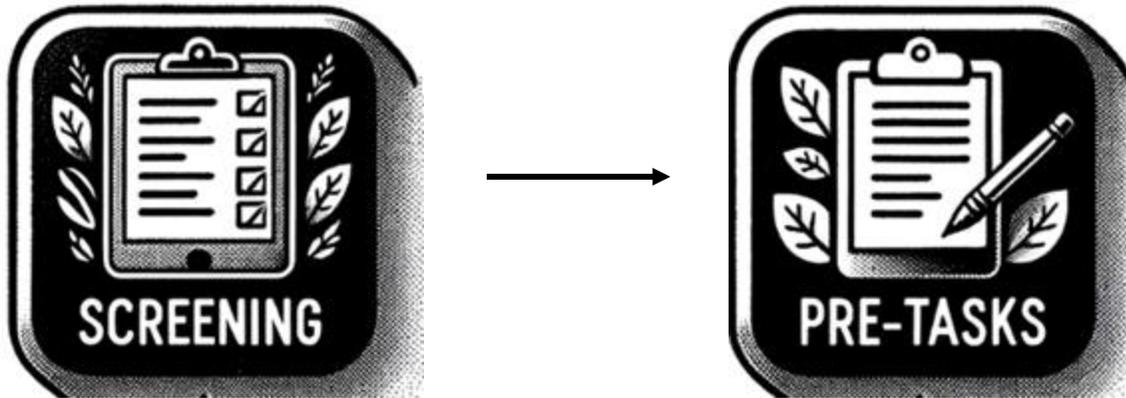


DP Questions

from Eligibility Survey

- (6) Have you heard of the term differential privacy (DP) before?
 - (a) No
 - (b) Yes
- (7) Have you ever written code to implement differential privacy (DP) in any capacity?
 - (a) No
 - (b) Yes
- (8) In differential privacy, which value of the privacy parameter ϵ provides stronger privacy?
 - (a) $\epsilon = 0.1$
 - (b) $\epsilon = 1.0$
 - (c) I don't know
- (9) Releasing two differentially private statistics, one with $\epsilon_1 = 0.1$ and the other with $\epsilon_2 = 0.5$, results in a total privacy loss of:
 - (a) $\epsilon = 0.1$
 - (b) $\epsilon = 0.5$
 - (c) $\epsilon = 0.6$
 - (d) $\epsilon = 0.05$
 - (e) I don't know
- (10) If the mechanism M returns a number and satisfies differential privacy with $\epsilon = 0.1$, does $\text{abs}(M(x))$ satisfy differential privacy, where abs is the absolute value function?
 - (a) No, not necessarily
 - (b) Yes, for $\epsilon = 0.1$
 - (c) Yes, for some $\epsilon > 0.1$
 - (d) I don't know
- (11) Which of the following is an advantage of using Differential Privacy?
 - (a) It guarantees complete anonymity of the data subjects
 - (b) It ensures that the data is completely accurate
 - (c) It provides a tradeoff between privacy and utility of the data
 - (d) It is a computationally simple method for preserving privacy in large datasets
 - (e) I don't know

Study Design



- Invited qualified respondents to usability study on Microsoft Teams.
- Participants **shared screens** and learned about think-aloud methodology.
- Reviewed DP fundamentals and tool requirements via **handout and tutorial**.
- Given access to **tool documentation** and permitted to use Google search (but not StackOverflow).

Study Design



DP Tool Tutorial

Tumult Analytics tutorial ☆

File Edit View Insert Runtime Tools Help Last edited on August 18

Comment Share

+ Code + Text Connect GPU High-RAM

About this Tutorial

This tutorial describes basic usage of the Tumult Analytics platform to calculate differentially private statistics from a sensitive dataset.

Tumult Analytics is a library for conducting differentially private analyses. It's designed to be similar to existing tools for data analytics, like Spark and Pandas.

Install dependencies and download data

This cell installs Tumult Analytics. Run it, then scroll down to the beginning of the tutorial below

```
1 #@markdown Install dependencies and download data
2 import pandas as pd
3 import numpy as np
4 import matplotlib.pyplot as plt
5 from IPython.display import clear_c
6 import os
7 import sys
8 !pip install tmlt.analytics
```

Requirement already satisfied: tmlt.analytics in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: pandas<2.0.0,>=1.2.0 in /usr/local/lib/python3.10/d:
Requirement already satisfied: pyspark[sql]<=3.3.2,>=3.0.0 in /usr/local/lib/pythor
Requirement already satisfied: sympy<1.10.>=1.8 in /usr/local/lib/python3.10/dist-

Study Design



- **Three tasks:** perform differentially private data analysis using DP tools.
- Participants spent 60 minutes **coding solutions with the tool.**

Task	Description
Task 1	How crowded is the restaurant on weekdays? (total number of visits for each weekday)
Task 2	Total amount of time spent by visitors on each weekday (exclude weekends).
Task 3	Average amount of time spent by visitors on each weekday (exclude weekends)



COUNT

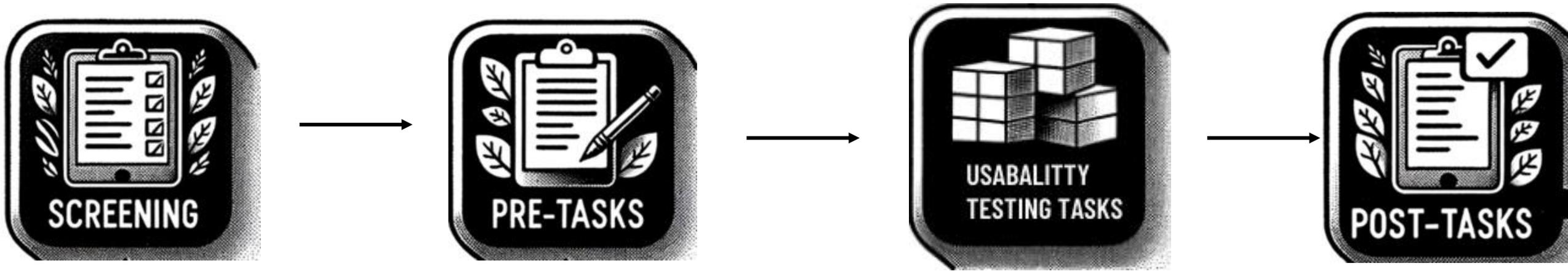


SUM



MEAN

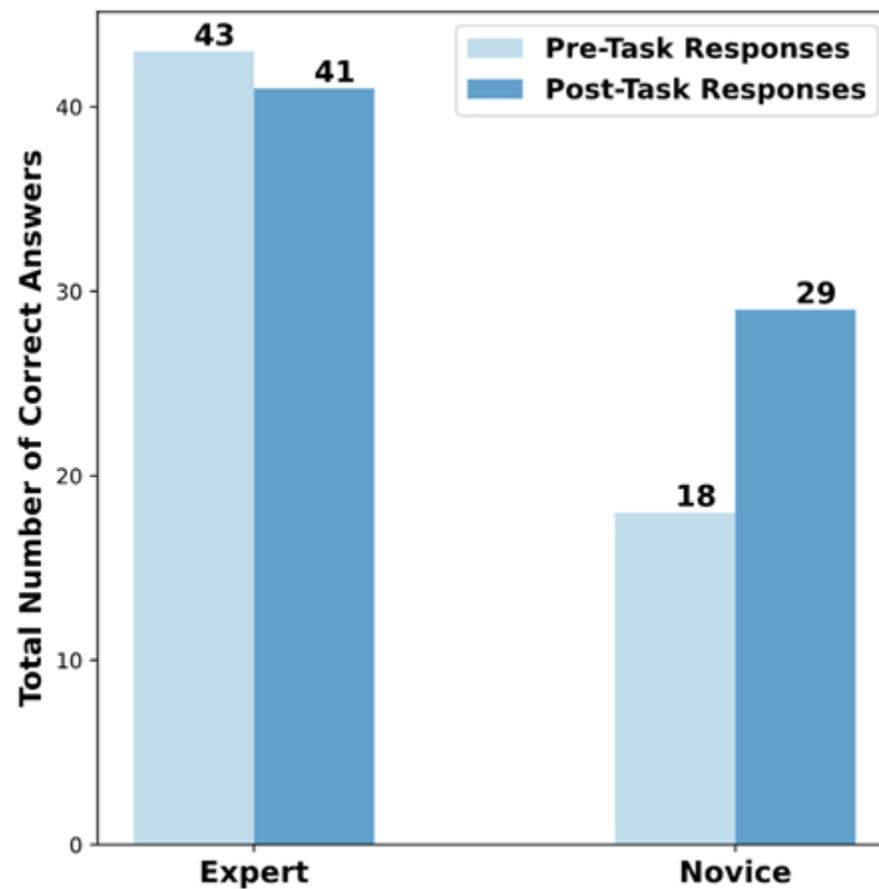
Study Design



- Participants completed a **post-task survey** and **interview**.
- Survey assessed learning outcomes, experiences, and confidence.
- Interview provided deeper insights into participants' preferences, challenges, and suggestions.

Results

- Novices **scored higher** on conceptual questions in post-task survey

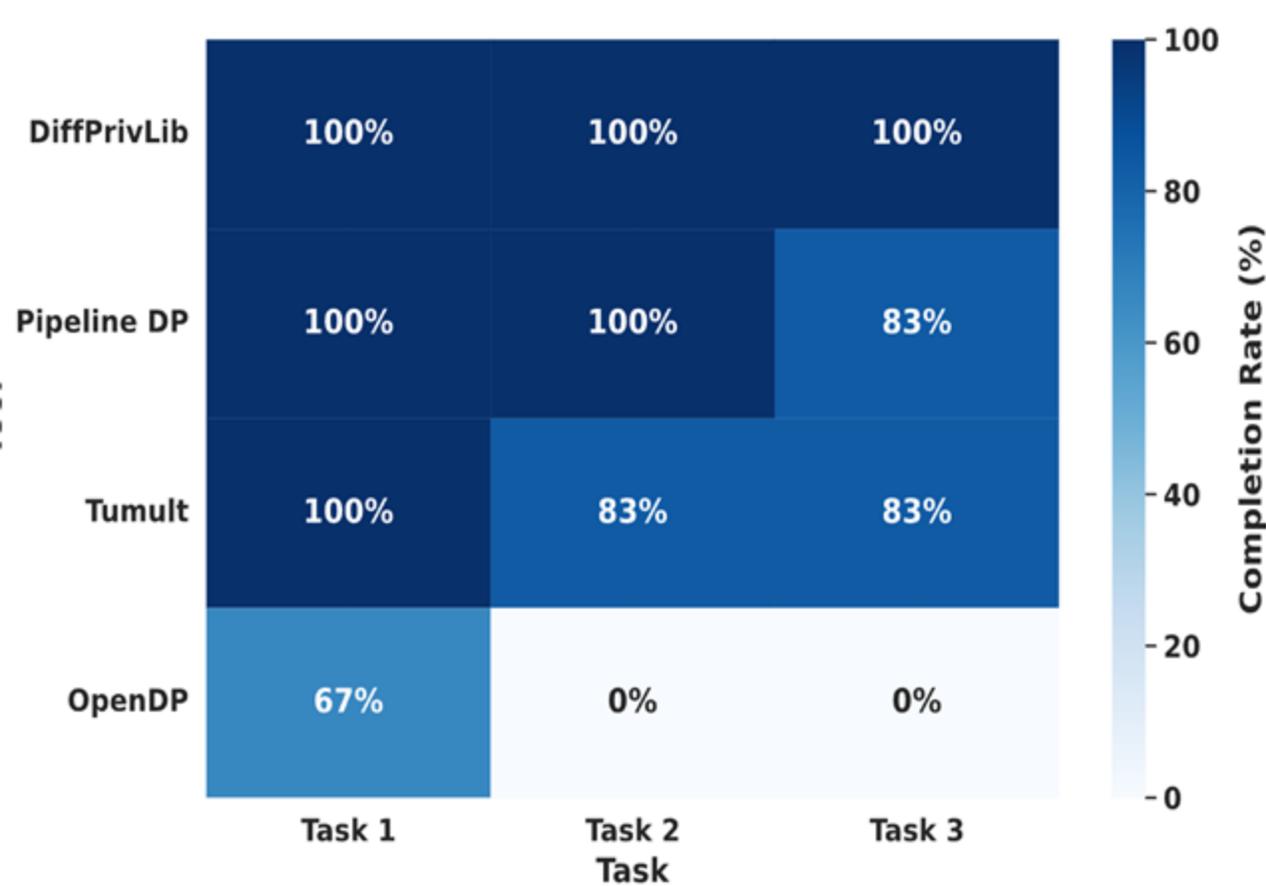


RQ2: tools differ in effectiveness

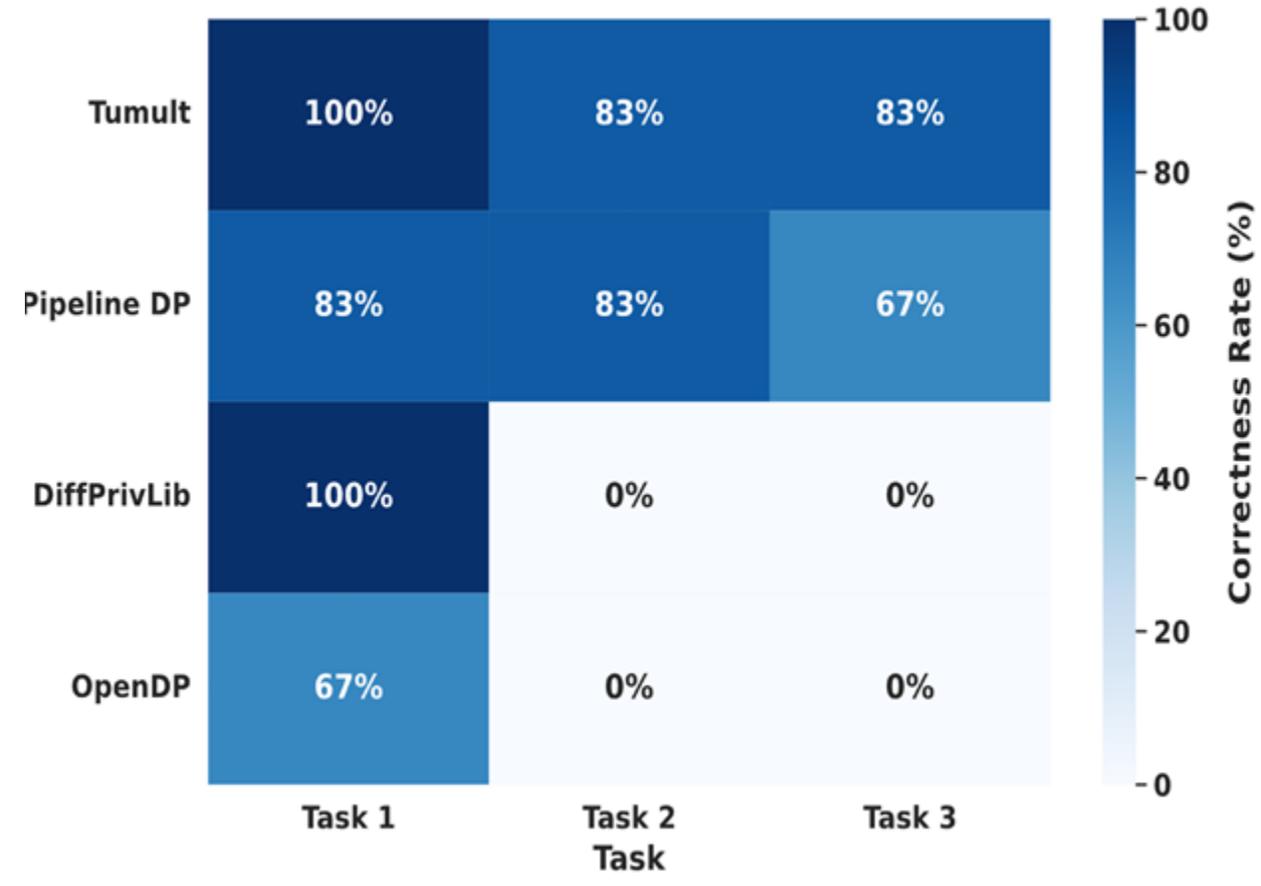
Completion Rate: code executed without error and produced correctly formatted responses.

Correctness Rate: code output satisfied DP and had comparable utility to our reference solutions.

Completion Rate For Each Tool

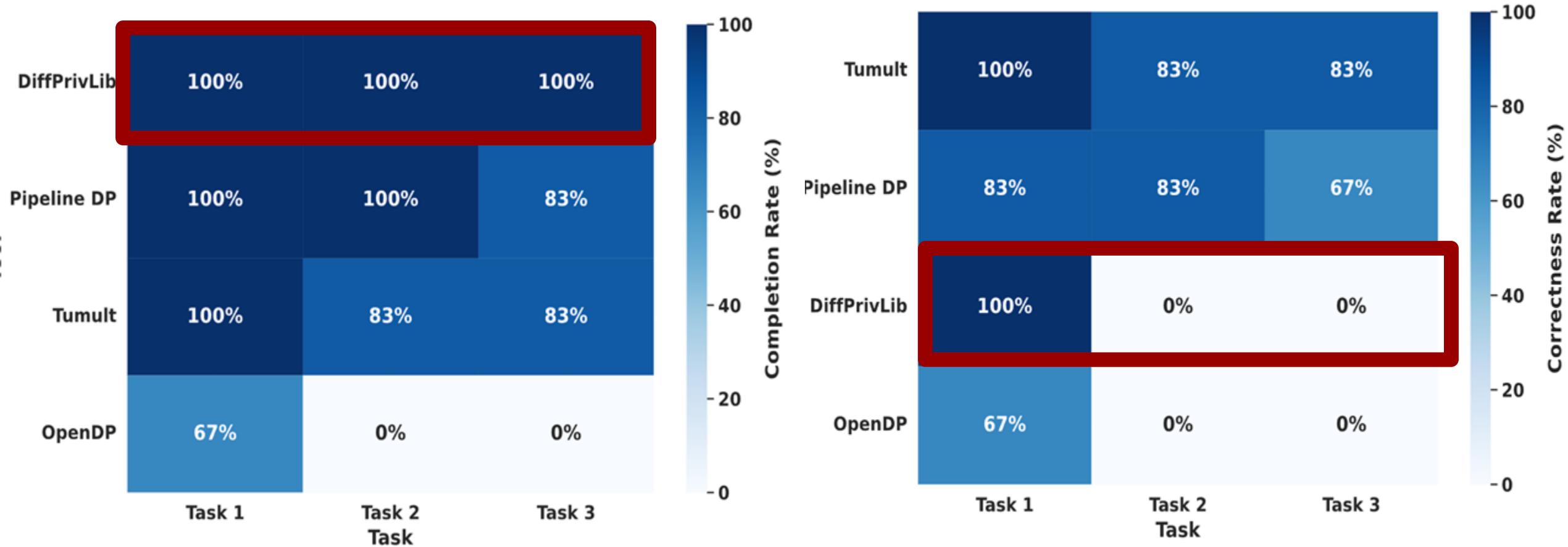


Correctness Rate For Each Tool



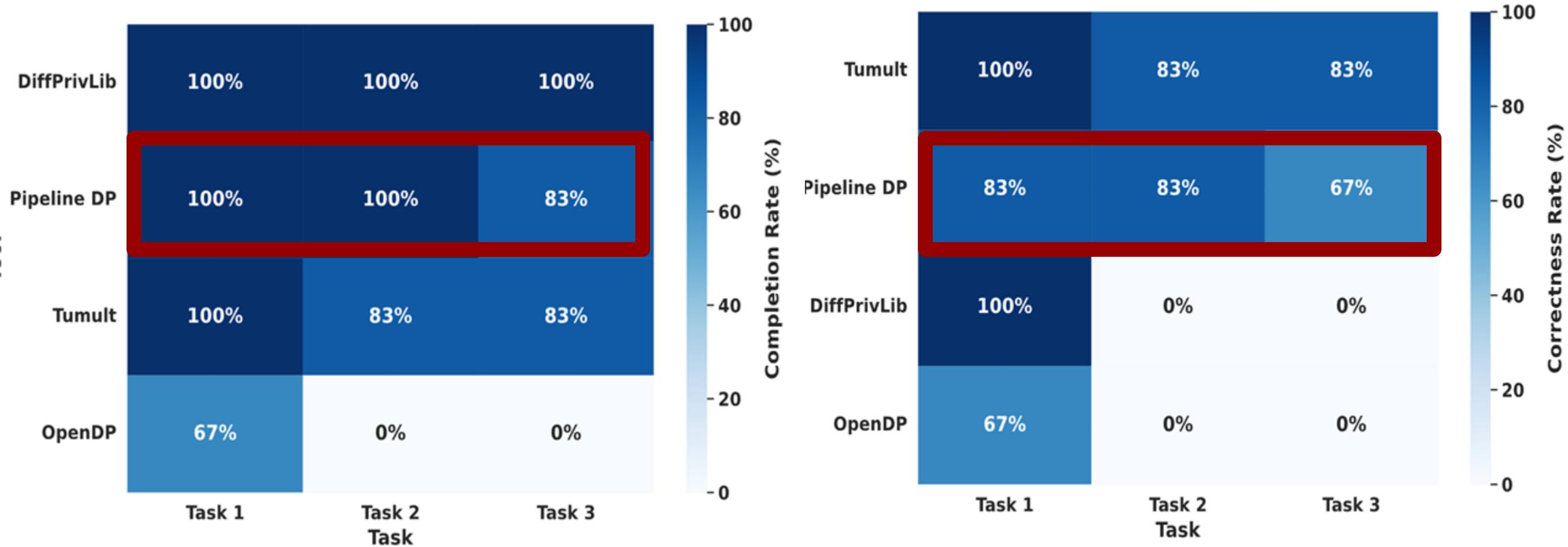
DiffPrivLib users **completed all tasks, but most were incorrect**

- All 6 participants violated dp
- Incorrect sensitivity settings / No clipping
- No error warning

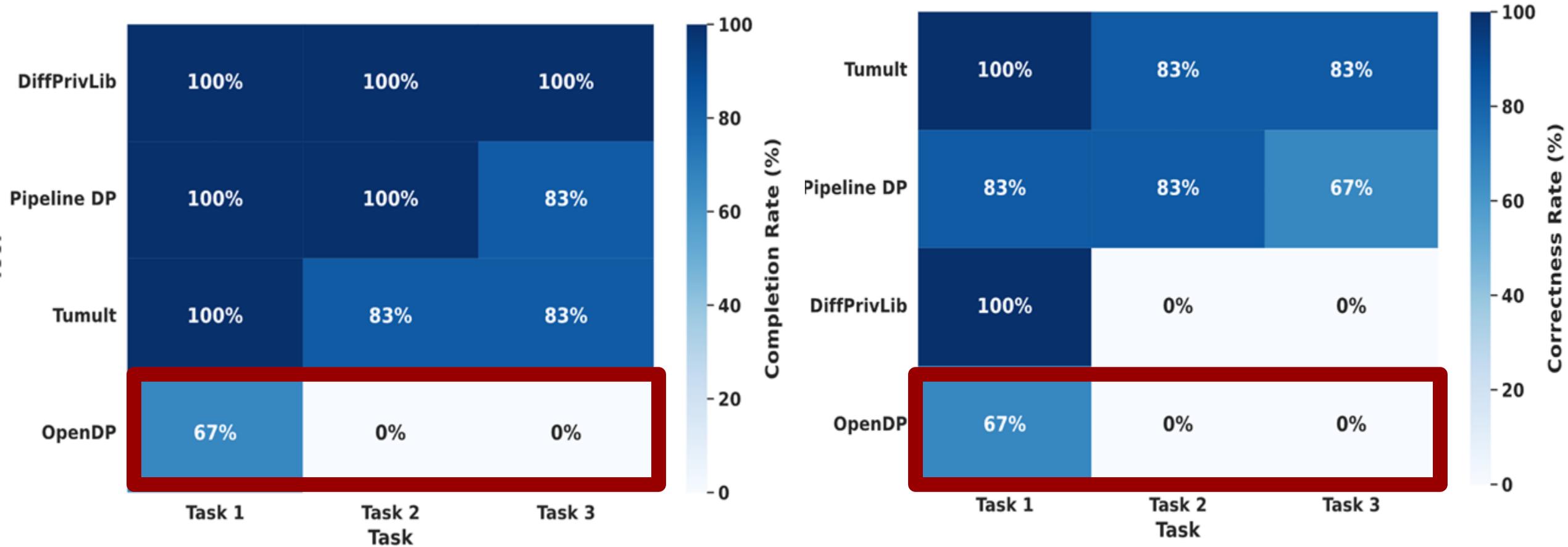


PipelineDP users **completed most tasks, but some were incorrect**

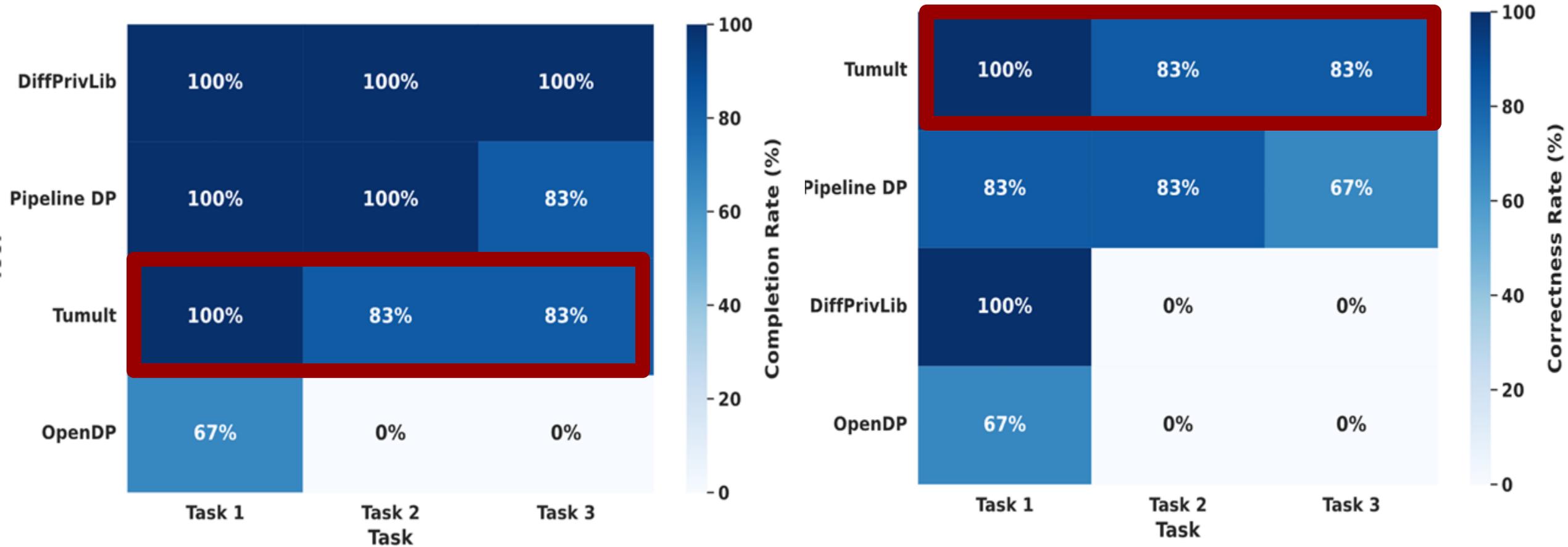
- Easy to make mistakes
- No way validate noisy results
- Confusion about privacy budget tracking



OpenDP users **completed fewest tasks, and all were correct**



Tumult Analytics users **completed most tasks, and all were correct**



API designs impacted completion rates.

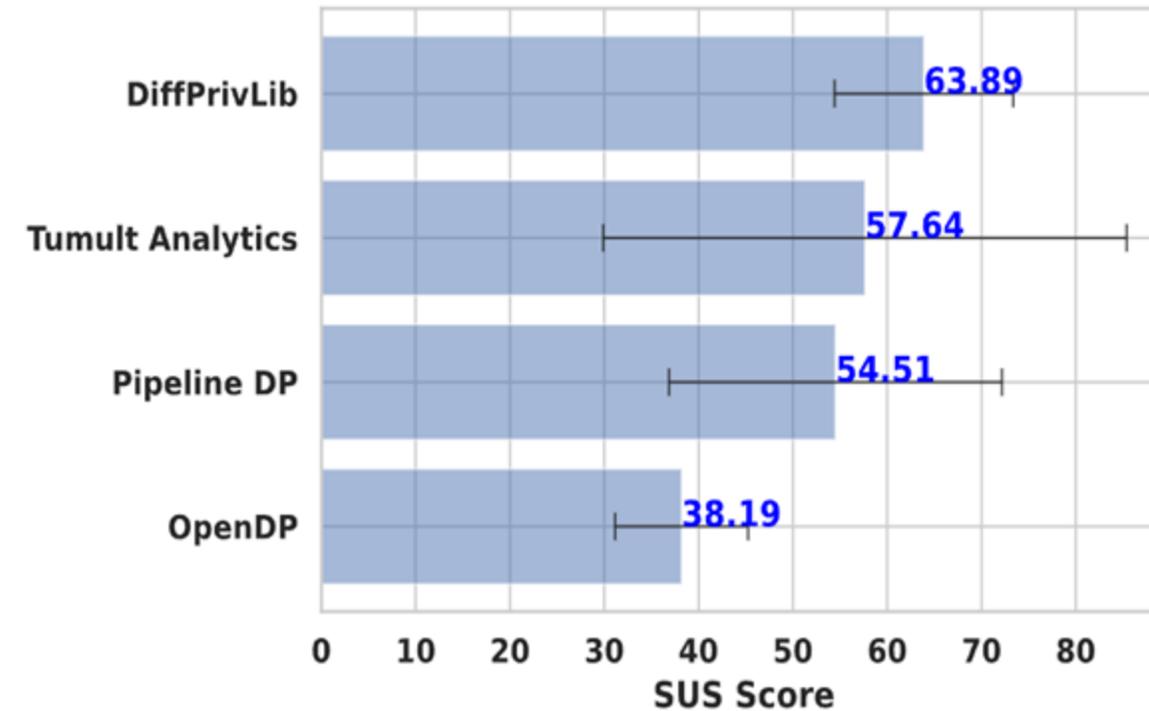
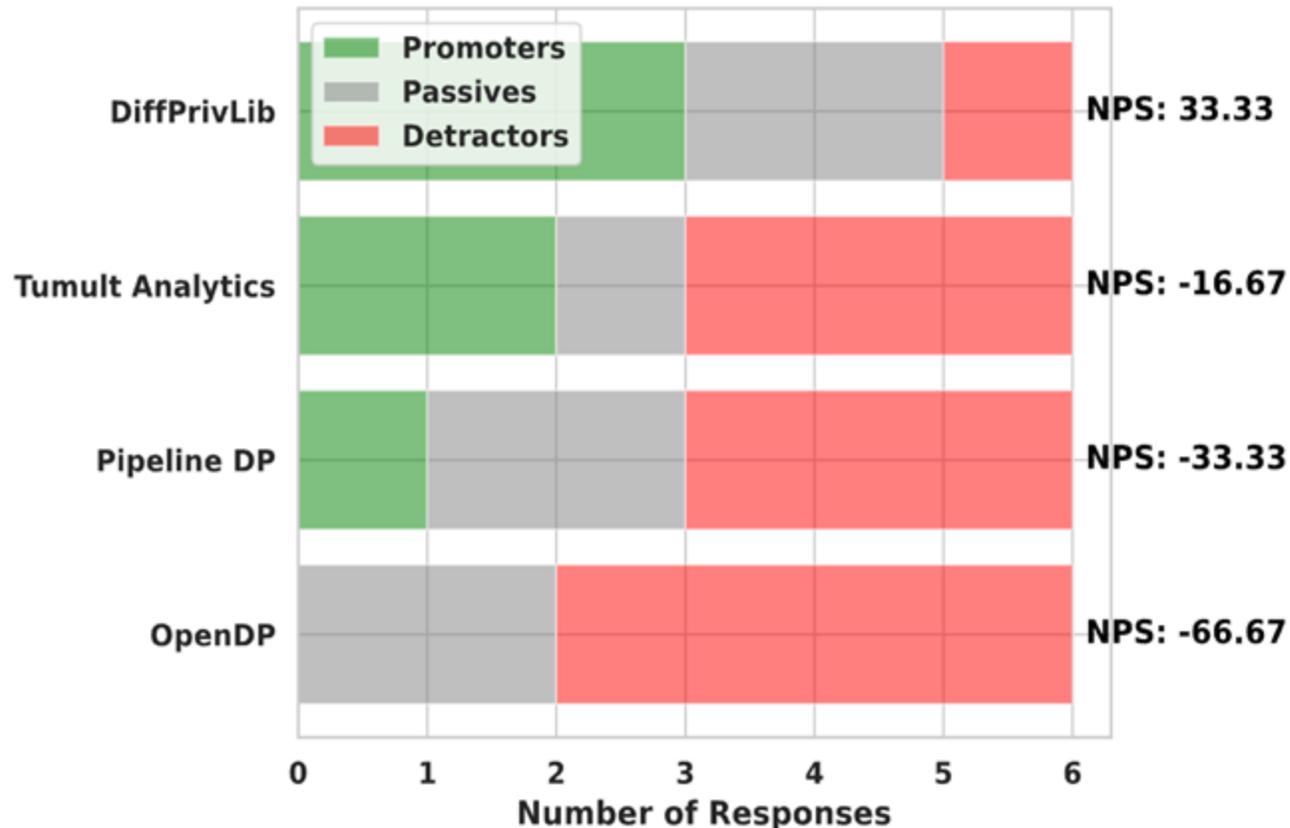
- DiffPrivLib uses a minimal API and works well with popular data analytics libraries like Pandas.
- Tumult Analytics mimics the Spark data analytics API.
- OpenDP requires understanding complex differential privacy details.

Participants preferred APIs similar to tools they already knew.

Tumult Analytics to Spark. *"I think the fact that it was very similar to Spark was really helpful,"* one expert participant (E006)

Diffprivlib Leads in User Satisfaction but DP Tools Need Improvement

- Participants most satisfied with DiffPrivLib
- Participants least satisfied with OpenDP



DP Violation vs Usability Tradeoff

API Design had an impact on all 3 parts we measured , and **it is possible to do well on all 3.**

Tool	Prevented Violations?	Completion Rate	Satisfaction
OpenDP	Yes	Low	Low
DiffPrivLib	No	High	High
PipelineDP	No	Low	Low
Tumult	Yes	High	High

Make API Design Intuitive

- **Leverage familiarity with mainstream APIs** (e.g. Pandas, Spark)
Participants appreciated tools that mimicked or used familiar APIs.

"I think the fact that it was very similar to Spark was really helpful...I have a decent amount of experience with Spark and Pandas, so that was very intuitive."

-Tumult Analytics

Improve Error Prevention & Recovery

- **Warn users about DP violations**

DiffPrivLib users did not realize they had violated DP.

- **Provide clear, actionable error messages**

OpenDP users were confused by Rust-related implementation details.

```

OpenDPException Traceback (most recent call last)
<ipython-input-48-58830e6b5f15> in <cell line: 6>()
      4 return time_spent_total >> make_base_discrete_laplace(scale=scale, D=AtomDomain[int])
      5
----> 6 binary_search_chain(status_dp, d_in=1, d_out=budget)(raw_data)

----- 2 frames -----
/usr/local/lib/python3.10/dist-packages/opendp/_lib.py in unwrap(result, type_)
    159
    160 # Rust stack traces follow from here:
-> 161 raise OpenDPException(variant, message, backtrace)
    162
    163

OpenDPException: Continued Rust stack trace:
  opendp_core_transformation_invoke
  opendp::core::Function<TI,T0>::make_chain::{{closure}}
  opendp::core::Function<TI,T0>::make_chain::{{closure}}
  opendp::core::Function<TI,T0>::make_chain::{{closure}}
  opendp::core::Function<TI,T0>::make_chain::{{closure}}
  opendp::core::Function<TI,T0>::make_chain::{{closure}}
  <opendp::core::Function<TI,T0> as opendp::ffi::any::IntoAnyFunctionExt>::into_any::{{closure}}
  opendp::transformations::dataframe::apply::make_apply_transformation_dataframe::{{closure}}
  opendp::data::Column::as_form
  FailedCast("tried to downcast to "Vec<i32>")

```

"I don't really know any Rust. Coming from a Python experience, [it] might be better to have error messages in Python that indicate the error in the line of Python." -OpenDP

Provide Usable Documentation and DP Foundations

- **Provide searchable documentation with lots of examples**
Users of all tools struggled with single-page documentation lacking examples.
Provide advice on what to do, not just how to do it (e.g which mechanism would be the best choice?)
- **Help users understand how to set privacy parameters**
(e.g. total privacy budget, ϵ per query, upper bound on data values, etc)

Thank you!

API design impacts **correctness**, **completion**, and **satisfaction**.

Takeaways

- Mimic existing APIs
- Raise errors for DP violations
- Provide usable documentation
- Help users with DP foundations

Presenter: **Ivoline Ngong**

Email: kngongiv@uvm.edu

Paper: <https://arxiv.org/pdf/2309.13506>

Study Materials: https://osf.io/ag2fj/?view_only=29a9bc2a30574befa9f3d0643951b9c6

