

# On the Computational Landscape of Replicable Learning



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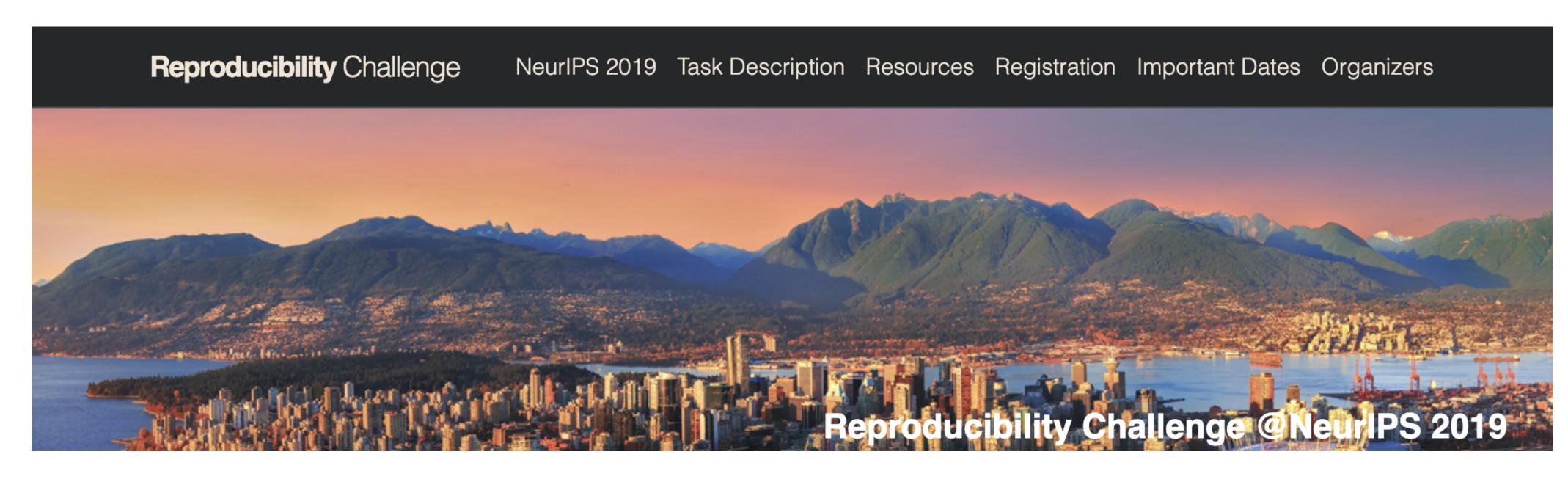
## **Replicability Crisis**

# nature Published: 25 May 2016

## 1,500 scientists lift the lid on reproducibility

Monya Baker

- Over 70% of researchers failed to replicate others' work
- Over 50% failed to replicate their own work!



- 2019 NeurlPS / ICLR Reproducibility Challenge (github.com/reproducibility-challenge)
- Ongoing ML Reproducibility Challenge (papersithcode.com/rc2022)

# Goal: Mathematical Study of Replicability

X data domain

•  $S_1, S_2 \sim_{i.i.d.} \mathcal{D}^n$  size n datasets

•  $\mathcal{D}$  distribution over X

ξ random binary string

**Definition (Replicable Algorithm)** [Impagliazzo, Lei, Pitassi, Sorrell '22] A randomized algorithm  $\mathcal{A}: X^n \to Y$  is  $\rho$ -replicable if

$$\Pr_{S_1,S_2,\xi} \left[ \mathcal{A}(S_1;\boldsymbol{\xi}) = \mathcal{A}(S_2;\boldsymbol{\xi}) \right] \ge 1 - \rho.$$

# PAC, Differentially Private, Online, and SQ Learning

- PAC Learning: for all  $\alpha, \beta$ , given a sufficiently large dataset S, the learner outputs a classifier  $\hat{h} = \mathcal{A}(S)$  satisfying  $\Pr_{(x,y)}[\hat{h}(x) \neq y] \leq \alpha$  with probability  $1 \beta$  over the draw of S.
- **DP Learning**: PAC learning requirements and  $(\varepsilon, \delta)$ -DP requirements, i.e. for all neighboring datasets S, S' and for all events E it holds that  $\Pr[\mathcal{A}(S) \in E] \leq e^{\varepsilon} \Pr[\mathcal{A}(S) \in E] + \delta$ .
- Online Learning: adversary picks "hard" function  $h^*$  and in every round t gives  $x_t$  to the learner; learner guesses a label  $\hat{y}_t$  and makes a mistake if  $\hat{y}_t \neq h^*(x_t)$ . The goal of the learner is to minimize # of mistakes.
- **SQ Learning**: instead of getting labeled samples as input, the learner has access to a (noisy) oracle that can answer statistical queries about the target.

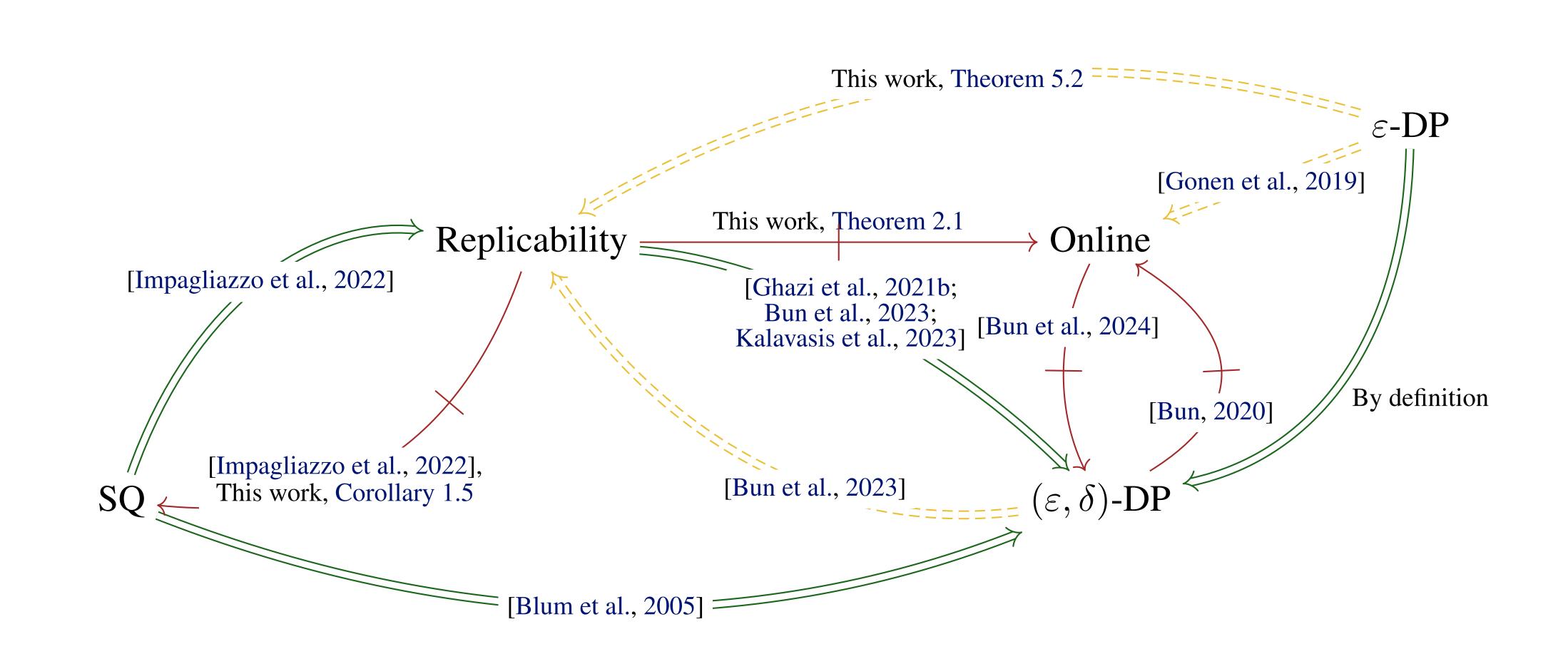
#### **Main Results**

#### Black-Box Transformations

A pure DP learner can be efficiently\* transformed into an online learner.

#### Separations under Cryptographic Assumptions

- There is a concept class that can be efficiently learned by a replicable PAC learner, but not an efficient online learner.
- There is a concept class that can be efficiently<sup>†</sup> learned by a replicable PAC learner, but not an efficient SQ learner.



#### **Future Work**

- Is there a computationally efficient transformation from online learners to replicable learners?
- \*Can we derive replicable learners from pure DP learners which are efficient with respect to the complexity of the underlying concept class?
- †Can we design efficient replicable algorithms for every distribution?



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