

# $\gamma$ -ABC: Approximate Bayesian Computation Based on a Robust Divergence Estimator



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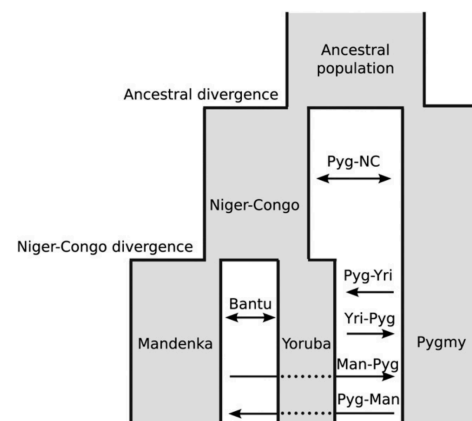
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# Approximate Bayesian Computation (ABC)

- ABC is a “likelihood-free” inference to approximately perform Bayesian inference on intractable models.
  - Assumption: we can conduct a simulation via likelihood

- Various Applications

- Evolutional biology
- Dynamic systems
- Economics
- Epidemiology
- Aeronautics
- Astronomy



[Wegmann et al., Genetics, 2009]

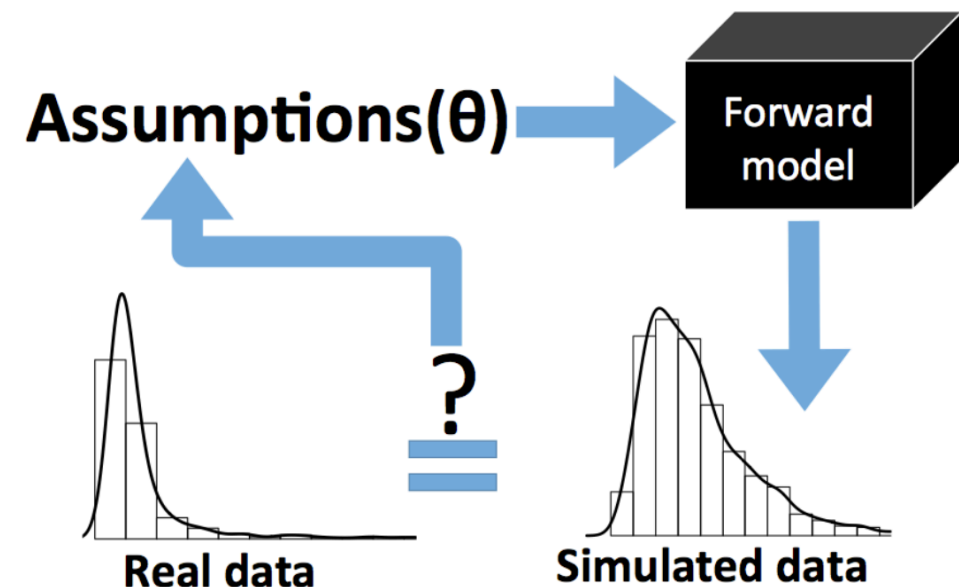


Image from [J. Cisewski, SAMSI Undergraduate Workshop, 2016]

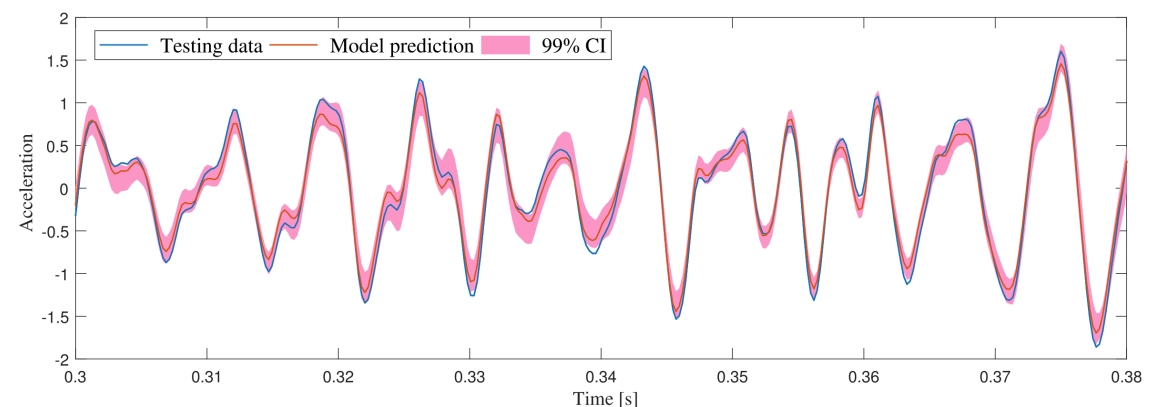


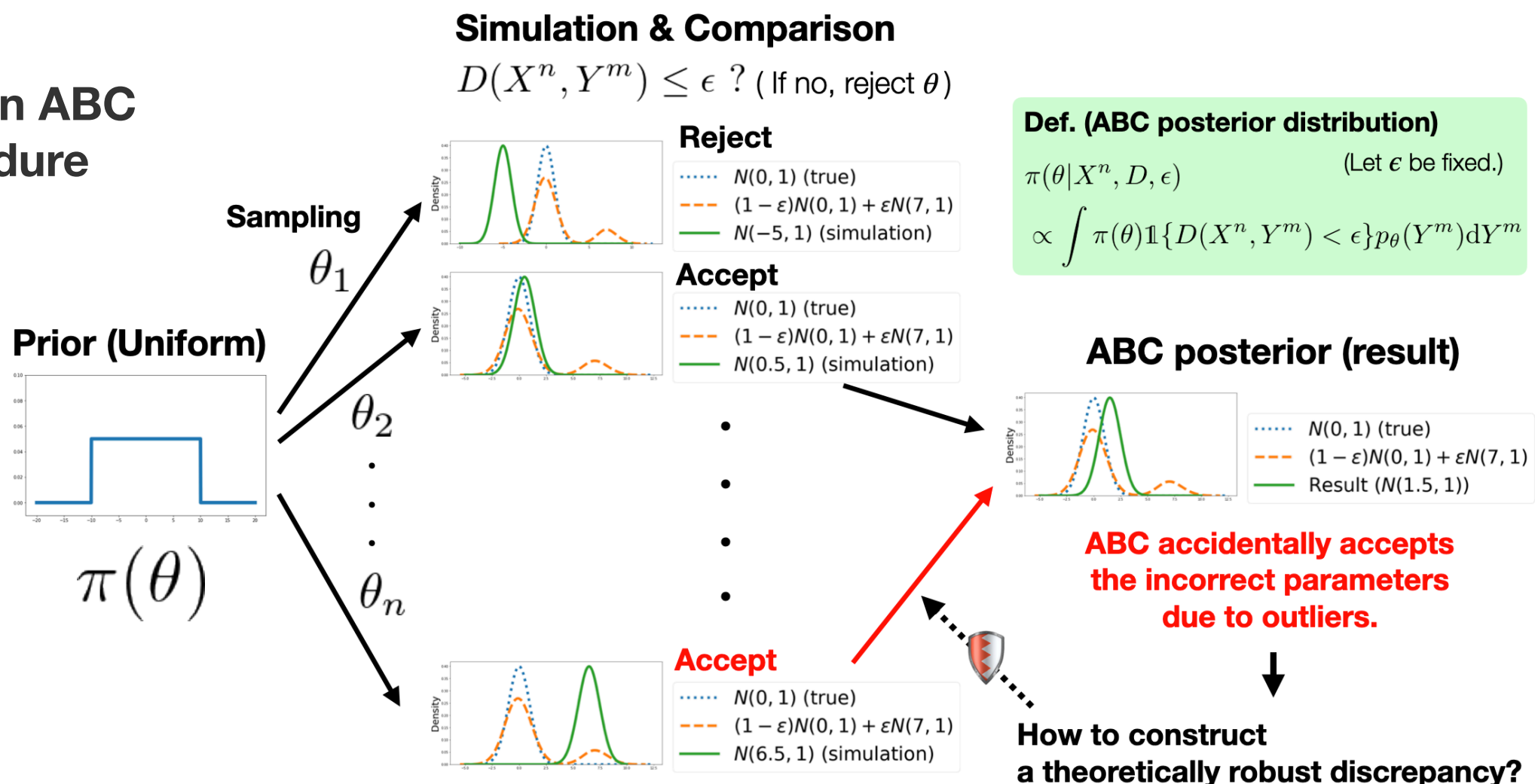
Fig. 24. Model prediction using the linear model under an excitation amplitude of 0.5 V ( $\varepsilon = 5.44$ ).

[Abdessalem et al., MSSP, 2019]

# Rejection ABC and Outliers

- Rejection ABC is the fundamental algorithm of ABC
  - This can be **sensitive to outliers** if a data discrepancy measure is chosen inappropriately.
  - There are no outlier-robust discrepancy measures for heavily contaminated data with theoretical guarantees.

## Rejection ABC procedure



# Rejection ABC and Outliers

- Rejection ABC is the fundamental algorithm of ABC
  - This can be **sensitive to outliers** if a data discrepancy measure is chosen inappropriately.
  - There are no outlier-robust discrepancy measures for heavily contaminated data with theoretical guarantees.

## Simulation & Comparison

$$D(X^n, Y^m) \leq \epsilon ? \text{ (If no, reject } \theta \text{)}$$

Reject

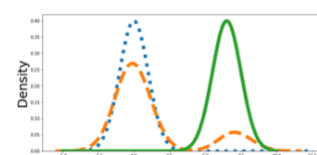
Def. (ABC posterior distribution)

$\pi(\theta | X^n, D, \epsilon)$  (Let  $\epsilon$  be fixed.)

Research question :

Can ABC has “theoretical robustness”  
for heavily contaminated data?

$\theta_n$



Accept

•  
.....  $N(0, 1)$  (true)  
- - -  $(1 - \epsilon)N(0, 1) + \epsilon N(7, 1)$   
—  $N(6.5, 1)$  (simulation)

ABC accidentally accepts  
the incorrect parameters  
due to outliers.

How to construct  
a theoretically robust discrepancy?

# Proposed method: $\gamma$ -divergence estimator

- **Idea:** Can the  $\gamma$ -divergence be used as a data discrepancy?
  - The  $\gamma$ -divergence possesses strong robustness for heavily contaminated data on **parametric** models.
- Using the  $k$ -NN density based nonparametric estimation

**Def. ( $k$ -NN based  $\gamma$ -divergence estimator)**

$$\hat{D}_\gamma(X^n \| Y^m) = \frac{1}{\gamma(1+\gamma)} \left( \log \frac{\left( \frac{1}{n} \sum_{i=1}^n \left( \frac{\bar{c}}{k} \hat{p}_k(x_i) \right)^\gamma \right) \left( \frac{1}{m} \sum_{j=1}^m \left( \frac{\bar{c}}{k} \hat{q}_k(y_j) \right)^\gamma \right)^\gamma}{\left( \frac{1}{n} \sum_{i=1}^n \left( \frac{\bar{c}}{k} \hat{q}_k(x_i) \right)^\gamma \right)^{1+\gamma}} \right)$$

$\hat{p}_k, \hat{q}_k$  : the  $k$ -NN density estimator on the observed and simulative data  
 $k$  : the number of neighbors  
 $\bar{c}$  : the volume of the  $d$ -dimensional unit ball



# The Robustness Guarantee of $\gamma$ -ABC

- Using Sensitivity Curve (SC)
  - Directly quantifying the influence of outliers on ABC posterior

**Def. (Sensitivity Curve)**

$$SC_{n+1}^{\theta}(X_0) := (n+1) \left( \overset{\text{With outlier}}{\hat{\pi}(\theta|X_{[X_0]}^n)} \overset{\text{Influence}}{\longleftrightarrow} \overset{\text{No outlier}}{\hat{\pi}(\theta|X^n)} \right)$$

$X_0$  : outlier       $\hat{\pi}(\theta|X^n) := \pi(\theta|X^n, \hat{D}_{\gamma}, \epsilon)$  : ABC-posterior with respect to  $X^n$   
 $X_{[X_0]}^n : (X_0, X_1, \dots, X_n)$

- $\gamma$ -ABC ignores an extreme outlier automatically.

**Thm. (Sensitivity Curve Analysis)**

The upper bound of SC on  $\gamma$ -ABC **converges to 0** as  $\|X_0\| \rightarrow \infty$

# Asymptotical Analysis

- The  $\gamma$ -divergence estimator has two essential asymptotic properties.
  - These results guarantee the validity as a divergence estimator.
  - Necessary to analyze the behavior of the ABC posterior (next page).

**Thm. (Asymptotic unbiasedness)**

$$\lim_{n,m \rightarrow \infty} \mathbb{E} \left[ \hat{D}_{\gamma}(X^n || Y^m) \right] = D_{\gamma}(p || q)$$

**Thm. (Almost sure convergence)**

$$\hat{D}_{\gamma}(X^n || Y^m) \xrightarrow{\text{a.s.}} D_{\gamma}(p || q)$$

$D_{\gamma}(p || q)$  : (exact)  $\gamma$ -divergence

# The ABC posterior Analysis

- $\gamma$ -ABC asymptotically collects the parameters with small  $\gamma$ -divergence.

## Corollary. (Asymptotic ABC posterior on $\gamma$ -ABC)

The ABC-posterior of  $\gamma$ -ABC satisfies

$$\pi(\theta|X^n; \hat{D}_\gamma, \epsilon) \rightarrow \pi(\theta|D_\gamma(p_{\theta^*} \| p_\theta) < \epsilon) \quad (a.s.)$$

Therefore,

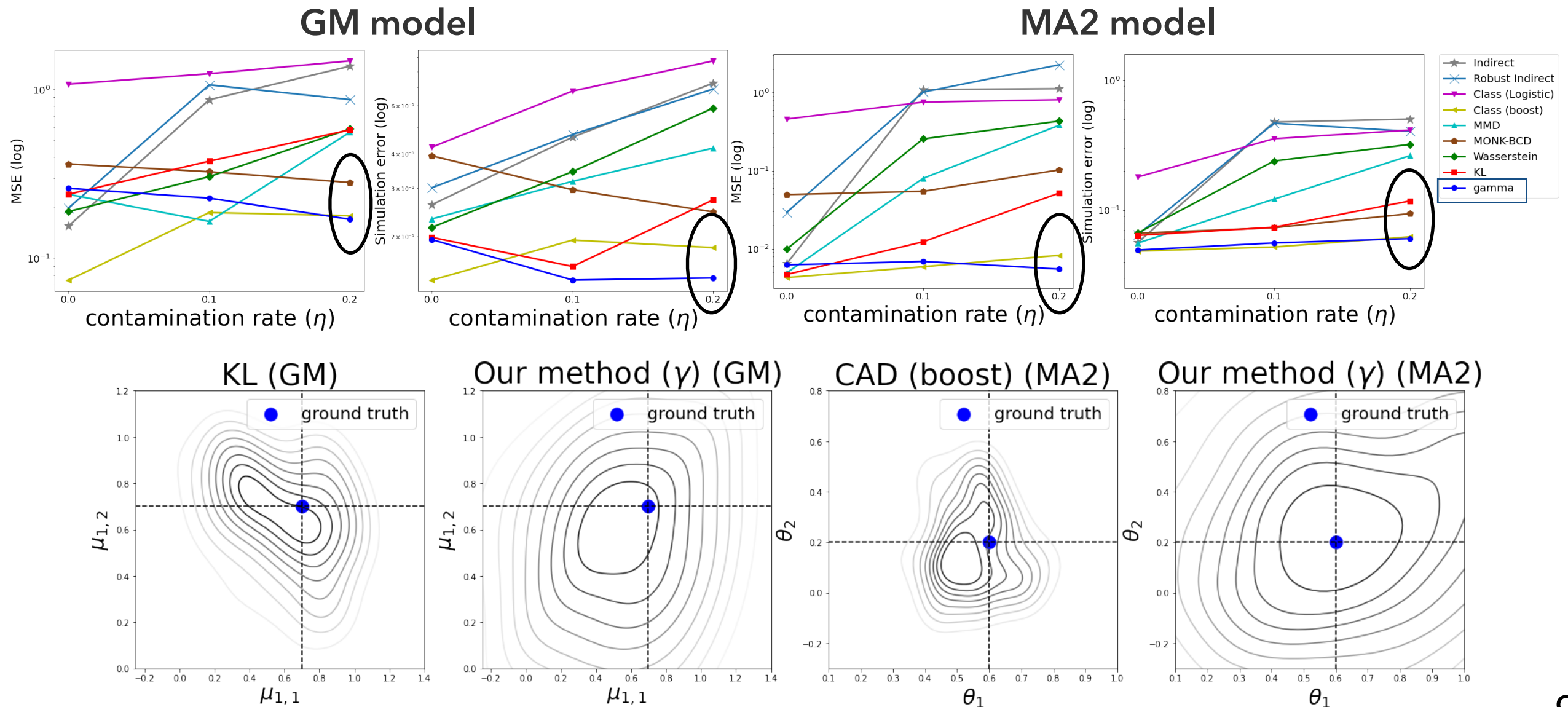
$$\lim_{n, m \rightarrow \infty} \pi(\theta|X^n; \hat{D}_\gamma, \epsilon) \propto \pi(\theta) \mathbb{1}\{D_\gamma(p_{\theta^*} \| p_\theta) < \epsilon\} \quad (a.s.)$$

- i.e.) the ABC posterior with our method converges to the MLE that minimizes the “exact”  $\gamma$ -divergence between the empirical distribution  $p_{\theta^*}$  and  $p_\theta$ .
- (MLE = Maximum Likelihood Estimator)



# Experiments

- $\gamma$ -ABC achieves better MSE and simulation error.
  - also places high density around the ground-truth parameter.
  - (e.g.) Gaussian mixture (GM) model, Mean-averaging (MA2) model



(KL: KL-discrepancy; CAD (boost): Classification Accuracy method with boosting)

# Conclusion

- High-level idea:
  - Constructing the outlier-robust discrepancy measure which can ignore outliers automatically.
- Contribution:
  - A nonparametric and outlier-robust discrepancy based on the  $\gamma$ -divergence.
  - Theoretical guarantee for robustness and validity on  $\gamma$ -ABC.
  - Guarantees for asymptotic convergence.
  - $\gamma$ -ABC achieves better performance on the heavily contaminated data.

