

TopP&R: Robust Support Estimation Approach for Evaluating Fidelity and Diversity in Generative Models



Pum jun Kim¹
UNIST



Yoojin Jang
UNIST



Jisu Kim
SNU
Inria



Jaejun Yoo*
UNIST

Image Generative Models and Evaluation Protocol

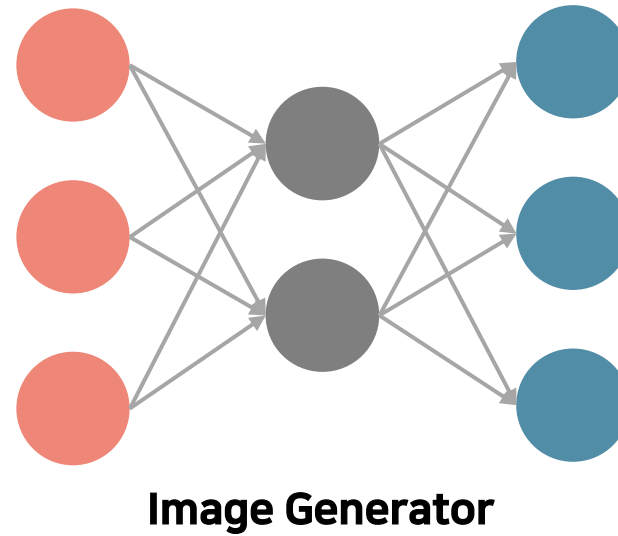
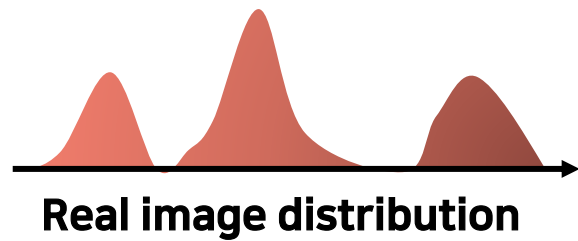


Image Generative Models and Evaluation Protocol

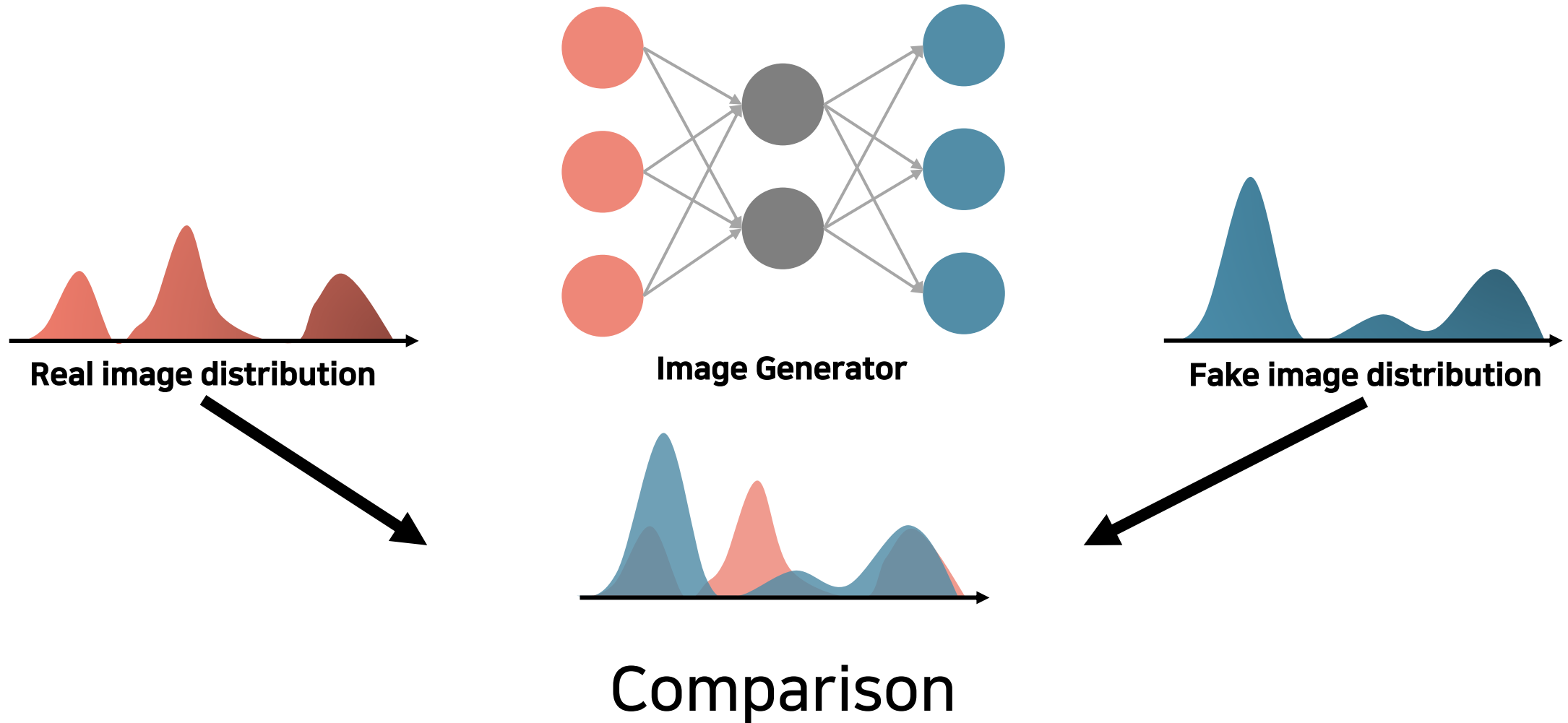


Image Generative Models and Evaluation Protocol

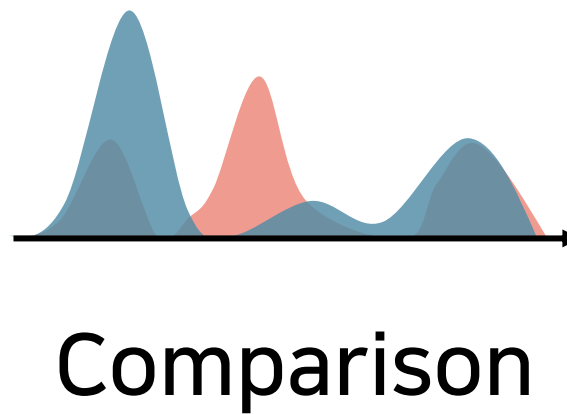
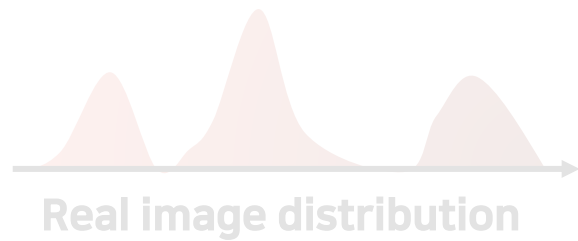
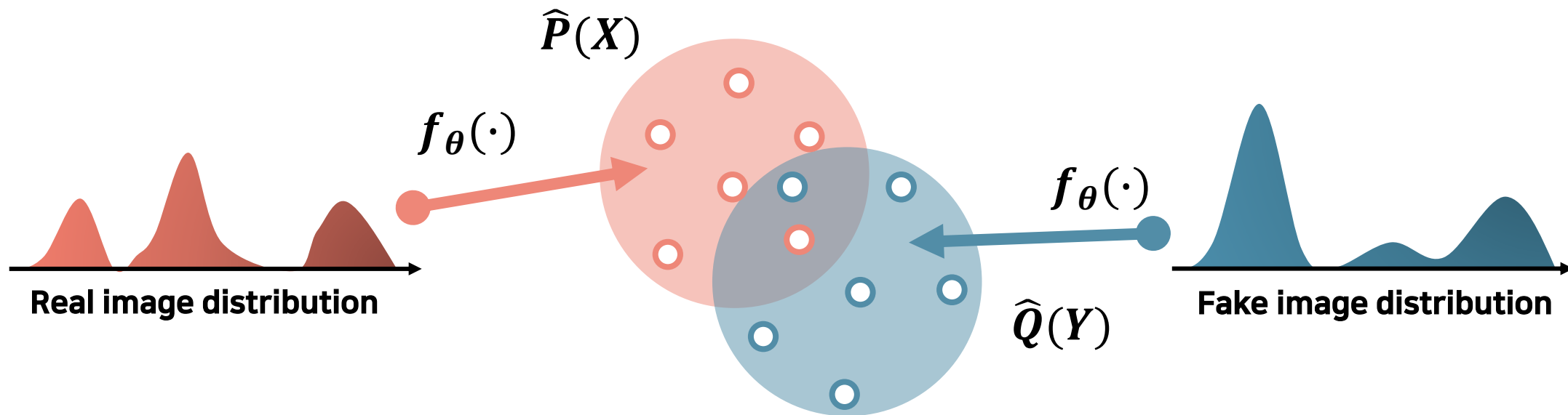
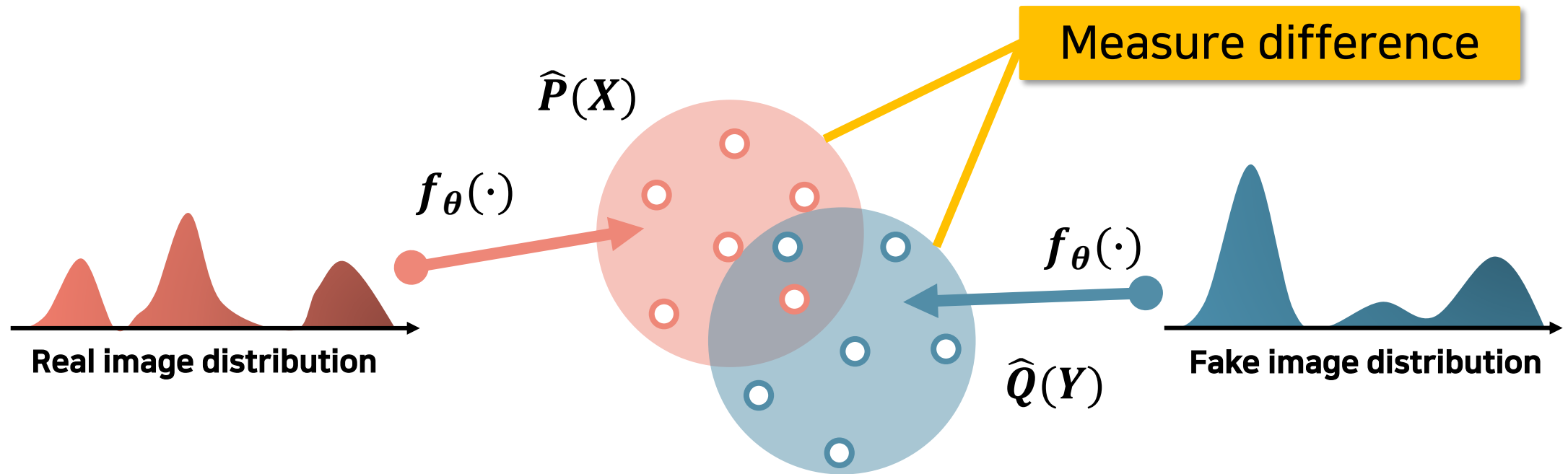


Image Generative Models and Evaluation Protocol



- $f_{\theta}(\cdot)$: Pretrained embedding network
- : Extracted real image features
 - : Extracted fake image features

Image Generative Models and Evaluation Protocol



- $f_\theta(\cdot)$: Pretrained embedding network
- : Extracted real image features
 - : Extracted fake image features

Image Generative Models and Evaluation Protocol

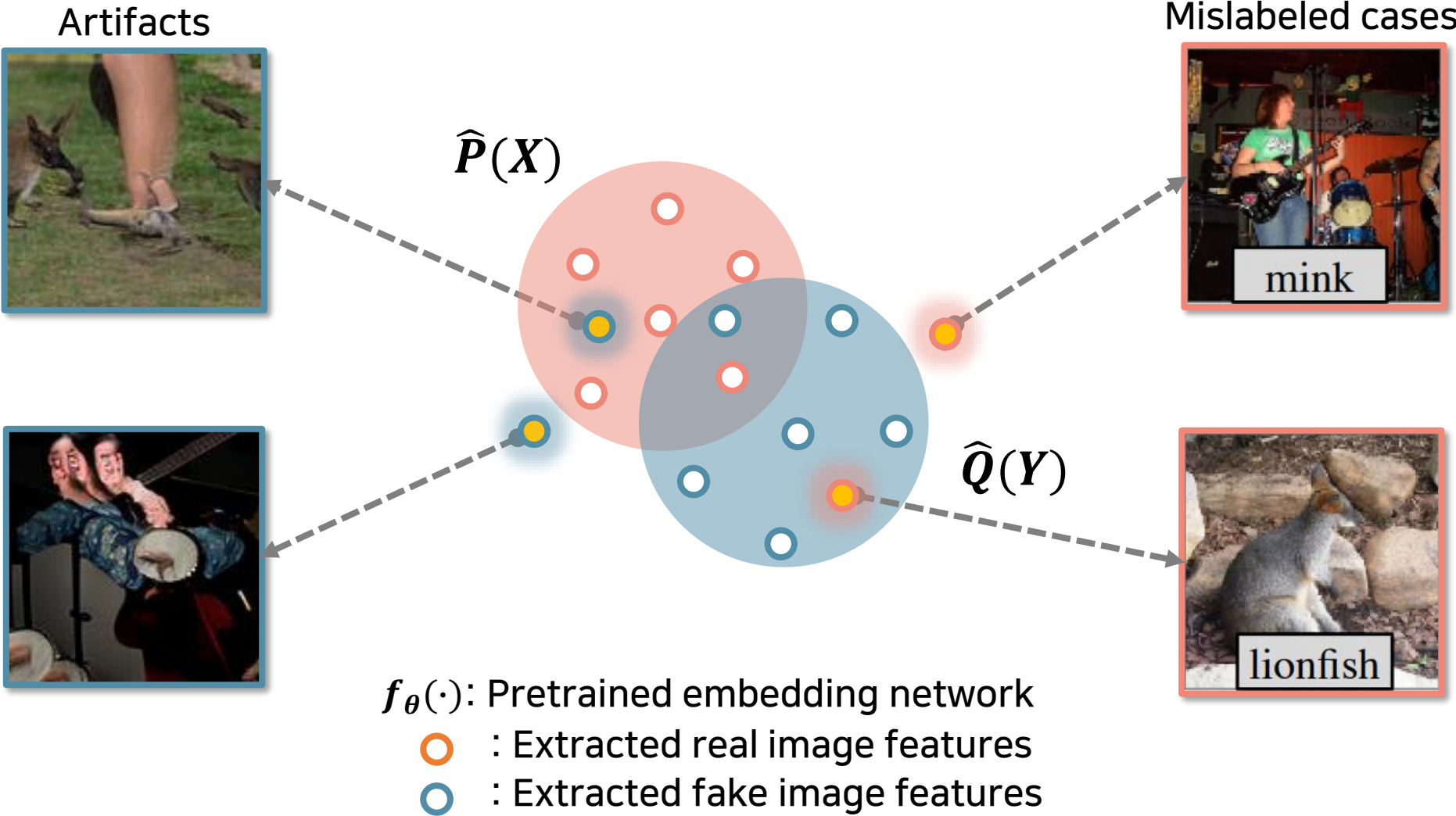
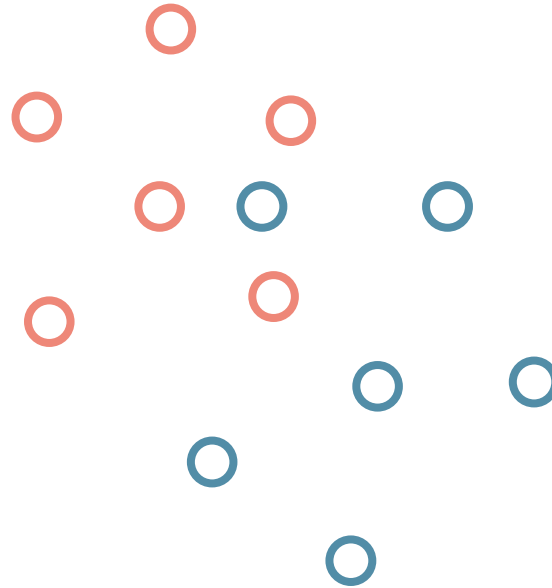


Image Generative Models and Evaluation Protocol

(1) Ideal estimation of distribution



○ : real image features

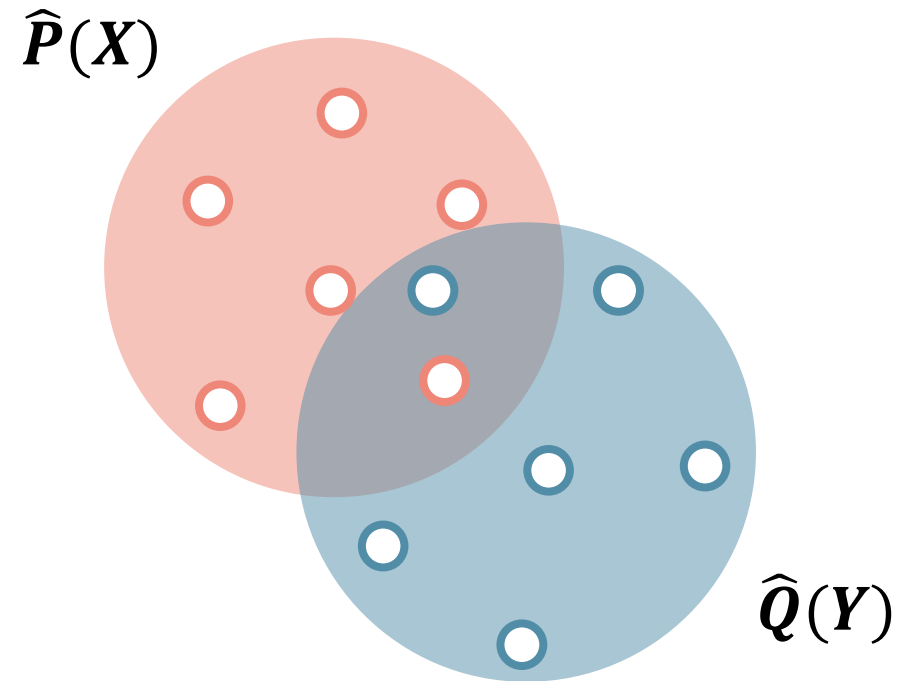
○ : fake image features

○ : real noisy features

○ : fake noisy features

Image Generative Models and Evaluation Protocol

(1) Ideal estimation of distribution



Correctly measured scores

$$\text{Fidelity} = Q(\text{supp}(P)) = 0.16$$

$$\text{Diversity} = P(\text{supp}(Q)) = 0.16$$

○ : real image features

○ : fake image features

○ : real noisy features

○ : fake noisy features

Image Generative Models and Evaluation Protocol

(2) Non-ideal estimation of distribution

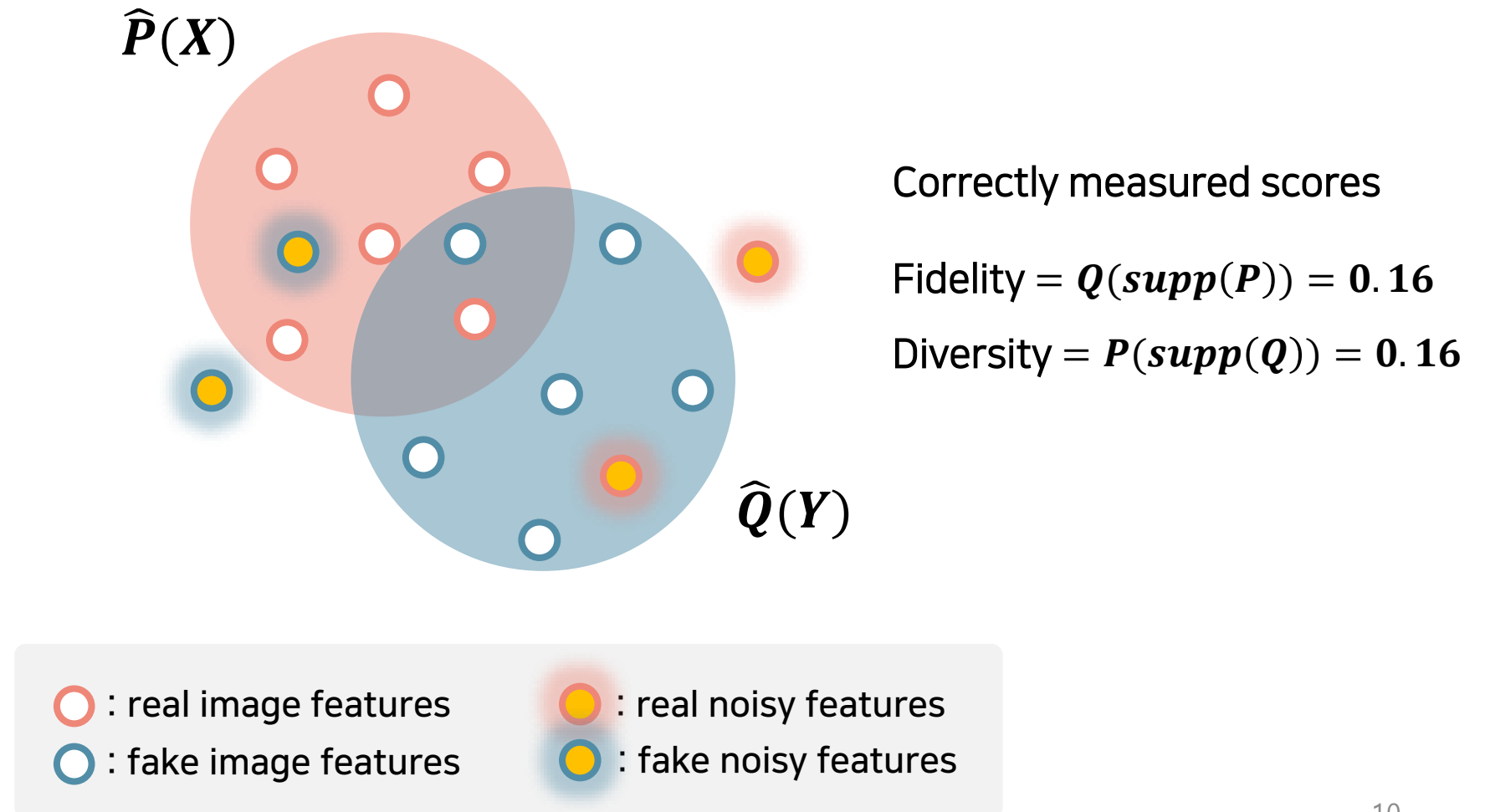
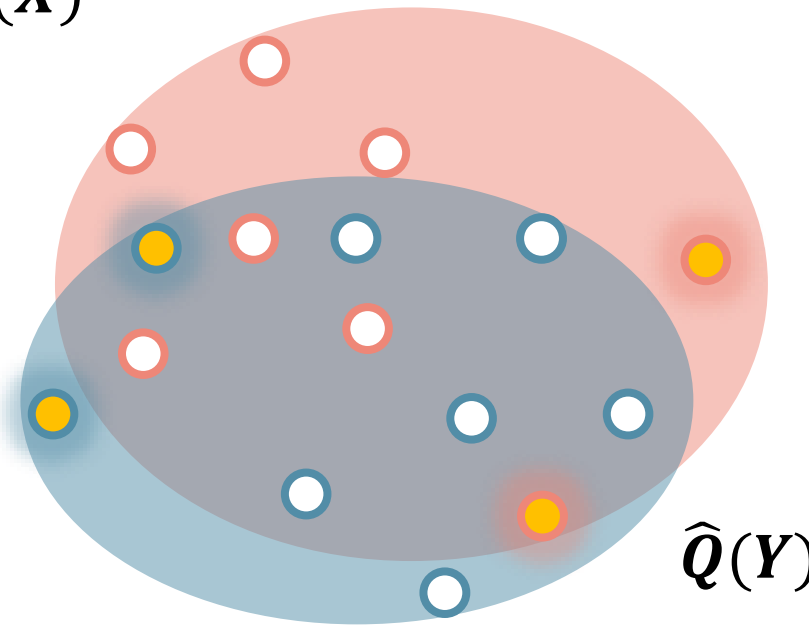


Image Generative Models and Evaluation Protocol

(2) Non-ideal estimation of distribution

$\hat{P}(X)$



Incorrectly measured scores

$$\text{Fidelity} = Q(\text{supp}(P)) = \mathbf{0.75}$$

$$\text{Diversity} = Q(\text{supp}(P)) = \mathbf{0.5}$$

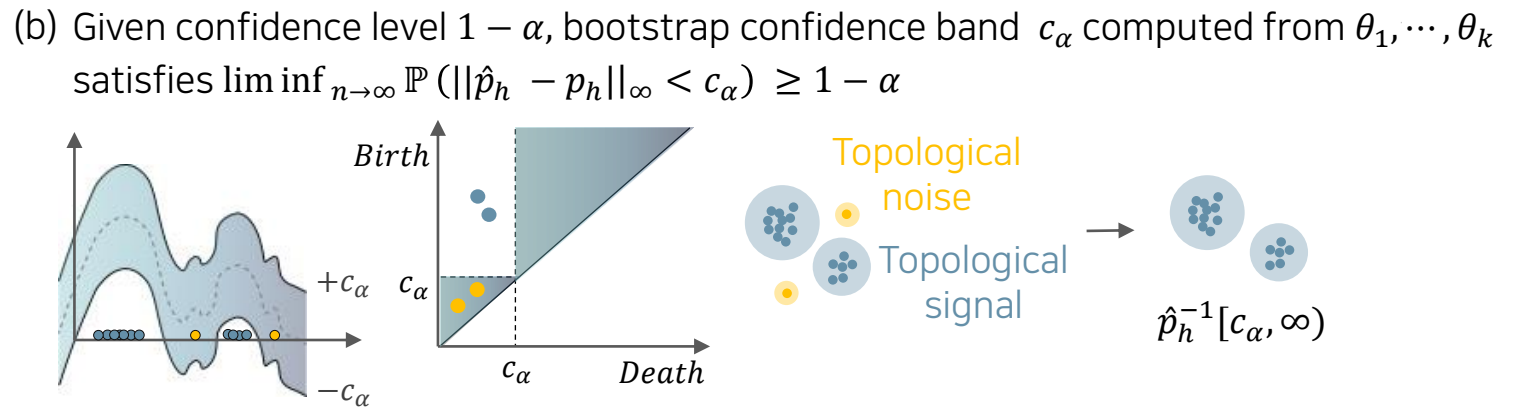
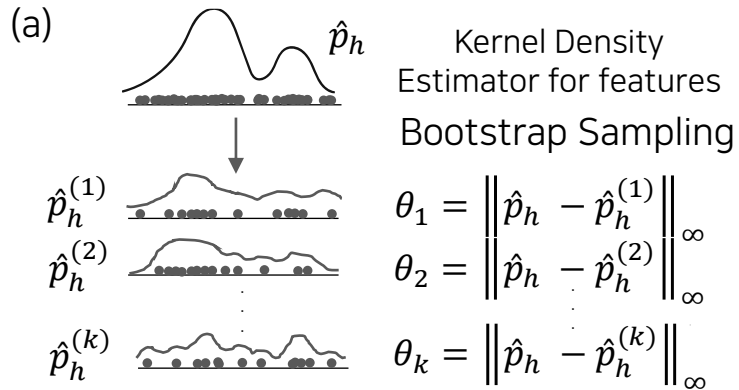
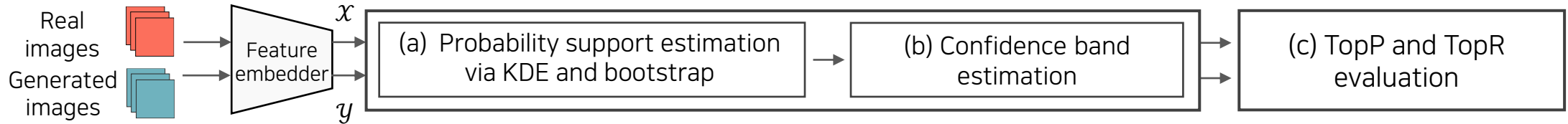
○ : real image features

○ : fake image features

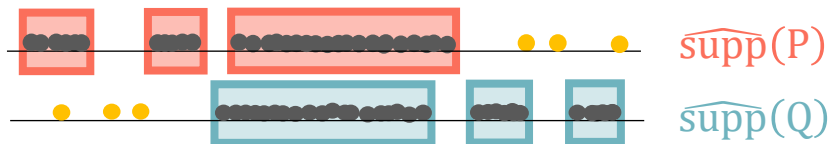
● : real noisy features

● : fake noisy features

Overview of TopP&R



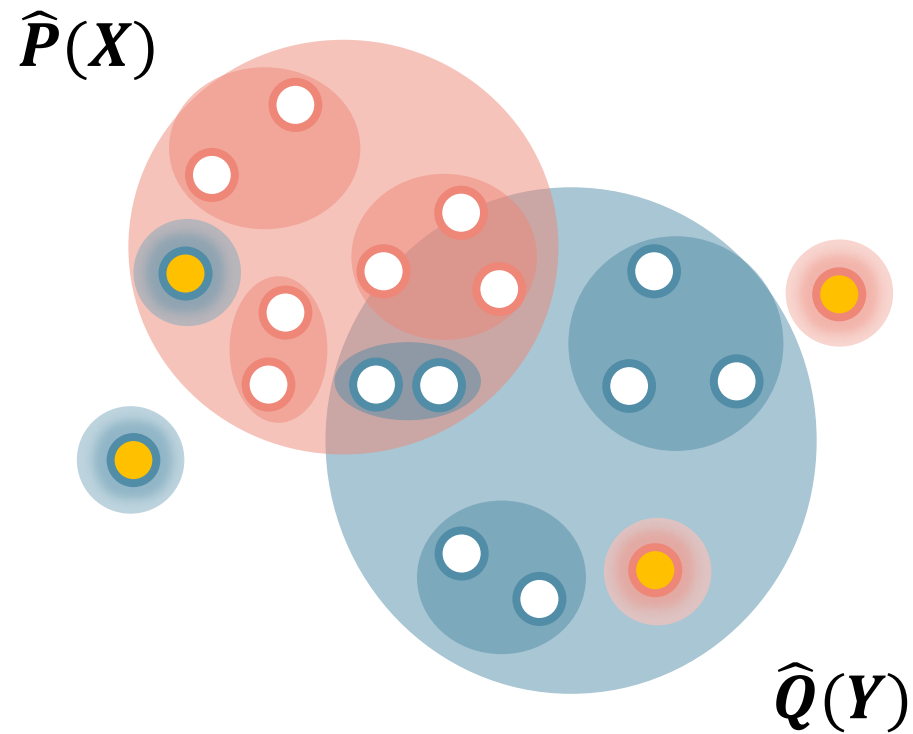
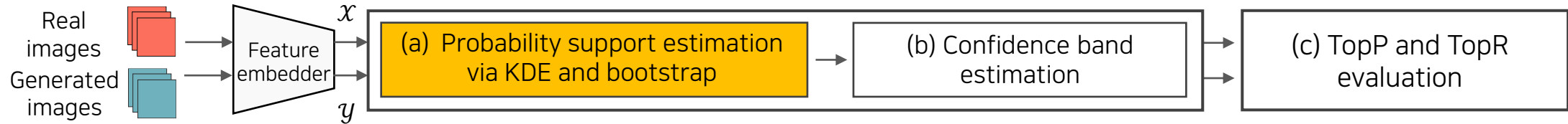
(c) Given $\widehat{\text{supp}}(P)$ for real features \mathcal{X} and $\widehat{\text{supp}}(Q)$ for generated features \mathcal{Y} ,



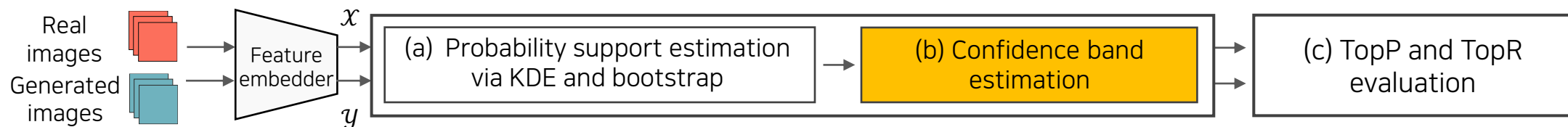
$$\text{Top}P_{\mathcal{X}}(\mathcal{Y}) := \frac{\sum_{j=1}^m \mathbb{1}(Y_j \in \widehat{\text{supp}}(P) \cap \widehat{\text{supp}}(Q))}{\sum_{j=1}^m \mathbb{1}(Y_j \in \widehat{\text{supp}}(Q))}$$

$$\text{Top}R_{\mathcal{Y}}(\mathcal{X}) := \frac{\sum_{i=1}^n \mathbb{1}(X_i \in \widehat{\text{supp}}(Q) \cap \widehat{\text{supp}}(P))}{\sum_{i=1}^n \mathbb{1}(X_i \in \widehat{\text{supp}}(P))}$$

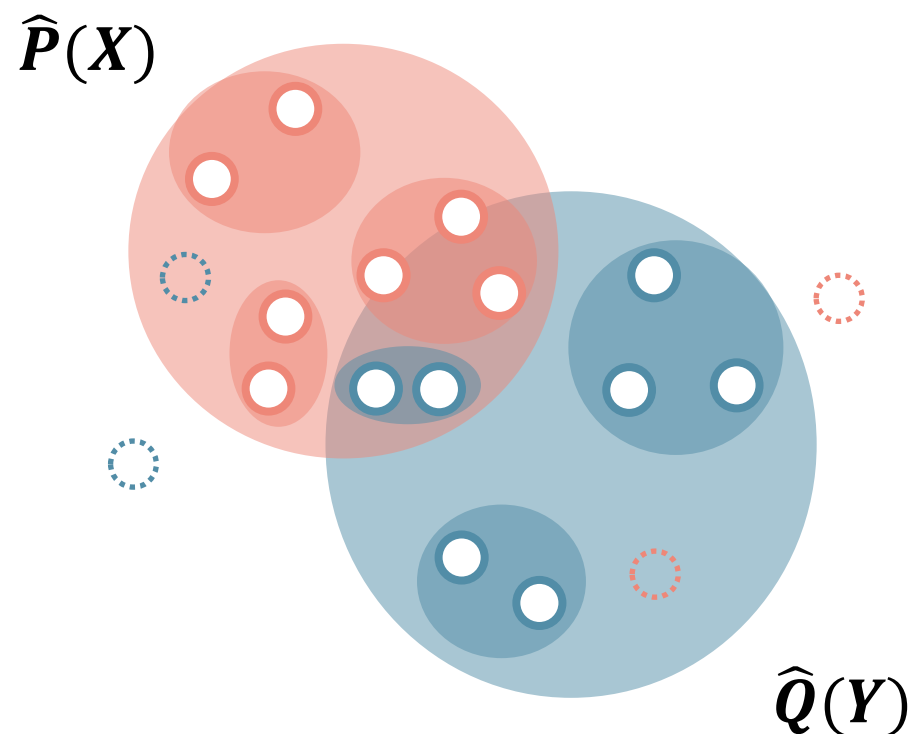
Overview of TopP&R



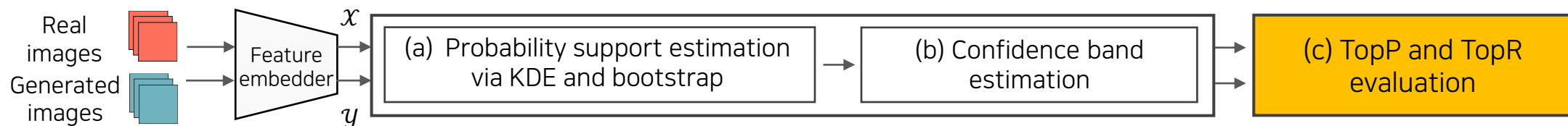
Overview of TopP&R



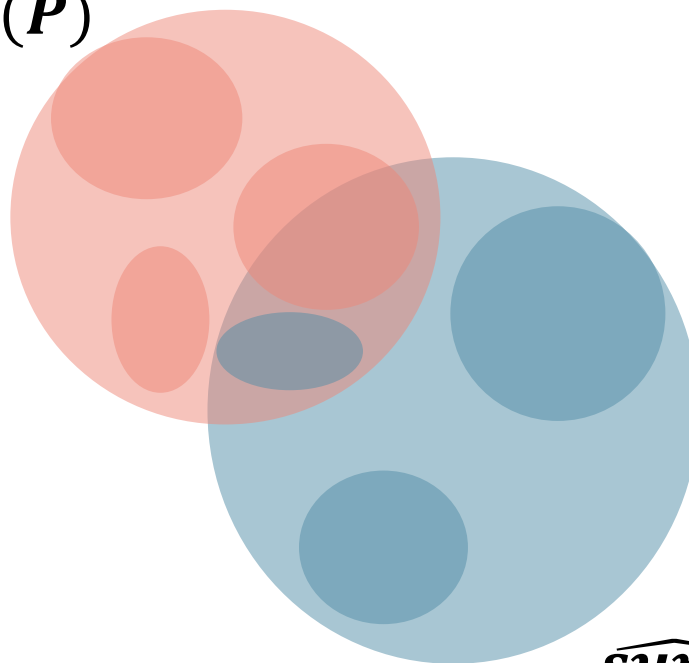
Exclude noisy features under statistical confidence level we set



Overview of TopP&R



$\widehat{supp}(P)$



$\widehat{supp}(Q)$

$TopP \xrightarrow{n \rightarrow \infty} precision$

$TopR \xrightarrow{n \rightarrow \infty} recall$

See our proposition 4.1
and theorem 4.2

Topological Data Analysis (TDA) as a Solution

Selecting a threshold that effectively removes noisy samples

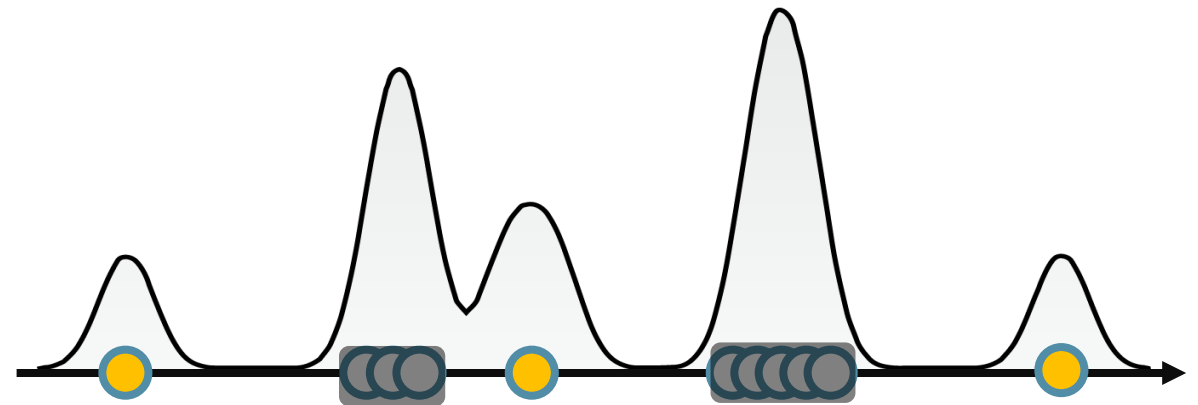
(1) Reference

○ : significant feature

● : noisy features

■ : support of estimated distribution

■ : ground truth support of distribution



Topological Data Analysis (TDA) as a Solution

Selecting a threshold that effectively removes noisy samples

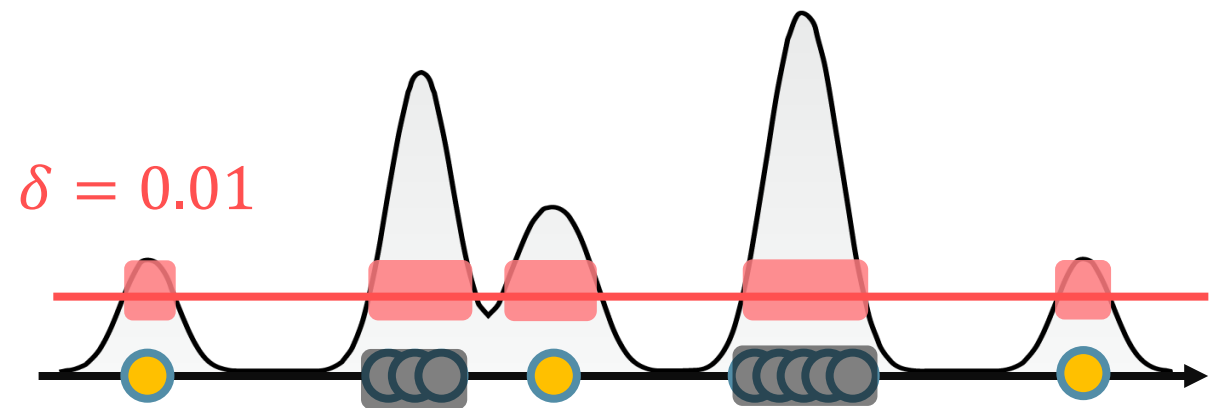
(2) When $\delta = 0.01$ (**over-estimated case**)

○ : significant feature

● : noisy features

■ : support of estimated distribution

■ : ground truth support of distribution



Topological Data Analysis (TDA) as a Solution

Selecting a threshold that effectively removes noisy samples

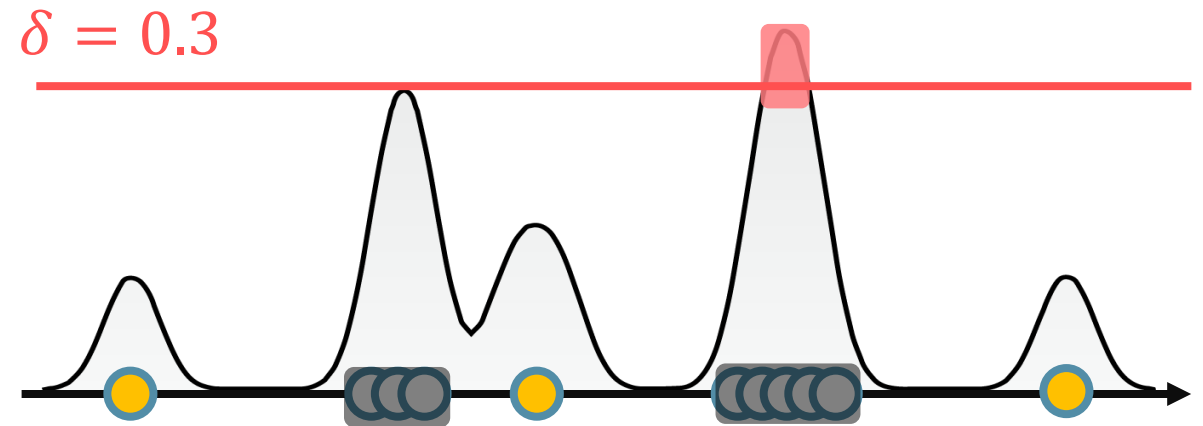
(3) When $\delta = 0.3$ (under-estimated case)

○ : significant feature

● : noisy features

■ : support of estimated distribution

■ : ground truth support of distribution



Topological Data Analysis (TDA) as a Solution

Selecting a threshold that effectively removes noisy samples

(4) $\delta \in [0, 1]$

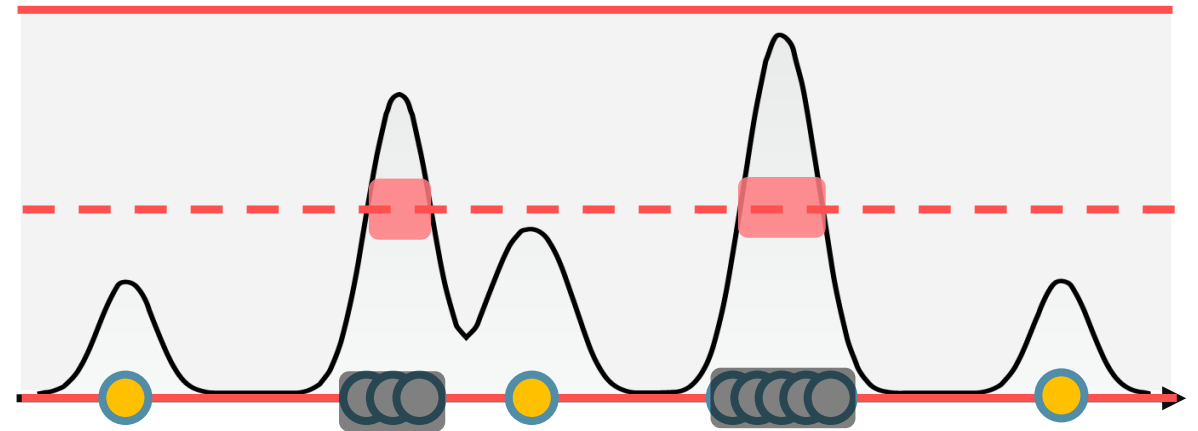
○ : significant feature

● : noisy features

■ : support of estimated distribution

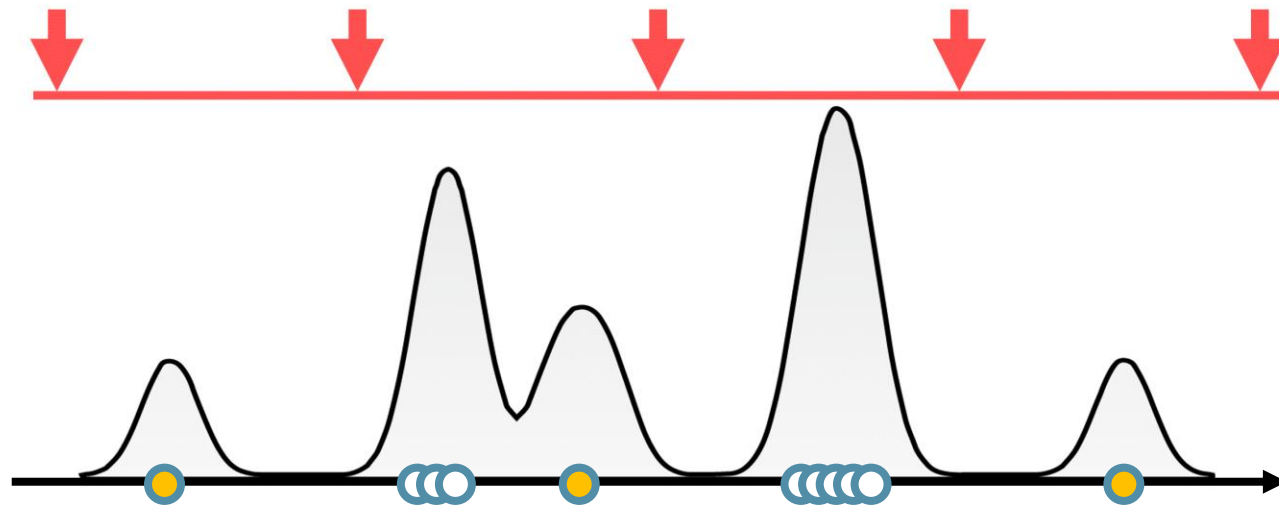
■ : ground truth support of distribution


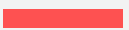


$\delta \in [0, 1]$ What is the optimal threshold?



Topological Data Analysis (TDA) as a Solution

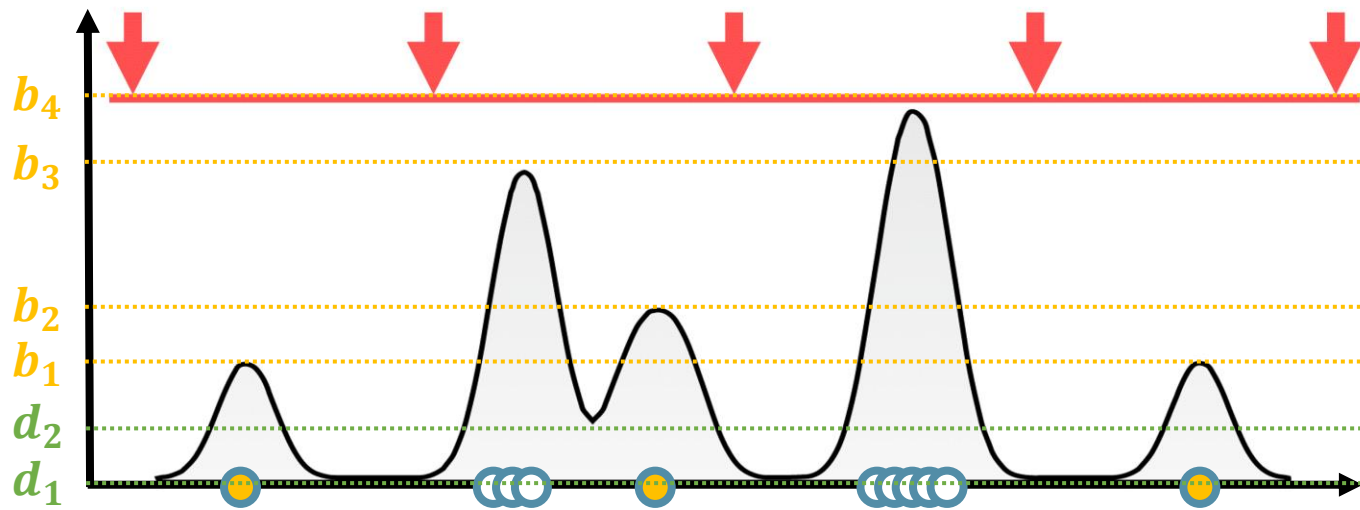
Tracking when homological feature appear and disappear



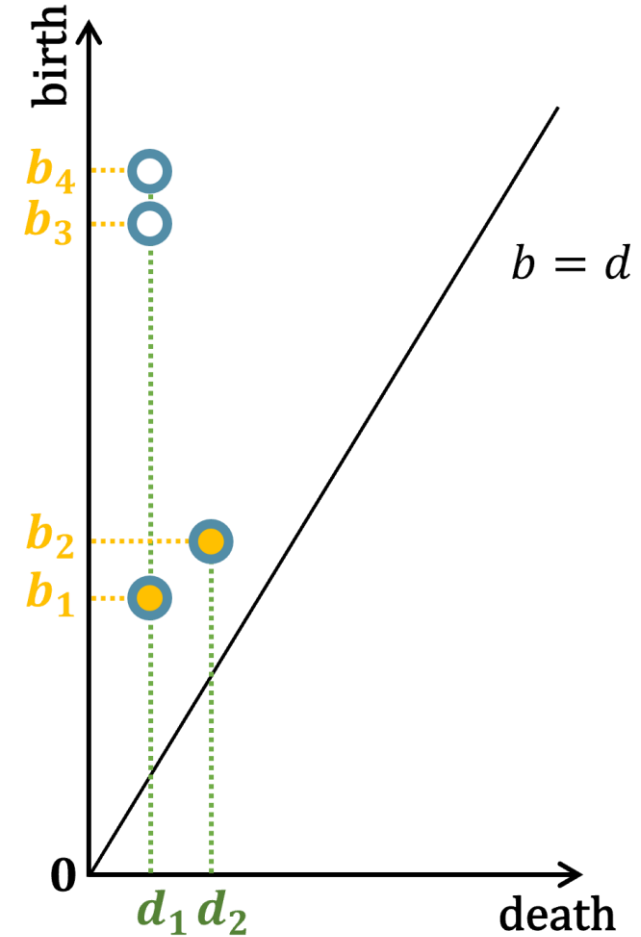
-  : 0-dim homological feature or connected component
-  : threshold δ
-  : significant feature
-  : noisy features

Topological Data Analysis (TDA) as a Solution

Tracking when homological feature appear and disappear

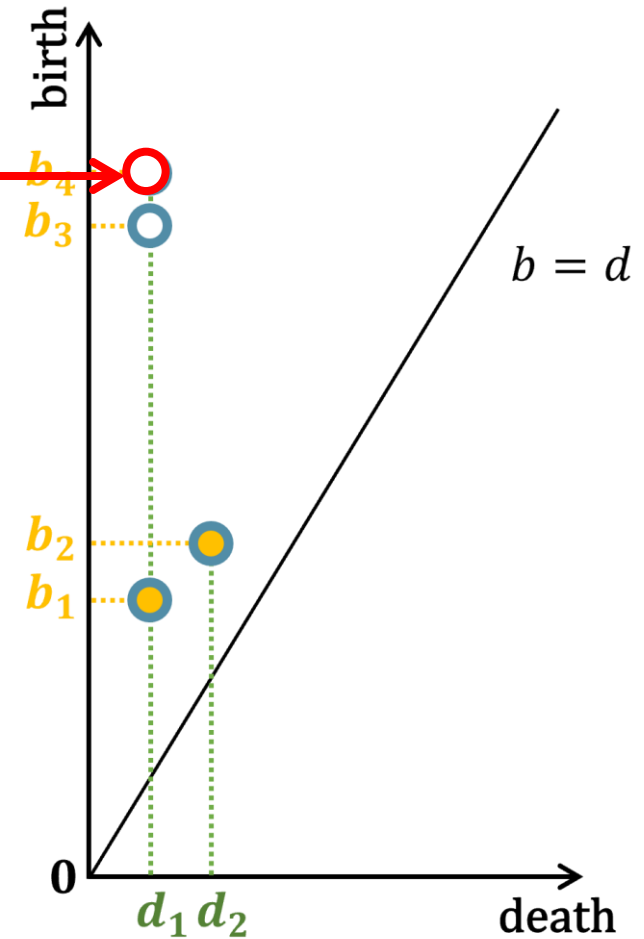
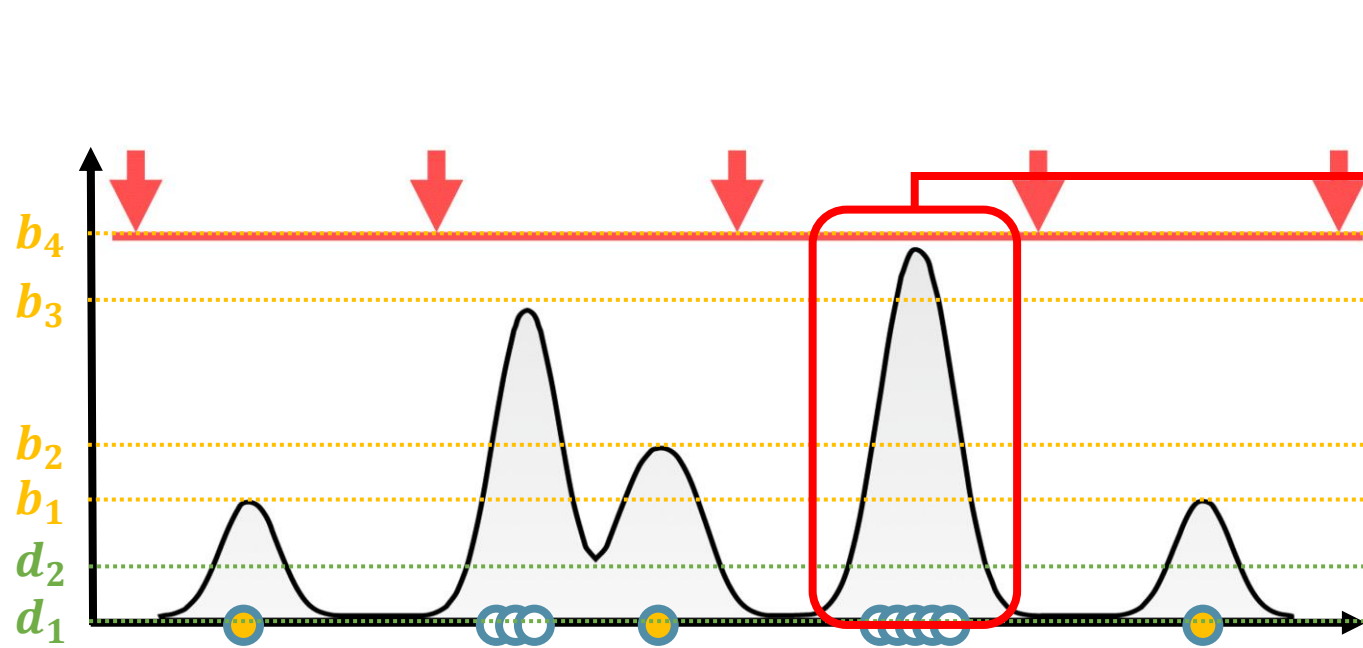


- ■ ■ : death of 0-dimensional homology happens
- ■ ■ : birth of 0-dimensional homology happens
- : 0-dim homological feature or connected component



Topological Data Analysis (TDA) as a Solution

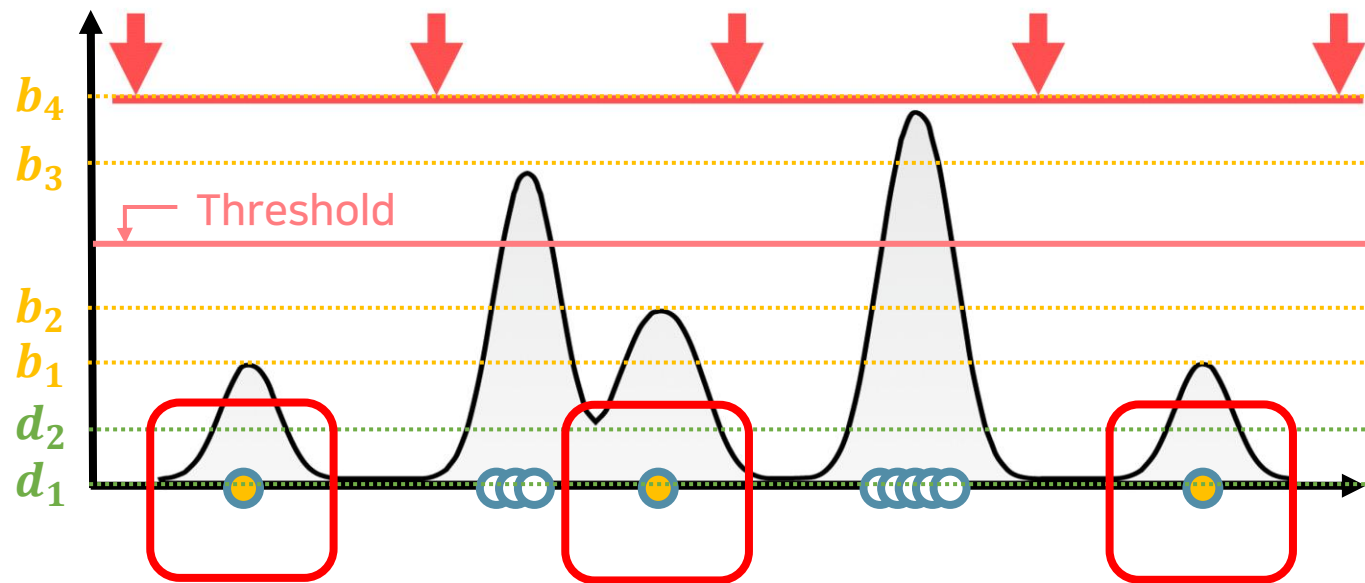
Tracking when homological feature appear and disappear



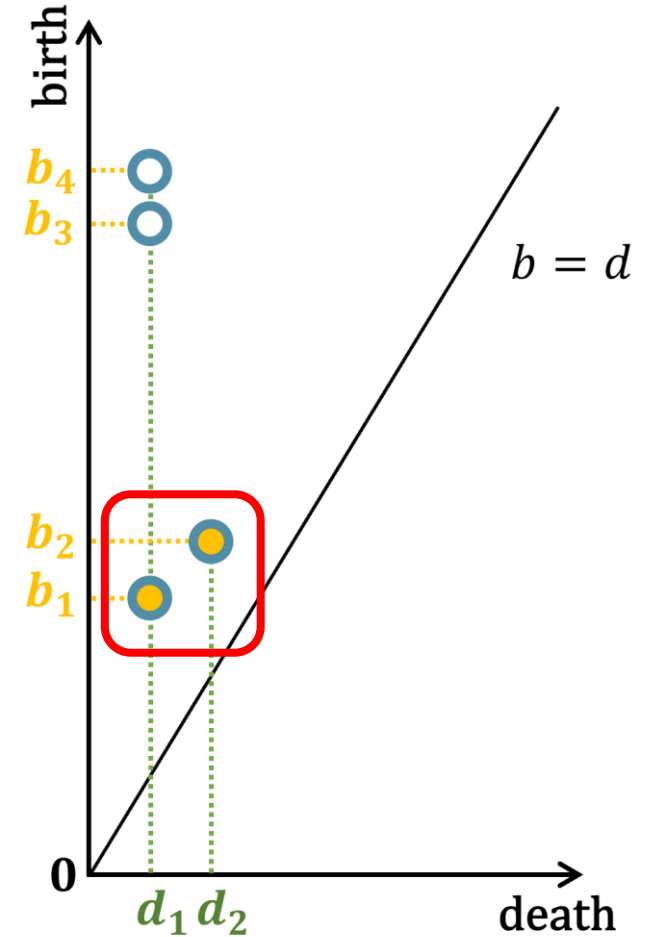
- ■ ■ : death of 0-dimensional homology happens
- ■ ■ : birth of 0-dimensional homology happens
- : 0-dim homological feature or connected component

Topological Data Analysis (TDA) as a Solution

Tracking when homological feature appear and disappear

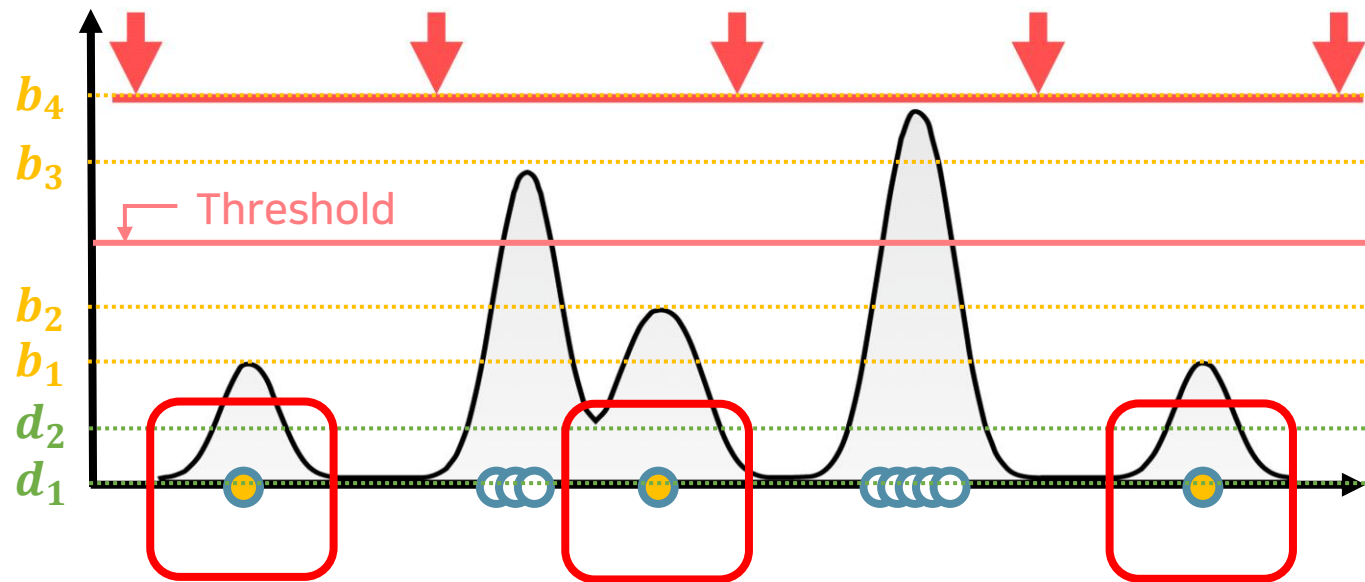


- ■ ■ : death of 0-dimensional homology happens
- ■ ■ : birth of 0-dimensional homology happens
- : 0-dim homological feature or connected component

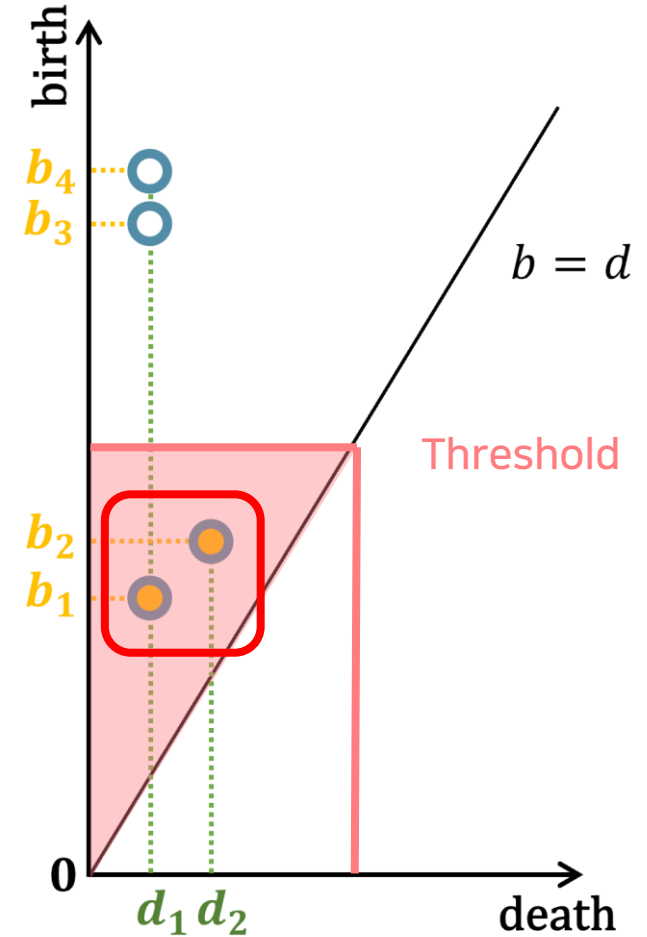


Topological Data Analysis (TDA) as a Solution

Tracking when homological feature appear and disappear

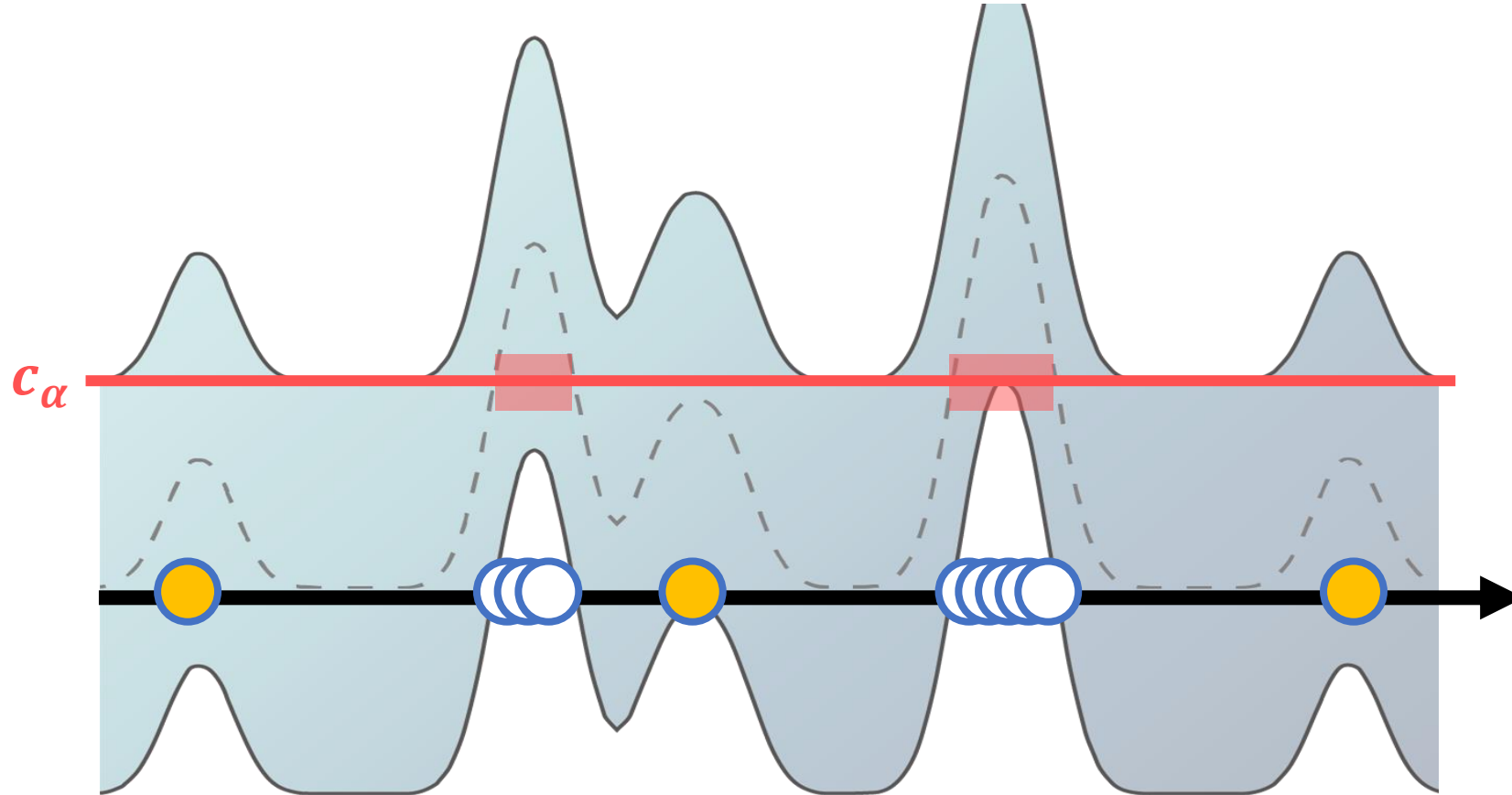


- ■ ■ : death of 0-dimensional homology happens
- ■ ■ : birth of 0-dimensional homology happens
- : 0-dim homological feature or connected component



Confidence Band Estimation

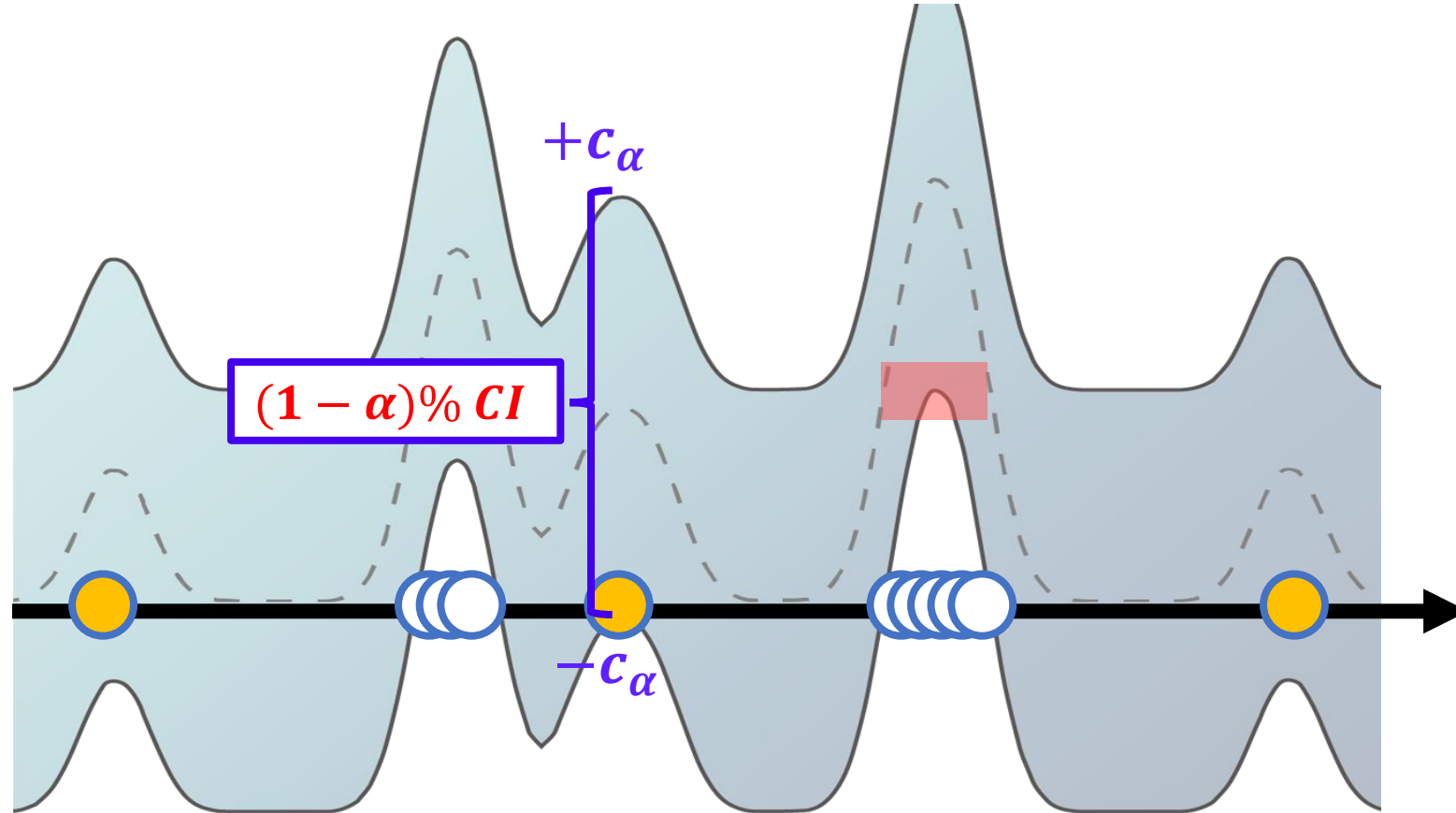
Finding the threshold c_α that selects statistically and topologically significant features



○ : significant feature ● : noisy features ■ : estimated support of distribution

Confidence Band Estimation

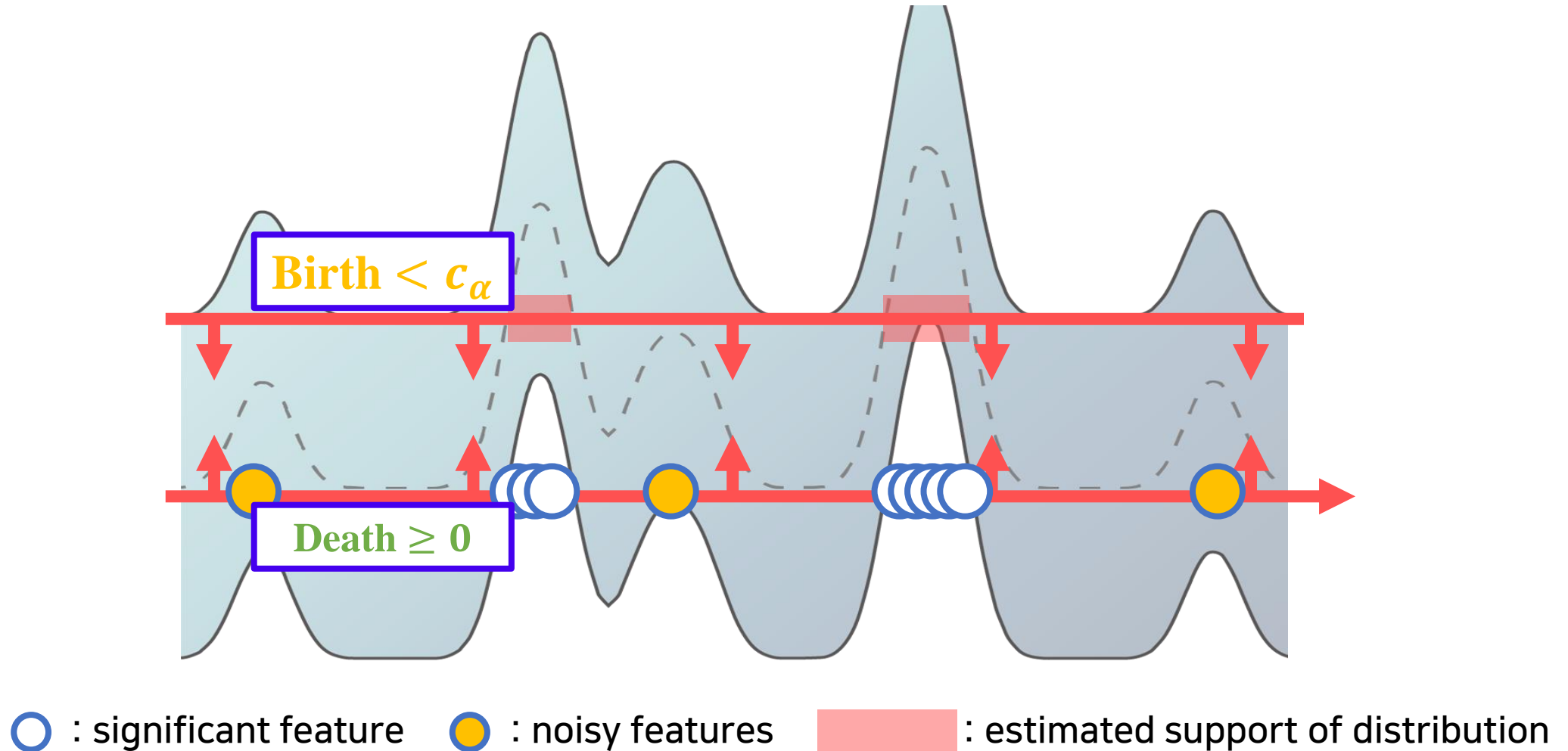
Finding the threshold c_α that selects statistically and topologically significant features



○ : significant feature ● : noisy features ■ : estimated support of distribution

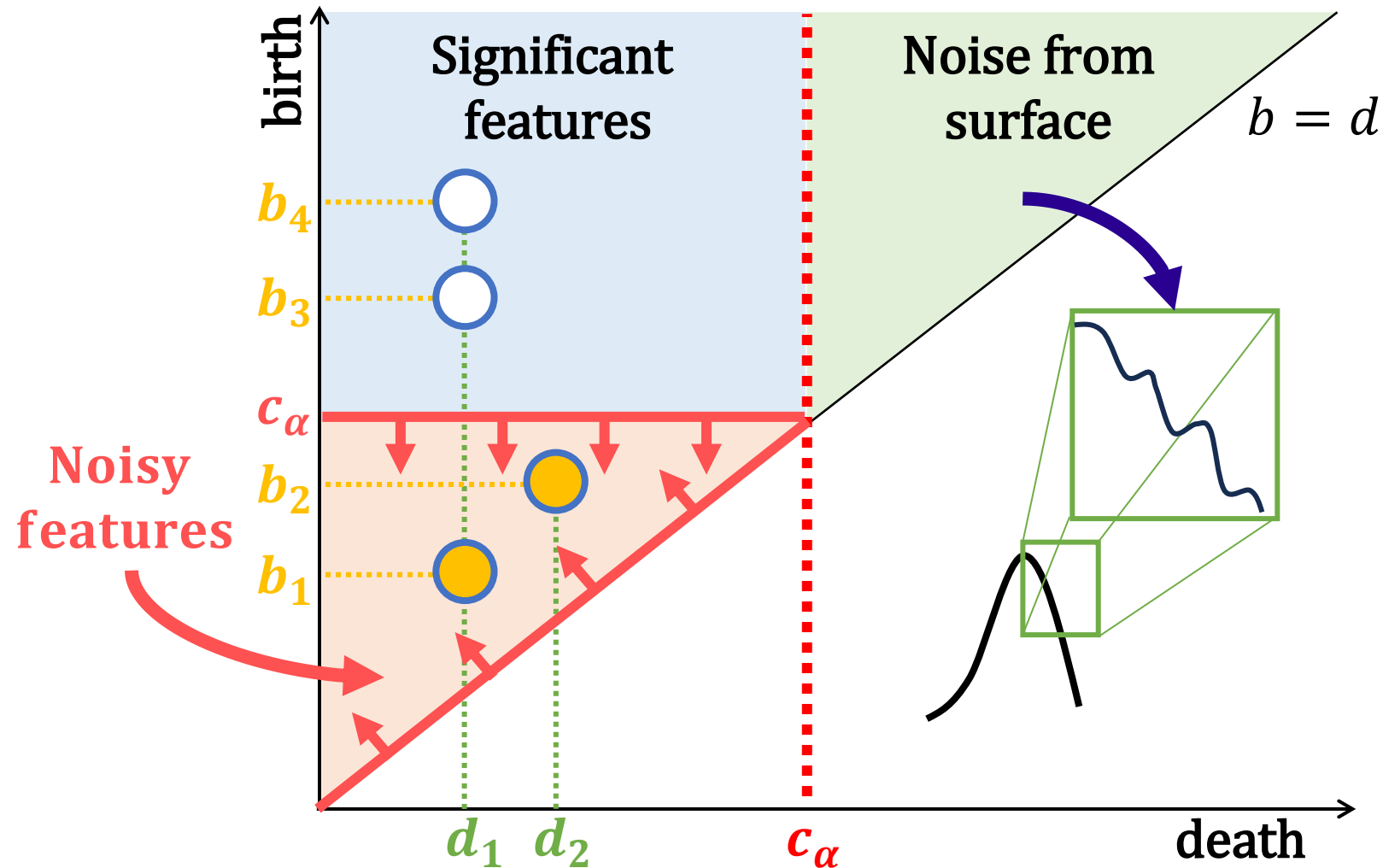
Confidence Band Estimation

Finding the threshold c_α that selects statistically and topologically significant features



Confidence Band Estimation

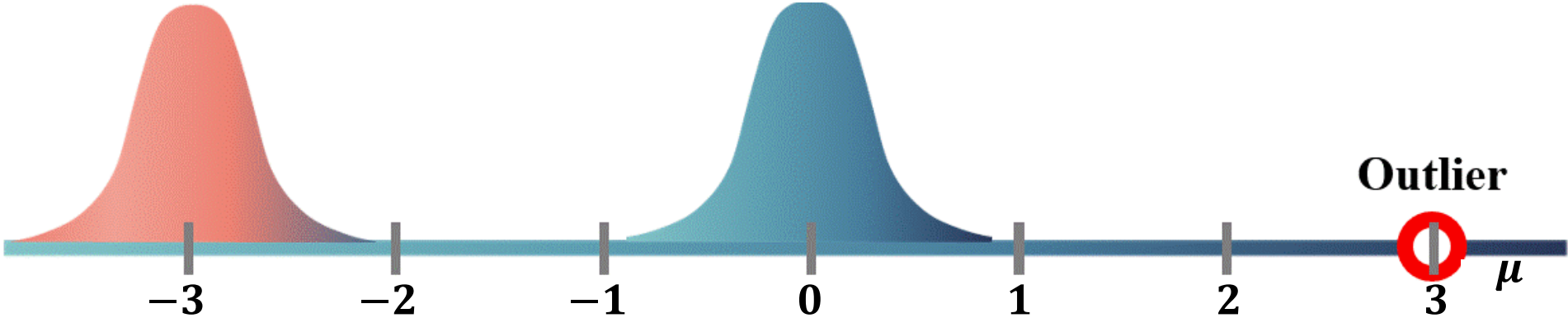
Finding the threshold c_α that selects statistically and topologically significant features



Experiments & Results – perturbation experiment

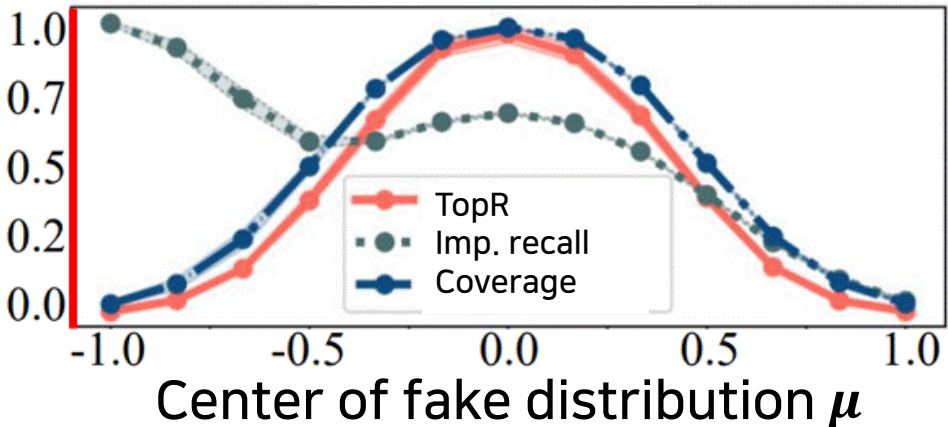
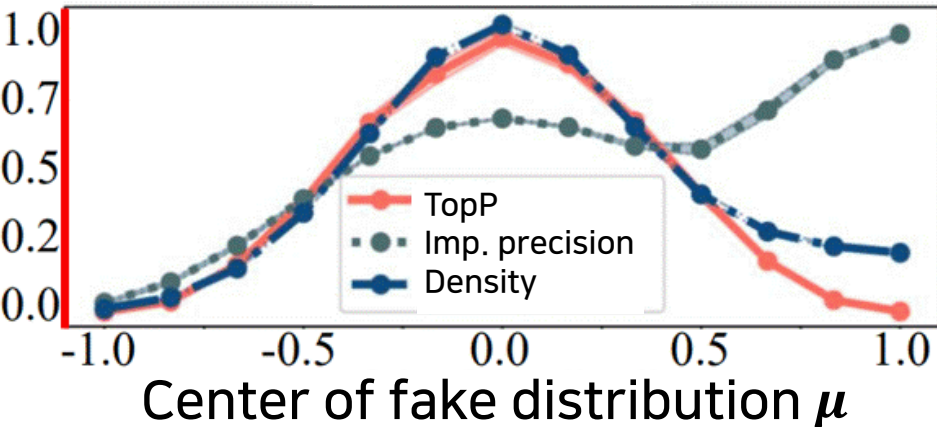
Fake distribution

Real distribution



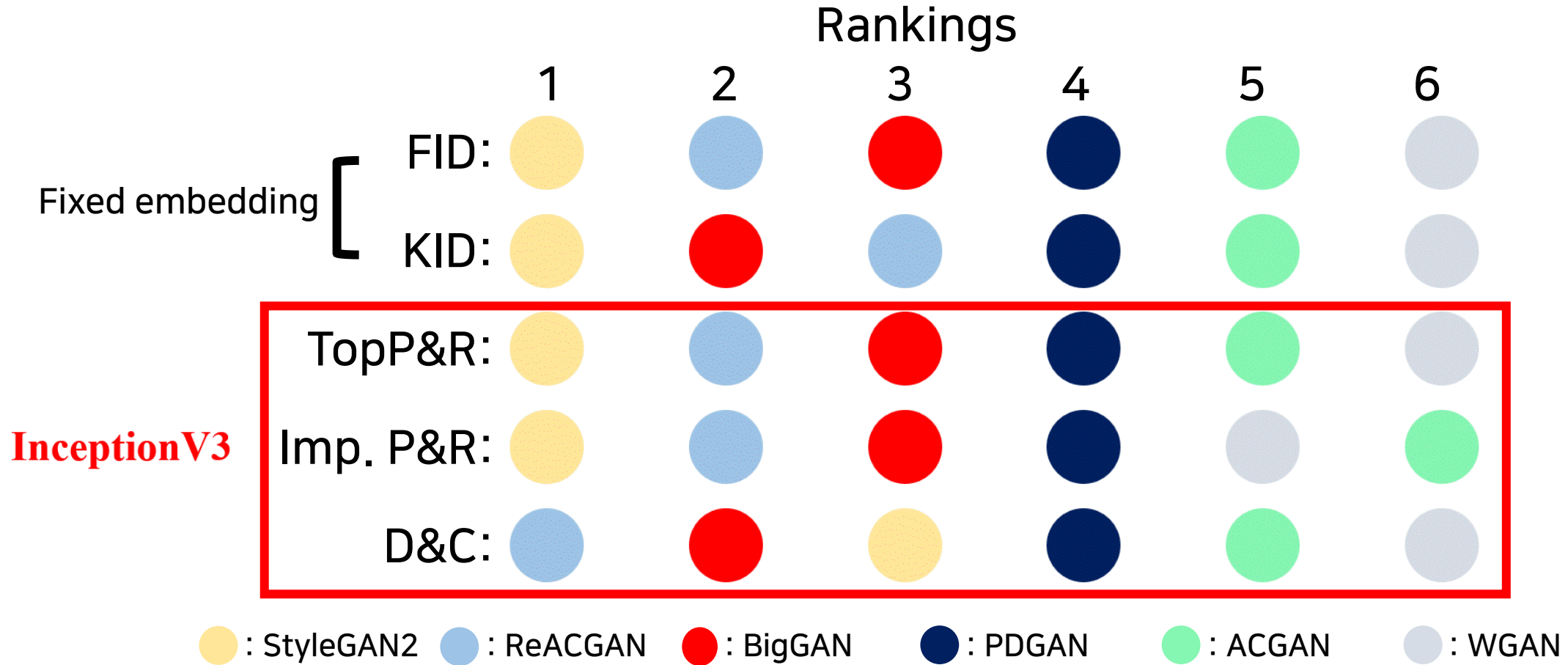
Fidelity

Diversity



Experiments & Results – ranking experiment

Metric's consistency "with FID and KID scores" & "with different embeddings"



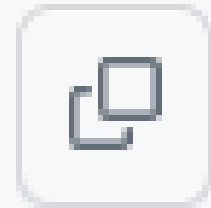
Thank you

Project Page



Quick Start!

```
pip install top-pr
```



Use our method by only pip command!