Kernel Stein Tests for Multiple Model Comparison

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Summary

- **Given**: l candidate models $\mathcal{M} = \{P_1, \ldots, P_l\}$ and n samples $\{\mathbf{y}_i\}_{i=1}^n \sim R$ from unknown data distribution R. In $\mathbb{R}^d$.
- **Goal**: For each model $P_i \in \mathcal{M}$, determine if it (the model) is worse that the best candidate model P_J in $\mathcal{M}$.
- **Contribution**:
  - Proposed two methods for constructing non-parametric tests for *multiple model comparison*.
    1. Mult: The dataset is split into two independent portions for selection (i.e., determining P_J) and testing.
    2. PSI: The same dataset is used for selection and testing.
  - When $l = 2$, PSI has provably higher true positive rate (TPR) than Mult.
  - Both methods control false positive rate (FPR).

Multiple Model Comparison

- Test $H_{0,i} : D(P_i, R) < D(P_J, R)$ v.s. $H_{1,i} : D(P_i, R) > D(P_J, R)$ where P_J is the best candidate model in $\mathcal{M}$.
- D = a discrepancy measure. Can be MMD or KSD.
- For each model P_i, we either have samples $\{\mathbf{x}_j\}_{j=1}^n \sim P_i$ (D = MMD) or have the log density $\log p_i(x)$ (D = KSD).
- J in P_J is unknown. Estimate best index $\widehat{J}$ from data (selection).
- We choose $P_{\widehat{J}} = \mathrm{argmin}_{P_i \in \mathcal{M}} \widehat{D}(P_i, R)$.
- Consider hypotheses conditioned on the selection
  - $H_{0,i} : D(P_i, R) \le D(P_{\widehat{J}}, R) \mid P_{\widehat{J}}$ is the best,
  - $H_{1,i} : D(P_i, R) > D(P_{\widehat{J}}, R) \mid P_{\widehat{J}}$ is the best.
- Conditional null hypothesis $\implies$ *valid* post selection tests that account for selection bias.

False and True Positive Rates

- We use false positive rate (FPR) and true positive rate (TPR) to measure the performance of our algorithm.
- True positive rate (TPR) is the proportion of models correctly designated as worse than the best P_J.
- False positive rate (FPR) is the proportion of models incorrectly designated as worse than the best P_J.
- A good test has high TPR and low FPR.

Test Statistic

Our test statistic is $\widehat{S} := \sqrt{n}[\widehat{D}(P_i, R) - \widehat{D}(P_{\widehat{J}}, R)]$ where $\widehat{D}$ is an unbiased estimator of KSD or MMD

- **Before selection**, $\widehat{S}$ is normally distributed as $n \to \infty$.
- **After selection**, $\widehat{S}$ under the *conditional null* is asymptotically:
  - **Normal** if the data are split into two independent portions: one for selection and the other for inference.
  - **Truncated normal** if the full dataset is used for both selection and testing, by the polyhedral lemma of Lee et. al. 2016.

- For all $i = 1, \ldots, l$, reject $H_{0,i}$ if $\widehat{S} > (1-\alpha)$-quantile of the distribution of $\hat{S}$ **after** selection.
- Reject $H_{0,i} \implies$ Model P_i is worse than the best $P_{\widehat{J}}$.
- This asymptotically controls the type-I error and FPR at α.

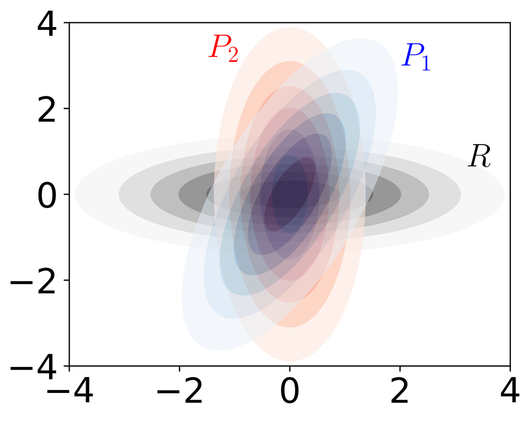
Theoretical Result

Proposition: Given two candidate models P_1 and P_2, then PSI has a higher TPR than Mult for both MMD and KSD.

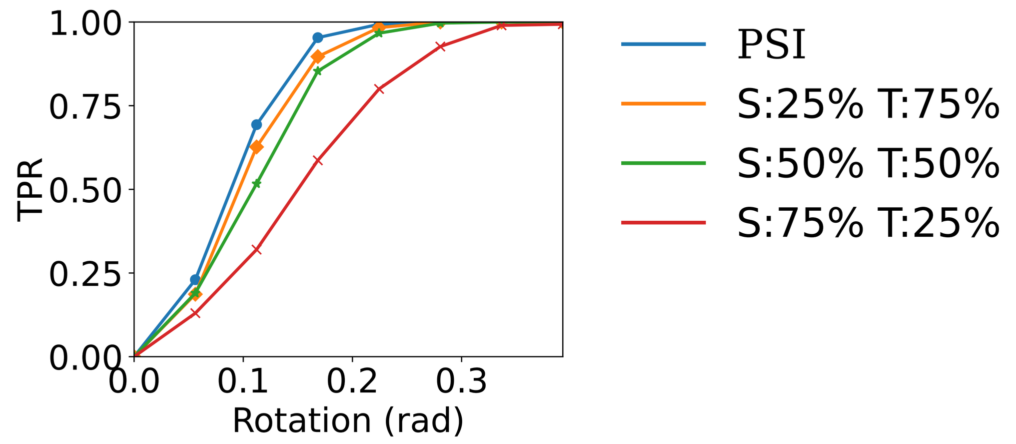
Toy Example (D = KSD)

- Initially, $P_1 \approx P_2$. Then, P_1 is then rotated away such that P_1 is closer to R than P_2.
- Rotating $P_1 \implies$ easier problem $\implies$ higher TPR.

The TPR of PSI is consistently higher than Mult with varying portion of data splits.



Problem

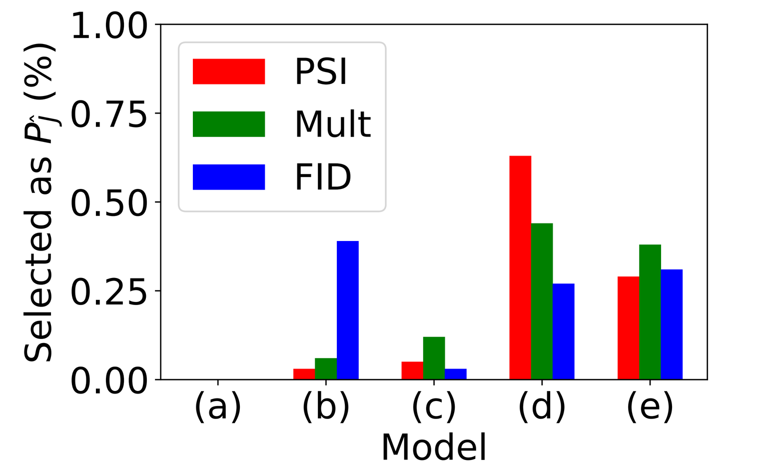


Notation: (S:a% T:b%) means a% and b% of the data are used for selection and testing, respectively.

Mixture of CelebA (D = MMD)

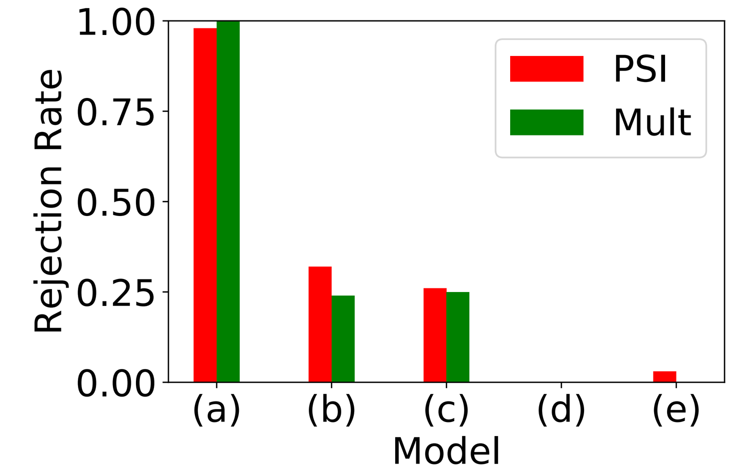
Task: If the true distribution is composed of 50% smile and 50% non-smile (images), which of the following models are the closest?

(a) GAN: Smile 50%, No-smile 50%.
(b) Real: Smile 60%, No-smile 40%.
(c) Real: Smile 40%, No-smile 60%.
(d) Real: Smile 51%, No-smile 49%.
(e) Real: Smile 52%, No-smile 48%.



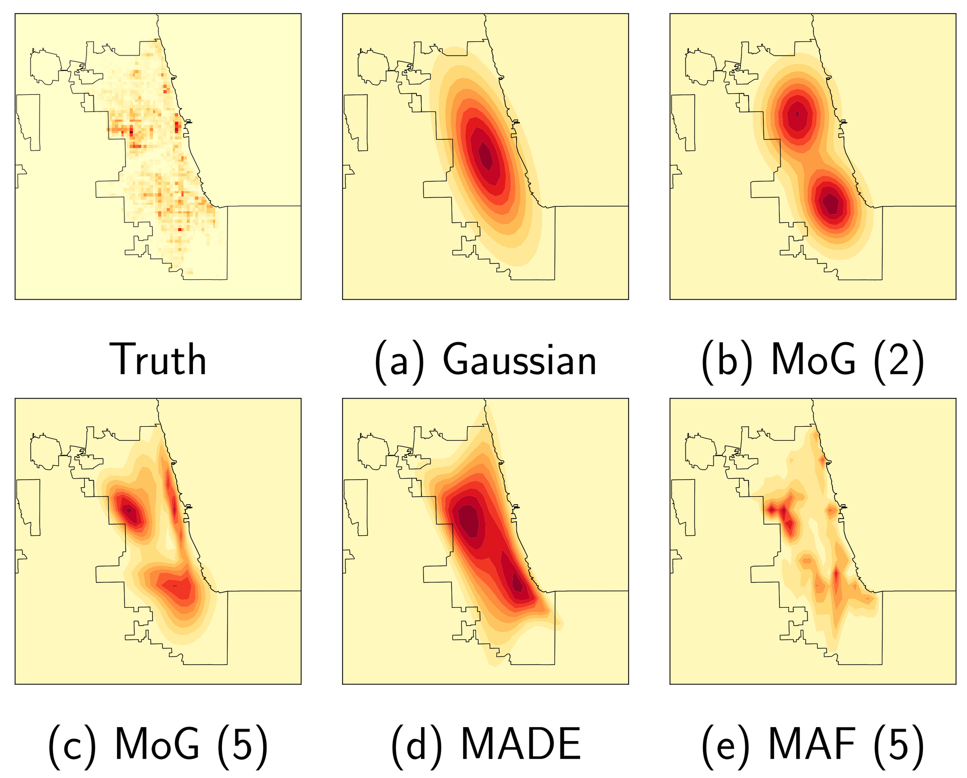
Results:

- Ranking by FID $\implies$ noisy selection.
- Testing indicates that (d) and (e) are the best. ☺
- Performance of PSI and Mult similar.



Chicago Crime (D = KSD)

Task: Best model for representing the crime activity in Chicago?



- Ranking by KSD $\implies$ (c) and (e) are selected.
- Negative Log Likelihood (NLL) favors the most complex model (e).
- PSI has higher rejection rate than Mult.