

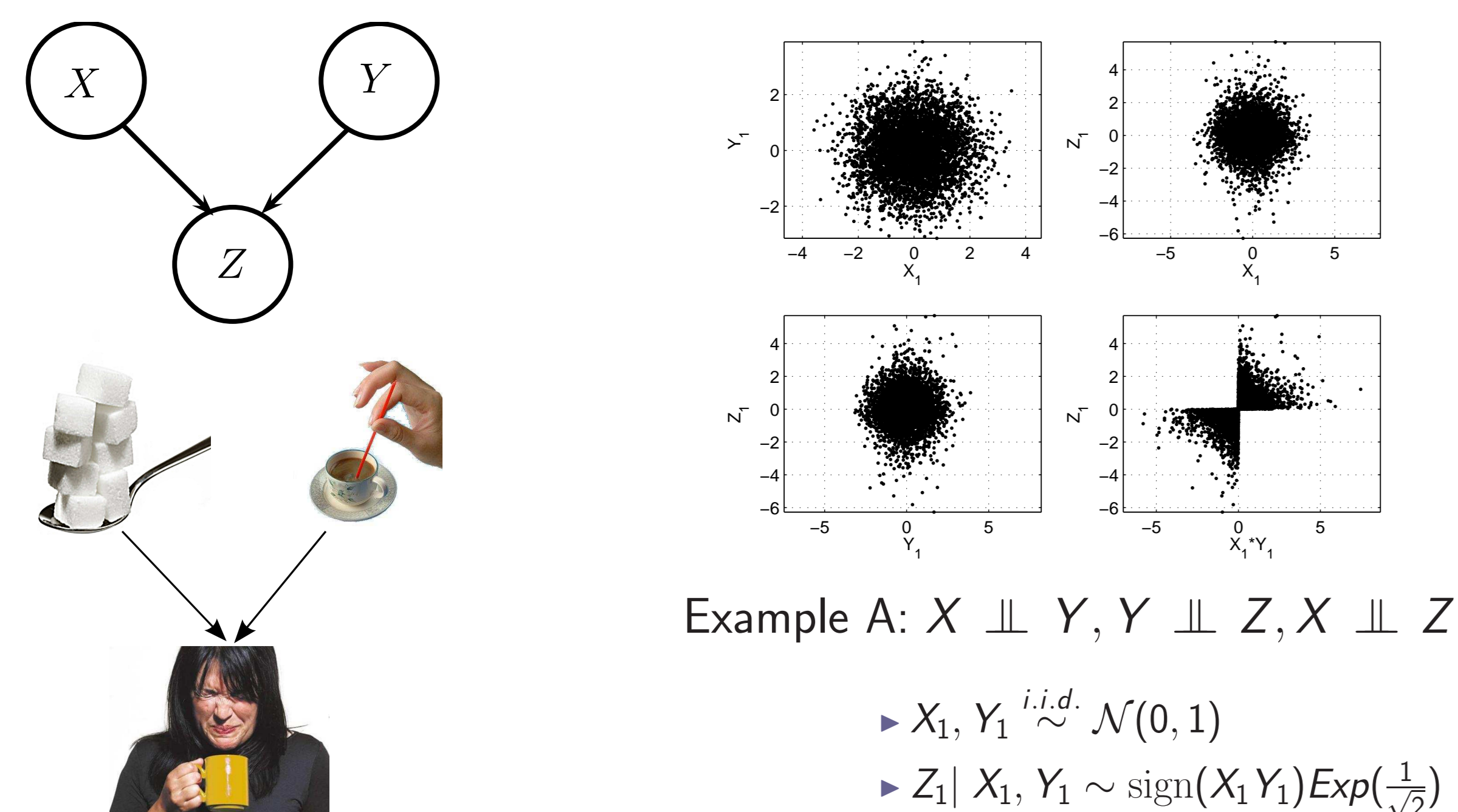
A Kernel Test for Three Variable Interactions

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Motivation: How to detect V-structures with pairwise weak (or nonexistent) association?



Embeddings of probability measures into RKHS

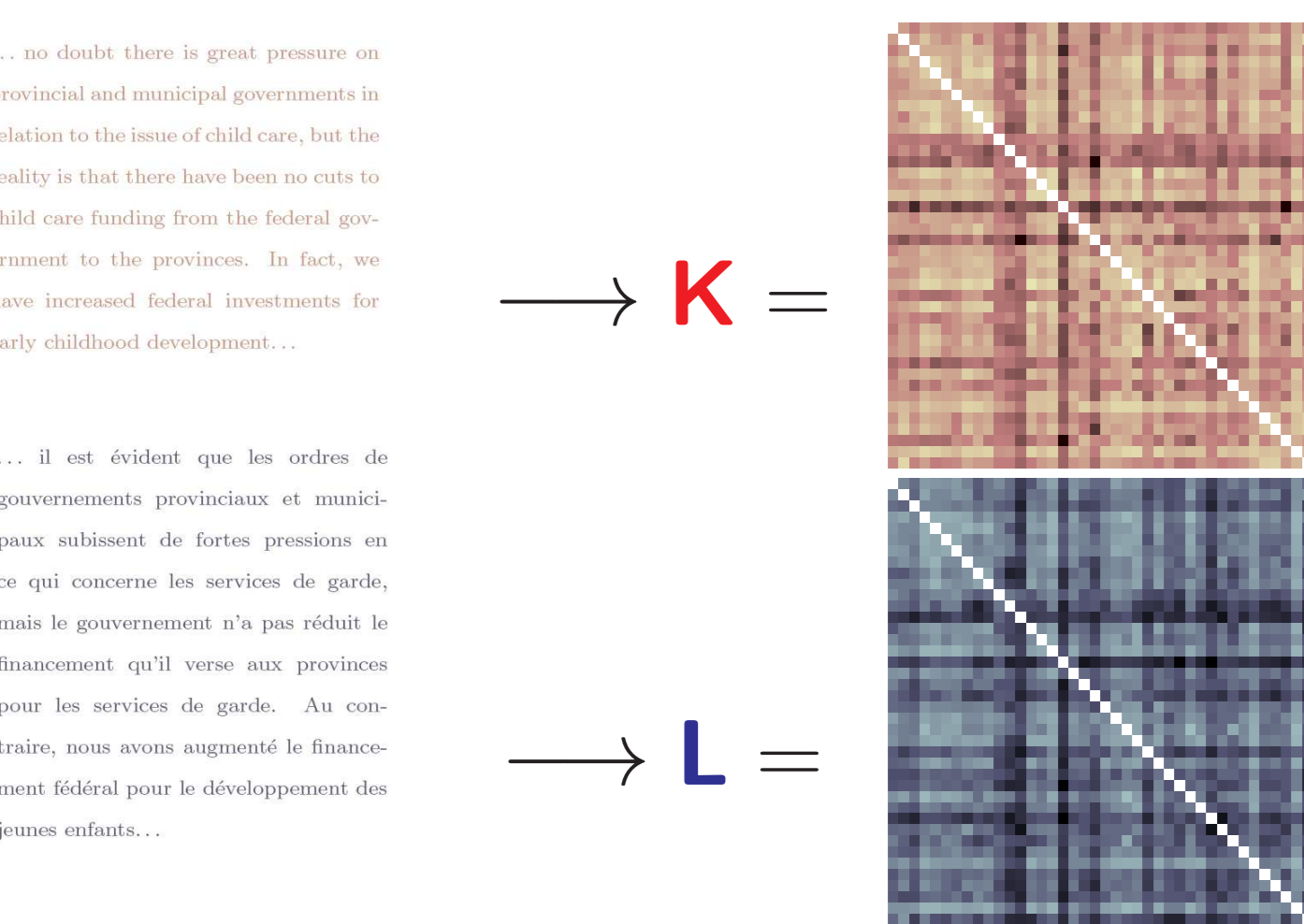
- Feature map:** $z \mapsto k(\cdot, z) \in \mathcal{H}_k$
instead of $z \mapsto (\varphi_1(z), \dots, \varphi_s(z)) \in \mathbb{R}^s$
- $\langle k(\cdot, z), k(\cdot, w) \rangle_{\mathcal{H}_k} = k(z, w)$ ← inner products easily **computed**
- Kernel embedding:** $P \mapsto \mu_k(P) = \mathbb{E}_{Z \sim P} k(\cdot, Z) \in \mathcal{H}_k$
instead of $P \mapsto (\mathbb{E}\varphi_1(Z), \dots, \mathbb{E}\varphi_s(Z)) \in \mathbb{R}^s$
- $\langle \mu_k(P), \mu_k(Q) \rangle_{\mathcal{H}_k} = \mathbb{E}_{Z \sim P, W \sim Q} k(Z, W)$ ← inner products easily **estimated**

Pairwise RKHS-based independence test

- Hilbert-Schmidt Independence Criterion** (Gretton et al 2005, 2008; Smola et al 2007):

$$\left\| \mu_k(\hat{P}_{XY}) - \mu_k(\hat{P}_X \hat{P}_Y) \right\|_{\mathcal{H}_k}^2 = \frac{1}{n^2} (\mathbf{H} \mathbf{K} \mathbf{H} \circ \mathbf{H} \mathbf{L} \mathbf{H})_{++}$$

- Powerful nonparametric independence tests that generalize (Sejdinovic et al 2013) distance covariance (**dCov**) of Szekely et al (2007)



$$\kappa \left(\begin{matrix} \circ & \circ \\ \circ & \circ \end{matrix} \right) = \kappa \left(\begin{matrix} \circ & \circ \\ \circ & \circ \end{matrix} \right) \times l \left(\begin{matrix} \circ & \circ \\ \circ & \circ \end{matrix} \right)$$

- HSIC** = $\frac{1}{n^2} (\mathbf{H} \mathbf{K} \mathbf{H}, \mathbf{H} \mathbf{L} \mathbf{H})$
- $\mathbf{H} = \mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T$ (centering matrix)
- $\mathbf{A}_{++} = \sum_{i=1}^n \sum_{j=1}^n A_{ij}$

Hilbert-Schmidt norm of the covariance operator in the feature space

How to detect a V-structure using the existing RKHS-based tests?

Assuming $X \perp\!\!\!\perp Y$ has been established:

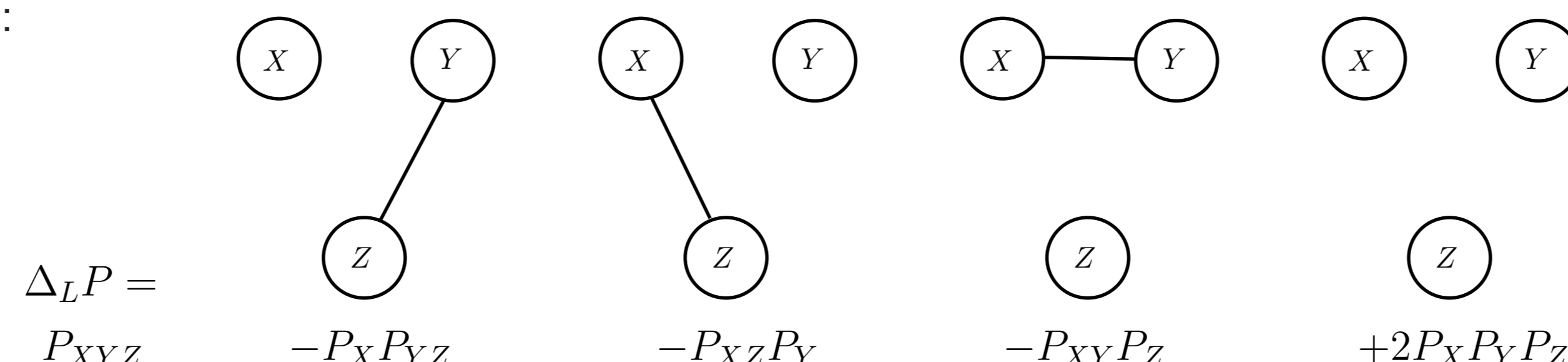
- Conditional independence test:** $\mathbf{H}_0 : X \perp\!\!\!\perp Y | Z$ (Zhang et al 2011) or
- Factorisation test:** $\mathbf{H}_0 : (X, Y) \perp\!\!\!\perp Z \vee (X, Z) \perp\!\!\!\perp Y \vee (Y, Z) \perp\!\!\!\perp X$
(multiple standard two-variable tests)
- compute p -values for each of the marginal tests
- apply Holm-Bonferroni sequentially rejective correction (Holm 1979)

Capturing factorisations directly: Interaction Measures (Lancaster, 1969)

Interaction measure of $(X_1, \dots, X_D) \sim P_X$ is a signed measure ΔP that **vanishes whenever P can be factorised** in a non-trivial way as a product of its (possibly multivariate) marginals.

$D = 2$: $\Delta_L P = P_{XY} - P_X P_Y$

$D = 3$:



Inner product estimators

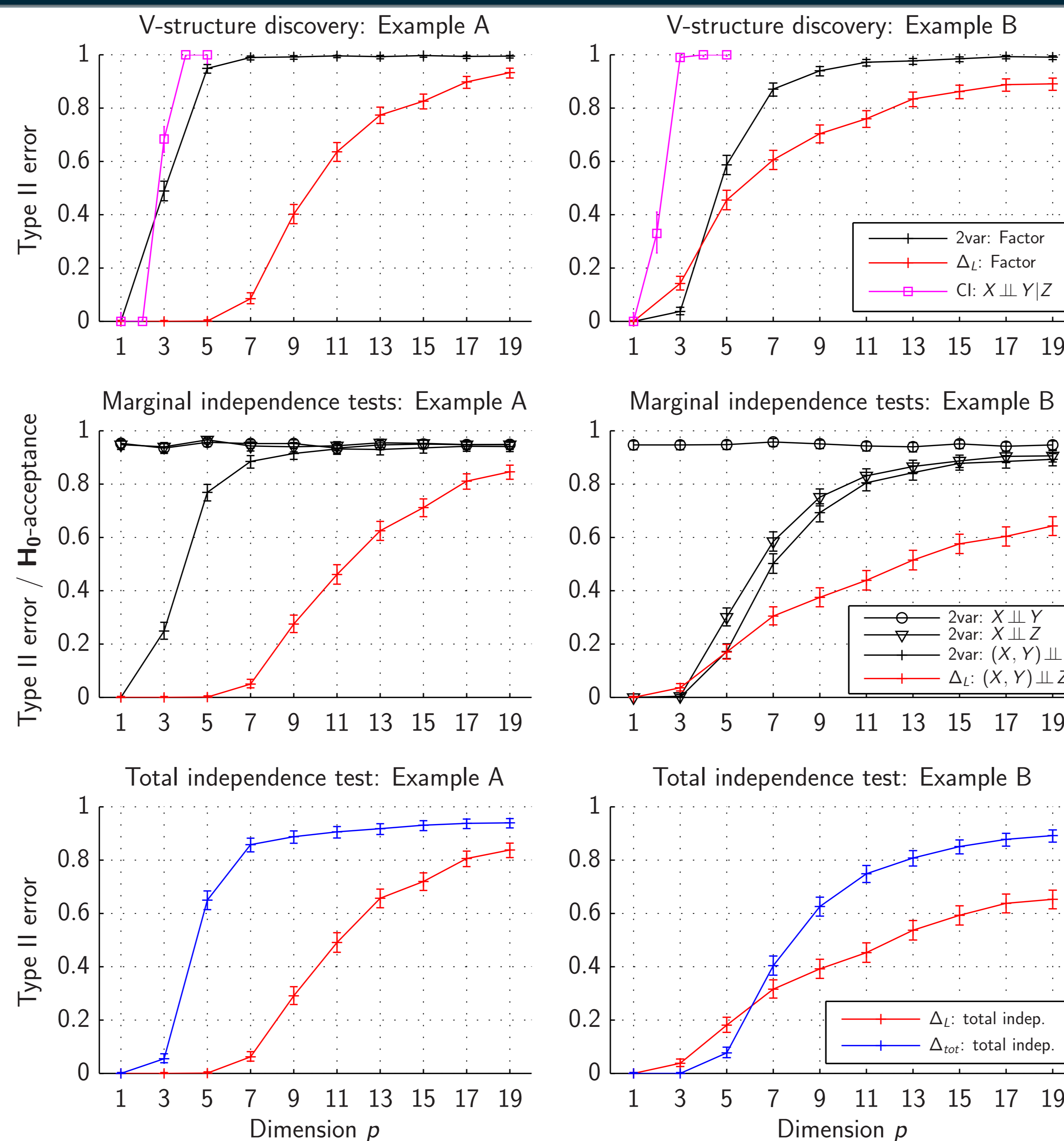
$\nu \setminus \nu'$	P_{XYZ}	$P_{XY} P_Z$	$P_{XZ} P_Y$	$P_{YZ} P_X$	$P_X P_Y P_Z$
P_{XYZ}	$(\mathbf{K} \circ \mathbf{L} \circ \mathbf{M})_{++}$	$((\mathbf{K} \circ \mathbf{L}) \mathbf{M})_{++}$	$((\mathbf{K} \circ \mathbf{M}) \mathbf{L})_{++}$	$((\mathbf{M} \circ \mathbf{L}) \mathbf{K})_{++}$	$\text{tr}(\mathbf{K}_+ \circ \mathbf{L}_+ \circ \mathbf{M}_+)$
$P_{XY} P_Z$		$(\mathbf{K} \circ \mathbf{L})_{++} \mathbf{M}_{++}$	$(\mathbf{M} \mathbf{K} \mathbf{L})_{++}$	$(\mathbf{K} \mathbf{L} \mathbf{M})_{++}$	$(\mathbf{K} \mathbf{L})_{++} \mathbf{M}_{++}$
$P_{XZ} P_Y$			$(\mathbf{K} \circ \mathbf{M})_{++} \mathbf{L}_{++}$	$(\mathbf{K} \mathbf{M} \mathbf{L})_{++}$	$(\mathbf{K} \mathbf{M})_{++} \mathbf{L}_{++}$
$P_{YZ} P_X$				$(\mathbf{L} \circ \mathbf{M})_{++} \mathbf{K}_{++}$	$(\mathbf{L} \mathbf{M})_{++} \mathbf{K}_{++}$
$P_X P_Y P_Z$					$\mathbf{K}_{++} \mathbf{L}_{++} \mathbf{M}_{++}$

Table: V-statistic estimators of $\langle \mu_k \nu, \mu_k \nu' \rangle_{\mathcal{H}_k}$, with $\kappa = k \otimes l \otimes m$

$$\left\| \mu_k(\Delta_L \hat{P}) \right\|_{\mathcal{H}_k}^2 = \frac{1}{n^2} (\mathbf{H} \mathbf{K} \mathbf{H} \circ \mathbf{H} \mathbf{L} \mathbf{H} \circ \mathbf{H} \mathbf{M} \mathbf{H})_{++}$$

Norm of the empirical joint central moment in the feature space

Results: gaussian kernel with median distance bandwidth, $n = 500$



What kind of interactions does the Lancaster statistic capture?

If $\kappa = k \otimes l \otimes m$ is **integrally strictly positive definite** (Sriperumbudur, 2010), then

$$\left\| \mu_k(\Delta_L P) \right\|_{\mathcal{H}_k} = 0 \Leftrightarrow \Delta_L P = 0.$$

Theorem: $\left\| \mu_k(\Delta_L P) \right\|_{\mathcal{H}_k} = 0 \Leftrightarrow \mathbb{E}_{XYZ}[(f(X) - \mathbb{E}f)(g(Y) - \mathbb{E}g)(h(Z) - \mathbb{E}h)] = 0$
for all $f \in \mathcal{H}_k, g \in \mathcal{H}_l, h \in \mathcal{H}_m$.

However, $\Delta_L P = 0 \not\Rightarrow (X, Y) \perp\!\!\!\perp Z \vee (X, Z) \perp\!\!\!\perp Y \vee (Y, Z) \perp\!\!\!\perp X$

Counterexample: X, Y, Z binary and $P(x, y, z) = \begin{cases} 0.2 & x = y = z, \\ 0.1 & \text{otherwise.} \end{cases}$

Example B

- Pairwise dependence present, but weaker**

- $X_1, Y_1 \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$
- $Z_1 | X_1, Y_1 \sim \begin{cases} X_1^2 + \mathcal{N}(0, 0.01), & w.p. 1/3, \\ Y_1^2 + \mathcal{N}(0, 0.01), & w.p. 1/3, \\ X_1 Y_1 + \mathcal{N}(0, 0.01), & w.p. 1/3. \end{cases}$
- $X_{2,p}, Y_{2,p}, Z_{2,p} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \mathbf{I}_{p-1})$

Permutation tests based on Lancaster statistic

- Marginal independence test, e.g., $\mathbf{H}_0 : (X, Y) \perp\!\!\!\perp Z$: estimate null distribution using $(X^{(i)}, Y^{(i)}, Z^{(\sigma i)})_{i=1}^n, \sigma \in S_n$
- Factorisation test: multiple marginal independence tests with Holm-Bonferroni correction
- Total independence test $\mathbf{H}_0 : P_{XYZ} = P_X P_Y P_Z$: estimate null distribution using $(X^{(i)}, Y^{(\tau i)}, Z^{(\sigma i)})_{i=1}^n, \sigma, \tau \in S_n$

Total independence test $\mathbf{H}_0 : P_X = \prod_{i=1}^D P_{X_i}$

For $(X_1, \dots, X_D) \sim P_X$, and $\kappa = \otimes_{i=1}^D k^{(i)}$:

$$\left\| \mu_k \left(\hat{P}_X - \prod_{i=1}^D \hat{P}_{X_i} \right) \right\|_{\mathcal{H}_k}^2 = \frac{1}{n^2} \sum_{a=1}^n \sum_{b=1}^n \prod_{i=1}^D K_{ab}^{(i)} - \frac{2}{n^{D+1}} \sum_{a=1}^n \prod_{i=1}^D \sum_{b=1}^n K_{ab}^{(i)} + \frac{1}{n^{2D}} \prod_{i=1}^D \sum_{a=1}^n \sum_{b=1}^n K_{ab}^{(i)}$$

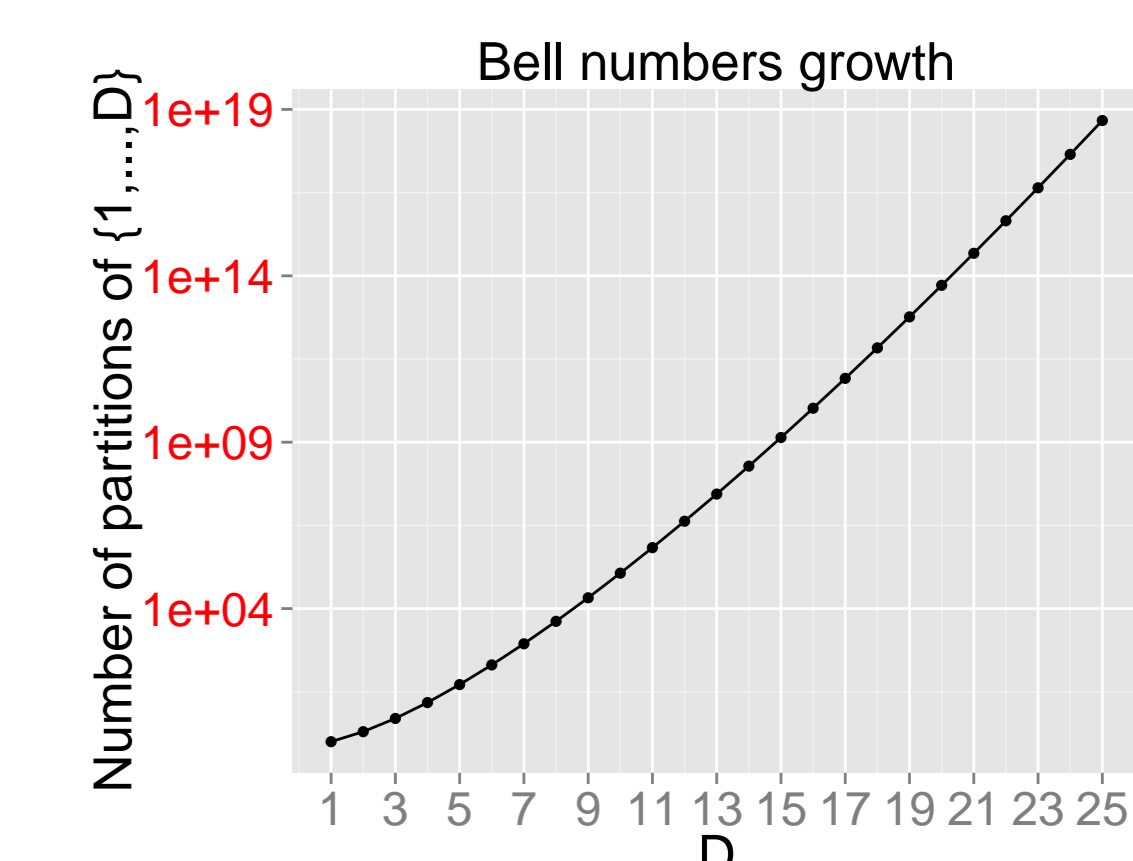
Coincides with the test proposed by Kankainen (1995) using empirical characteristic functions: similar relationship to that between **dCov** and **HSIC** (Sejdinovic et al, 2013)

Interaction for $D \geq 4$

- Interaction measure valid for all D (Streitberg, 1990):

$$\Delta_S P = \sum_{\pi} (-1)^{|\pi|-1} (|\pi| - 1)! J_{\pi} P$$

- For a partition π , J_{π} associates to the joint the corresponding factorization, e.g., $J_{13|2|4} P = P_{X_1 X_3} P_{X_2} P_{X_4}$.
- Overall expression does not collapse and summing over all partitions is required.



$\mu_k(\Delta_L P)$: joint central moment in the RKHS vs. $\mu_k(\Delta_S P)$: joint cumulants in the RKHS

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