

*

	Γ	Δ	Θ	Λ	Ξ	Π	Σ	Υ	Φ	Ψ	Ω
<code>\mit</code>	Γ	Δ	Θ	Λ	Ξ	Π	Σ	Υ	Φ	Ψ	Ω

alpha	A	α	beta	B	β
gamma	Γ	γ	delta	Δ	δ
epsilon	E	ϵ, ε	zeta	Z	ζ
eta	H	η	theta	Θ	θ, ϑ
iota	I	ι	kappa	K	κ
lambda	Λ	λ	mu	M	μ
nu	N	ν	omicron	O	o
xi	Ξ	ξ	pi	Π	π, ϖ
rho	P	ρ, ϱ	sigma	Σ	σ, ς
tau	T	τ	upsilon	Υ	υ
phi	Φ	ϕ, φ	chi	X	χ
psi	Ψ	ψ	omega	Ω	ω

*: wangjunjie2013@gmail.com

1 Inference via low-dimensional couplings

The transport map T can be viewed as a transformation that moves particles : given a collection of samples from v_η , T rearranges them in accordance with the new distribution v_π

Optimal transport maps, for instance, define couplings that minimize a particular integrated transport cost expressing the effort required to rearrange samples. In recent years, several other couplings have been proposed for use in statistical problems, e.g.,

- parametric approximations – Moselhy, T. and Marzouk, Y. (2012). Bayesian inference with optimal maps. *Journal of Computational Physics* 231 78157850.
- Knote-Rosenblatt rearrangement– Rosenblatt, M. (1952). Remarks on a multivariate transformation. *The Annals of Mathematical Statistics* 470472
- coupling induced by ODE flows— Heng, J., Doucet, A. and Pokern, Y. (2015). Gibbs flow for approximate transport with applications to Bayesian computation. arXiv:1509.08787. Daum, F. and Huang, J. (2008). Particle flow for nonlinear filters with log-homotopy. In *SPIE Defense and Security Symposium* 696918696918. International Society for Optics and Photonics. Anderes, E. and Coram, M. (2012). A general spline representation for nonparametric and semiparametric density estimates using diffeomorphisms. arXiv:1205.5314.

Yet the construction, representation, and evaluation of all these maps grows challenging in high dimensions.

The central contribution of this paper is to **establish a link between the conditional independence structure of the target measure and the existence of special low dimensional coupling. These couplings are induced by transport maps that are sparse or decomposable.**