

## $W_{1,+}$ -interpolation of probability measures on graphs

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### Abstract

We generalize an equation introduced by Benamou and Brenier in [BB00] and characterizing Wasserstein  $W_p$ -geodesics for  $p > 1$ , from the continuous setting of probability distributions on a Riemannian manifold to the discrete setting of probability distributions on a general graph.

Given an initial and a final distributions  $(f_0(x))_{x \in G}$ ,  $(f_1(x))_{x \in G}$ , we prove the existence of a curve  $(f_t(x))_{t \in [0,1], x \in G}$  satisfying this Benamou-Brenier equation. We also show that such a curve can be described as a mixture of binomial distributions with respect to a coupling that is solution of a certain optimization problem.

**Keywords:** Optimal transport ; Wasserstein distances ; Discrete probability.

**AMS MSC 2010:** 60J10 ; 60Dxx.

Submitted to EJP on February 21, 2014, final version accepted on September 15, 2014.

## 1 Introduction

Given some  $p \geq 1$ , we consider the space  $\mathcal{P}_p(X)$  of probability distributions over a metric space  $(X, d)$  having a finite  $p$ -th moment. On this space we define the Wasserstein distance  $W_p$  by

$$W_p(\mu_0, \mu_1)^p := \inf_{\pi \in \Pi(\mu_0, \mu_1)} \int_{X \times X} d(x_0, x_1)^p d\pi(x_0, x_1), \quad (1.1)$$

where the set  $\Pi(\mu_0, \mu_1)$  is the set of couplings of  $\mu_0$  and  $\mu_1$ , i.e. the set of probability distributions  $\pi$  on  $X \times X$  having  $\mu_0$  and  $\mu_1$  as marginals.

A comprehensive study of the Problem (1.1), called Monge-Kantorovitch problem, can be found in Villani's textbooks [Vil03] and [Vil08]. What is important for our purposes is that it is possible to prove, under very general assumptions, the existence of a minimizer  $\pi \in \Pi(\mu_0, \mu_1)$  for problem (1.1), called optimal coupling, and that  $W_p$  is indeed a metric on  $\mathcal{P}_p(X)$ . The couple  $(\mathcal{P}_p(X), W_p)$  will be called the  $W_p$ -Wasserstein space over the metric space  $(X, d)$ .

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Given a metric space  $(X, d)$  and a continuous curve  $(\gamma_t)_{t \in [0,1]}$  on the space  $(X, d)$ , i.e. a continuous mapping  $\gamma : [0, 1] \rightarrow (X, d)$ , we define the length of  $(\gamma_t)_{t \in [0,1]}$  by

$$L(\gamma) := \sup_{0=t_0 \leq \dots \leq t_N=1} \sum_{i=0}^{N-1} d(\gamma_{t_i}, \gamma_{t_{i+1}}). \tag{1.2}$$

The inequality  $L(\gamma) \geq d(\gamma_0, \gamma_1)$  always holds. A curve  $(\gamma_t)_{t \in [0,1]}$  with  $\gamma_0 = x, \gamma_1 = y$  and  $L(\gamma) = d(x, y)$  is called a geodesic joining  $x$  to  $y$ . The metric space  $(X, d)$  is called geodesic space if each couple of points  $x, y \in X$  is joined by at least one continuous geodesic. A large class of geodesic spaces is given by compact Riemannian manifolds. It is important to remark that a discrete metric space  $(X, d)$  (like a graph with its usual distance) cannot be a geodesic space, because by definition of the discrete topology there does not exist continuous curves from  $[0, 1]$  to  $(X, d)$ .

A natural question about Wasserstein spaces is the following: given two prescribed probability distributions  $\mu_0, \mu_1 \in \mathcal{P}_p(X)$ , does there exist a geodesic joining  $\mu_0$  to  $\mu_1$ ? In other terms, is the metric space  $(\mathcal{P}_p(X), W_p)$  a geodesic space? A partial answer is given by the following:

**Proposition 1.1.** *If  $(X, d)$  is a geodesic space, then the metric space  $(\mathcal{P}_p(X), W_p)$  is also a geodesic space.*

In particular, each couple  $\mu_0, \mu_1 \in \mathcal{P}_2(X)$  can be joined by a curve  $(\mu_t)_{t \in [0,1]}$  of minimal length for  $W_2$ , called  $W_2$ -Wasserstein geodesic.

In their seminal papers [Stu06a], [Stu06b] and [LV09], Sturm, and independently Lott and Villani studied the links between the geometry of a measured geodesic space  $(X, d, \nu)$  and the behaviour of the entropy functional along the  $W_2$ -Wasserstein geodesics on  $\mathcal{P}_2(X)$ . For instance,  $(X, d, \nu)$  is said to satisfy the curvature condition  $CD(K, \infty)$  for some  $K \in \mathbb{R}$  if for each couple of probability distributions  $\mu_0, \mu_1 \in \mathcal{P}_2(X)$  there exists a  $W_2$ -geodesic  $(\mu_t)_{t \in [0,1]}$  such that

$$\forall t \in [0, 1], H_\nu(\mu_t) \leq (1-t)H_\nu(\mu_0) + tH_\nu(\mu_1) - K \frac{t(1-t)}{2} W_2(\mu_0, \mu_1)^2, \tag{1.3}$$

where the relative entropy functional  $H_\nu(\cdot)$  is defined by

$$H_\nu(\rho\nu) := \int_X \rho(x) \log(\rho(x)) d\nu(x) \tag{1.4}$$

if  $\mu = \rho\nu$  for some density  $\rho$ , and by  $H_\nu(\mu) = \infty$  otherwise.

If the measured geodesic space  $(X, d, \nu)$  is a compact Riemannian manifold with its usual distance and its normalized volume measure, the curvature condition  $CD(K, \infty)$  is shown to be equivalent to the bound  $\text{Ric} \geq K$  on the Ricci curvature tensor. Another important property is the stability of the condition  $CD(K, \infty)$  under measured Gromov-Hausdorff convergence.

Moreover, if  $CD(K, \infty)$  is satisfied for some  $K > 0$ , one can prove functional inequalities on  $(X, d, \nu)$  such as the logarithmic Sobolev inequality, which asserts that

$$H_\nu(f d\nu) \leq \frac{1}{2K} \int_X \frac{|\nabla^- f|^2}{f} d\nu, \tag{1.5}$$

for any Lipschitz probability density  $f$  and where  $|\nabla^- f|$  is to be seen as a particular form of the norm of a gradient. As a corollary, it can be shown that under the condition

$CD(K, \infty)$  for  $K > 0$  a Poincaré inequality holds: for any Lipschitz function  $h : X \rightarrow \mathbb{R}$  such that  $\int_X h d\nu = 0$ , we have

$$\int_X h^2 d\nu \leq \frac{1}{2K} \int_X |\nabla^- h|^2 d\nu. \tag{1.6}$$

Since the works of Sturm and Lott-Villani, the theory of measured geodesic spaces satisfying  $CD(K, \infty)$  has been thoroughly studied in a large number of papers, among which the most impressive are the works by Ambrosio, Gigli and Savaré (see for instance [AGS12]) and by Erbar, Kuwada and Sturm ([EKS13]).

Several obstacles prevent us from a direct generalization of Sturm-Lott-Villani theory to the framework of discrete metric spaces. Indeed, if  $(X, d)$  is a graph with its usual distance, equation (1.1) still defines a metric on the space  $\mathcal{P}_p(X)$ , but if  $p > 1$  then the length of non-trivial curves in  $(\mathcal{P}(X), W_p)$  is  $+\infty$ . (The reader can be convinced of this fact by considering the two-point space  $X := \{0, 1\}$  and the curve  $(\mu_t)_{t \in [0,1]}$  defined on  $\mathcal{P}_p(X)$  by  $\mu_t(0) := 1 - t$  and  $\mu_t(1) := t$ . We then have  $W_p(\mu_t, \mu_{t'}) = |t - t'|^{1/p}$ , from which we deduce by equation (1.2) that the length of  $\mu$  in the metric space  $(\mathcal{P}_p(X), W_p)$  is  $+\infty$ .) In particular, Wasserstein  $W_2$ -geodesics do not exist in general.

Several solutions have been proposed to overcome this difficulty, and there are now many different definitions of Ricci curvature bounds on discrete spaces. The most notable of them are the coarse Ricci curvature, defined by Ollivier in [Oll09], and the Erbar-Maas curvature, defined in [EM12]. The latter is based on the study of the gradient flow of the entropy and present some similarities with our own approach. Another approach by Gozlan, Roberto, Samson and Tetali, see [GRST12], is based on the construction of interpolating curves between probability distributions on a graph. These interpolating curves are defined as mixtures of binomial distributions, which is reminiscent of the interpolating curves we introduce in this paper.

In this paper, we place ourselves in the framework of a connected and locally finite graph  $G$ , endowed with its usual graph distance and the counting measure as the reference measure. In this framework, a probability distribution will be denoted by its density, i.e. by a function  $f : G \rightarrow \mathbb{R}_+$  such that  $\sum_{x \in G} f(x) = 1$ . Given two probability measures  $f_0$  and  $f_1$  on  $G$ , we investigate the question of the generalization of the notion of  $W_p$ -geodesic joining  $f_0$  to  $f_1$  in a setting where such a curve does not exist. Our goal is to provide a way to choose, among the set of all  $W_1$ -geodesics joining  $f_0$  to  $f_1$ , a curve which shares some properties satisfied by  $W_p$ -geodesics for  $p > 1$ . Such curves will be called  $W_{1,+}$  geodesics on the graph  $G$ .

This article is to be seen as the first of a two-paper research work. A following article will investigate the convexity properties of the entropy functional along those particular  $W_1$  geodesics, in the view of obtaining a discrete version of equation (1.3) strong enough to imply discrete versions of log-Sobolev or Poincaré inequalities. This ultimate goal has to be kept in mind even in this present paper because it will motivate the definition of a  $W_{1,+}$ -geodesic between  $f_0$  and  $f_1$ : along such a curve, some technical tools will allow us to give bounds on the second derivative of the entropy.

Our starting point is the article [BB99], by Benamou and Brenier. In this paper, the authors reformulate the Monge-Kantorovitch problem in terms of velocity fields and prove the following:

**Theorem 1.2.** *Let  $\mu_0, \mu_1$  be two probability distributions on a Riemannian manifold  $(M, g)$  and  $p > 1$ . Then*

$$W_p(\mu_0, \mu_1)^p = \inf \int_M \int_0^1 |v_t(x)|^p d\mu_t(x) dt, \tag{1.7}$$

the infimum being taken over the families of probability distributions  $(\mu_t) := (f_t d \text{vol})$  joining  $\mu_0$  to  $\mu_1$  and all velocity fields  $(v_t(x))$  satisfying

$$\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot (f_t(x)v_t(x)), \tag{1.8}$$

where  $\nabla \cdot$  is the divergence operator on  $M$ . Moreover the minimizing curve  $(\mu_t)_{t \in [0,1]}$  is the  $W_p$  geodesic joining  $\mu_0$  to  $\mu_1$ .

This theorem has been extended to the framework of separable Hilbert spaces by Ambrosio, Gigli and Savr  in [AGS].

The strategy used by Erbar and Maas in [EM12] is based on a generalization of the minimization problem (1.7) in the framework of discrete Markov chains. Our approach will consist in defining a discrete version of a characterization of its solutions. More precisely, as pointed in [BB99], the formal optimality condition for the optimization problem (1.7) can be written:

$$\frac{\partial}{\partial t} v_t(x) = -v_t(x)\nabla \cdot v_t(x). \tag{1.9}$$

Another point of view on the formal optimality condition (1.9) is provided by writing the velocity field  $(v_t(x))$  as the gradient of a family of convex functions  $v_t := \text{grad } \Phi_t$ . As explained for instance in [OV00], it can be proven that such a function  $\Phi$  satisfies the Hamilton-Jacobi equation

$$\frac{\partial}{\partial t} \Phi_t + \frac{1}{2} |\nabla \Phi_t|^2 = 0. \tag{1.10}$$

It suffices to consider the gradient of equation (1.10) to recover equation (1.9).

The links between the convexity of the entropy  $H(t)$  of  $\mu_t$  and the Ricci curvature tensor on the manifold  $M$  are seen on the following heuristic formula, established by Otto and Villani in [OV00]:

$$H''(t) = \int_M [\text{Tr}((D^2\Phi_t)^T D^2\Phi_t) + \nabla \Phi_t \cdot \text{Ric } \nabla \Phi_t] d\mu_t. \tag{1.11}$$

In particular, the non-negativity of the tensor Ric easily implies that  $H''(t) \geq 0$ .

The formal optimality condition (1.9) on velocity fields makes sense only when  $v$  is regular enough. The question of the regularity of optimal couplings is a difficult topic, see for instance [AGS]. However, what is important for our purposes is that (1.9) can be used to construct  $W_2$ -geodesics: if  $(f_t(x))$  is a smooth family of probability densities satisfying the transport equation (1.8) for a smooth velocity field  $(v_t(x))_{t \in [0,1], x \in M}$  satisfying the condition (1.9), then the curve  $(f_t(x))$  is a  $W_2$ -geodesic.

In the simpler framework of the real line  $\mathbb{R}$  with its usual distance and the Lebesgue reference measure, it is possible to give an equivalent statement of this result without introducing explicitly the velocity field:

**Proposition 1.3.** *Let  $(f_t(x))$  be a family of smooth probability densities on  $\mathbb{R}$ . We define the families of functions*

$$g_t(x) := - \int_{-\infty}^x \frac{\partial}{\partial t} f_t(z) dz, \quad h_t(x) := - \int_{-\infty}^x \frac{\partial}{\partial t} g_t(z) dz. \tag{1.12}$$

*We suppose that  $g_t > 0$  and that the following one-dimensional Benamou-Brenier condition holds:*

$$f_t(x)h_t(x) = g_t(x)^2. \tag{1.13}$$

*Then  $(f_t(x))$  is a  $W_p$ -geodesic for any  $p > 1$ .*

*Proof.* To prove Proposition 1.3, it suffices to realize that equation (1.13) easily implies equation (1.9): the condition  $g_t > 0$  implies that we also have  $f_t > 0$  and  $h_t > 0$ , we can thus introduce the velocity function  $v_t(x) := g_t(x)/f_t(x)$ , which is positive and smooth. The transport equation (1.8) is then satisfied, the divergence operator  $\nabla \cdot$  being here the derivative  $\partial/\partial x$ . Moreover, the Benamou-Brenier condition (1.13) is equivalent to the condition  $v_t(x) = h_t(x)/g_t(x)$ . We then write

$$\begin{aligned} \frac{\partial}{\partial t} \log(v_t(x)) &= \frac{1}{g_t(x)} \frac{\partial}{\partial t} g_t(x) - \frac{1}{f_t(x)} \frac{\partial}{\partial t} f_t(x) \\ &= -v_t(x) \left( \frac{1}{h_t(x)} \frac{\partial}{\partial x} h_t(x) - \frac{1}{g_t(x)} \frac{\partial}{\partial x} g_t(x) \right) \\ &= -v_t(x) \frac{\partial}{\partial x} \log(v_t(x)), \end{aligned}$$

which implies equation (1.9) as desired.  $\square$

Apart from regularity issues, which will not play an important role in a discrete framework, the main restriction made in the statement of Proposition 1.3 is the non-degeneracy condition  $g_t(z) > 0$ . It is quite easy to prove that such a condition implies that  $f_0$  is stochastically dominated by  $f_1$ . In the setting of graphs, we will introduce the notion of  $W_1$ -orientation (see Paragraph 2.2) in order to force the function  $g_t$  to stay positive.

The main purpose of this article is to study curves in the space of probability distributions on a graph which satisfy a discrete version of the Benamou-Brenier condition (1.13).

- The goal of Section 2 is to provide a generalization of equations (1.12) and (1.13) to this discrete setting. We will first show that these equations can be recovered in a particular form in the case of contraction of measures. Given a couple of probability measures  $f_0, f_1$  defined on  $G$ , we then endow  $G$  with an orientation which will allow us to give a general definition of  $W_{1,+}$ -geodesics on  $G$ . The terminology " $W_{1,+}$ -geodesic" will be explained by considering a discrete version of problem (1.7) when  $p > 1$  is close to 1.
- In Section 3, we are looking for necessary conditions satisfied by  $W_{1,+}$ -geodesics on  $G$ . In particular, we will prove in Theorem 3.19 that if  $f_0$  and  $f_1$  are finitely supported, then any  $W_{1,+}$ -geodesic  $(f_t)$  can be written as a mixture of binomial measures supported on geodesics of  $G$ .
- In Section 4 we prove the existence of  $W_{1,+}$ -geodesics  $(f_t)$  with prescribed initial and final measures  $f_0$  and  $f_1$ . The construction of such curves suggests strong links with the "Entropic Interpolations" studied in a recent series of papers by Léonard.

## 2 The discrete Benamou-Brenier condition

In this paper, we consider a locally finite and connected graph  $G$ . A path  $\gamma$  on  $G$  of length  $n = L(\gamma)$  is a collection of vertices  $\gamma_0, \dots, \gamma_n \in G$  such that  $\gamma_i \sim \gamma_{i+1}$  for every  $i = 0, \dots, n-1$ , where the relation  $x \sim y$  means that  $(xy)$  is in the edge set of the graph  $G$ . To any path  $\gamma : \{0, \dots, n\} \rightarrow G$  are associated its endpoints  $e_0(\gamma) := \gamma(0)$  and  $e_1(\gamma) := \gamma(n)$ .

We will use the usual graph distance on  $G$ :  $d(x, y)$  is the length of the shortest path joining  $x$  to  $y$ . The set of geodesics joining  $x$  to  $y$ , denoted by  $\Gamma_{x,y}$ , is the set of paths  $\gamma$  joining  $x$  to  $y$  such that  $L(\gamma) = d(x, y)$ . The set of all geodesics on  $G$  is denoted by  $\Gamma(G)$ .

**Remark 2.1.** In this paper, the word ‘geodesic’ is used for two slightly different, although closely related, objects. If  $(X, d)$  is a geodesic space, a geodesic is a continuous curve  $\gamma : [0, 1] \rightarrow (X, d)$  of minimal length. In the setting of a graph  $G$ , a geodesic is a sequence  $\gamma : \{0, \dots, n\} \rightarrow G$  which is also length-minimizing in the sense that  $d(\gamma(0), \gamma(n)) = n$ . As there is no continuous curve  $\gamma : [0, 1] \rightarrow G$ , there is no ambiguity.

A coupling  $\pi \in \Pi(f_0, f_1)$  is said to be a  $W_p$ -optimal coupling for some  $p \geq 1$  if it is a minimizer for the functional

$$I_p : \pi \rightarrow \sum_{x,y \in G \times G} d(x,y)^p \pi(x,y). \tag{2.1}$$

We denote by  $\Pi_p(f_0, f_1)$  the set of  $W_p$ -optimal couplings.

**Remark 2.2.** The equality  $I_p(\alpha\pi_1 + (1 - \alpha)\pi_2) = \alpha I_p(\pi_1) + (1 - \alpha)I_p(\pi_2)$  proves that the set  $\Pi_p(f_0, f_1)$  is a convex subset of  $\Pi(f_0, f_1)$ .

**2.1 Contraction of measures and the Benamou-Brenier equation**

Among early attempts to generalize particular Wasserstein geodesics to the discrete case, one important example is given by the thinning operation:

**Definition 2.3.** Let  $f$  be a probability distribution finitely supported on  $\mathbb{Z}_+$ . The thinning of  $f$  is the family  $(T_t f)$  of probability distributions defined by

$$T_t f(k) := \sum_{l \geq 0} \text{bin}_{l,t}(k) f(l) = \sum_{l \geq 0} \binom{l}{k} t^k (1 - t)^{l-k} f(l), \tag{2.2}$$

where by convention  $\binom{l}{k} = 0$  if  $l < 0$  or if  $k \notin \{0, \dots, l\}$ .

In particular,  $(T_t f)$  is an interpolation between the Dirac measure  $T_0 f(k) = \delta(k = 0)$  and  $T_1 f = f$ . The operation  $f \mapsto T_t f$  is often seen as a discrete version of the operation

$$f(x) \mapsto f_t(x) := \frac{1}{t} f\left(\frac{x}{t}\right), \tag{2.3}$$

and is for instance used to state a weak law of small numbers (see [HJK10]) about the limit in distribution of  $T_{1/n} f^{*n}$  when  $n \rightarrow \infty$ .

We know that, given a smooth probability density  $f$  on  $\mathbb{R}$ , the family  $(f_t)$  defined by equation (2.3) is a  $W_p$ -geodesic for any  $p \geq 1$ . According to Sturm-Lott-Villani theory, the metric space  $(\mathbb{R}, |\cdot|)$  satisfies the condition  $CD(0, \infty)$ , so the entropy  $H(t)$  of  $f_t$  with respect to the Lebesgue measure is a convex function of  $t$ . On the other hand, a theorem by Johnson and Yu (see [YJ09]) asserts that the entropy of the thinning  $T_t f$  is also a convex function of  $t$ . The proof of this fact given in [Hil14] relies on the following:

**Proposition 2.4.** Let  $(f_t) := (T_t f)$  be the thinning family associated to a probability distribution  $f := f_1$  supported on  $\mathbb{Z}_+$ . We define the families of functions  $(g_t)$  and  $(h_t)$  by

$$g_t(k) := - \sum_{l \leq k} \frac{\partial}{\partial t} f_t(k), \quad h_t(k) := - \sum_{l \leq k} \frac{\partial}{\partial t} g_t(k). \tag{2.4}$$

The triple  $f_t, g_t, h_t$  then satisfies the discrete Benamou-Brenier equation:

$$\forall k \in \mathbb{Z}, \quad f_t(k) h_t(k - 1) = g_t(k) g_t(k - 1). \tag{2.5}$$

Moreover,  $g_t(k) \geq 0$ , and if  $g_t(k) = 0$  then either  $f_t(k + 1) = 0$  or  $h_t(k) = 0$ .

**Remark 2.5.** Denoting by  $\nabla_1$  (resp.  $\nabla_2$ ) the left derivative operator (resp. the left second derivative operator) defined by  $\nabla_1 u(k) := u(k) - u(k - 1)$  (resp.  $\nabla_2 u(k) = u(k) - 2u(k - 1) + u(k - 2)$ ), we thus have

$$\frac{\partial f_t(k)}{\partial t} = -\nabla_1 g_t(k), \quad \frac{\partial^2 f_t(k)}{\partial t^2} = \nabla_2 h_t(k).$$

The proof of the convexity of the entropy along thinning families relies so importantly on Proposition 2.4 that this proof can be used *verbatim* to prove a stronger statement:

**Proposition 2.6.** Let  $(f_t)$  be a family of finitely supported probability distributions on  $\mathbb{Z}$ . We suppose that the families of functions  $(g_t)$  and  $(h_t)$ , defined by equation (2.4), satisfy the discrete Benamou-Brenier equation (2.5) and the non-negativity condition  $g_t(k) \geq 0$ . Then the entropy  $H(t)$  of  $f_t$  is a convex function of  $t$ .

Because the similarities with equation (1.13), it seems legitimate to consider a family of measures satisfying equation (2.5) and the non-negativity condition  $g_t(k) \geq 0$  as a pseudo  $W_p$ -geodesic, for  $p > 1$ , along which the entropy functional is convex, which is reminiscent of Sturm-Lott-Villani theory.

The notion of thinning has been extended in [Hil14] to the setting of general graphs in the following way: we consider a probability distribution  $f_1$  defined on  $G$  and another probability measure  $f_0$  which is a Dirac mass at a given point  $o \in G$ . In this case, an interpolating curve  $(f_t)_{t \in [0,1]}$ , called contraction of  $f_1$  on  $o$ , is defined as a mixture of binomial distributions by

$$f_t := \sum_{z \in G} \frac{1}{|\Gamma_{o,z}|} \sum_{\gamma \in \Gamma(o,z)} \text{bin}_{\gamma,t}, \tag{2.6}$$

where the binomial distribution on  $\gamma$  is related to the classical binomial distribution by

$$\forall p \in \{0, \dots, L(\gamma)\}, \text{bin}_{\gamma,t}(\gamma(p)) := \text{bin}_{L(\gamma),t}(p) \tag{2.7}$$

and where  $|\Gamma_{o,z}|$  denotes the cardinality of the set  $\Gamma_{o,z}$  of geodesics joining  $o$  to  $z$ .

There is a canonical way to associate to each vertex  $o \in G$  an orientation on  $G$ :

**Definition 2.7.** Let us fix a vertex  $o \in G$ .

- We define a partial order on the set of vertices of  $G$  by writing  $x_1 \leq x_2$  if the vertex  $x_1$  belongs to a geodesic  $\gamma \in \Gamma_{o,x_2}$ .
- If  $x_1 \sim x_2$  and  $x_1 \leq x_2$ , we say that  $(x_1, x_2)$  is an oriented edge and we write  $(x_1 x_2)$  or  $x_1 \rightarrow x_2$ . We denote by  $(G, \rightarrow)$  the graph  $G$  endowed with this orientation.
- Given a vertex  $x_1 \in G$ , we define the (possibly empty) sets of vertices  $\mathcal{E}(x_1), \mathcal{F}(x_1)$  by

$$\mathcal{E}(x_1) := \{x_0 \in G : x_0 \rightarrow x_1\}, \quad \mathcal{F}(x_1) := \{x_2 \in G : x_1 \rightarrow x_2\}.$$

**Remark 2.8.** If  $x, y \in G$  are two vertices such that  $d(o, x) = d(o, y)$  and  $x \sim y$  then the edge  $(x, y) \in E(G)$  is not oriented. To be more rigorous, in the definition of  $(G, \rightarrow)$  one should discard such non-oriented edges.

To the oriented graph  $(G, \rightarrow)$  are associated two other oriented graphs:

**Definition 2.9.** The oriented edge graph  $(E(G), \rightarrow)$  is the graph of oriented couples  $x_1 \rightarrow x_2 \in G$ , oriented itself by the relation  $(x_1 x_2) \rightarrow (x_2 x_3)$ . In particular, for any  $(x_1 x_2) \in (E(G), \rightarrow)$  we have

$$\mathcal{E}((x_1 x_2)) = \{(x_0 x_1) : x_0 \in \mathcal{E}(x_1)\}, \quad \mathcal{F}((x_1 x_2)) = \{(x_2 x_3) : x_3 \in \mathcal{F}(x_2)\}.$$

Similarly, we define the graph of oriented triples  $(T(G), \rightarrow) := (E(E(G)), \rightarrow)$ , having as vertices the triples  $(x_1 x_2 x_3)$  with  $x_1 \rightarrow x_2 \rightarrow x_3$  and edges between each couple  $(x_0 x_1 x_2)$  and  $(x_1 x_2 x_3)$ .

**Remark 2.10.** The graph  $G$  being now oriented, the notation  $E(G)$  and  $T(G)$  stand for  $(E(G), \rightarrow)$  and  $(T(G), \rightarrow)$ , which is a slight abuse of notation. For instance,  $(xy) \in E(G)$  imply that  $x \rightarrow y$ . This remark will still be valid once introduced the  $W_1$ -orientation on  $G$ .

Orienting the graph  $G$  allows us to define a divergence operator:

**Definition 2.11.** The divergence of a function  $g : E(G) \rightarrow \mathbb{R}$  is the function  $\nabla \cdot g : G \rightarrow \mathbb{R}$  defined by

$$\forall x_1 \in G, \nabla \cdot g(x_1) := \sum_{x_2 \in \mathcal{F}(x_1)} g(x_1x_2) - \sum_{x_0 \in \mathcal{E}(x_1)} g(x_0x_1).$$

Similarly, the divergence of a function  $h : T(G) \rightarrow \mathbb{R}$  is the function  $\nabla \cdot h : E(G) \rightarrow \mathbb{R}$  defined by

$$\nabla \cdot h(x_1x_2) := \sum_{x_3 \in \mathcal{F}(x_2)} h(x_1x_2x_3) - \sum_{x_0 \in \mathcal{E}(x_1)} h(x_0x_1x_2).$$

We use this orientation to express the function  $f_t$  as a product of two functions satisfying interesting differential equations:

**Proposition 2.12.** There exists a couple  $(P_t), (Q_t)$  of families of non-negative functions on  $G$  such that:

1. We have  $f_t(x) = P_t(x)Q_t(x)$ .
2. The functions  $P$  and  $Q$  satisfy the equations

$$\frac{\partial}{\partial t} P_t(x_1) = \sum_{x_0 \in \mathcal{E}(x_1)} P_t(x_0), \quad \frac{\partial}{\partial t} Q_t(x_1) = - \sum_{x_2 \in \mathcal{F}(x_1)} Q_t(x_2). \quad (2.8)$$

This proposition is proven in [Hil14]. We can now use Definition 2.11 and Proposition 2.12 to state a generalized version of Proposition 2.4:

**Proposition 2.13.** We define the families of functions  $(g_t)$  and  $(h_t)$ , defined respectively on  $E(G)$  and  $T(G)$ , by

$$g_t(x_1x_2) := P_t(x_1)Q_t(x_2), \quad h_t(x_0x_1x_2) := P_t(x_0)Q_t(x_2). \quad (2.9)$$

1. The functions  $f, g$  and  $h$  satisfy the differential equations

$$\frac{\partial}{\partial t} f_t(x_1) = -\nabla \cdot g_t(x_1), \quad \frac{\partial}{\partial t} g_t(x_1x_2) = -\nabla \cdot h_t(x_1x_2). \quad (2.10)$$

2. For every oriented triple  $(x_0x_1x_2) \in T(G)$  we have

$$h_t(x_0x_1x_2)f_t(x_1) = g_t(x_0x_1)g_t(x_1x_2). \quad (2.11)$$

**Remark 2.14.** As in the thinning case, Proposition 2.13, and in particular equation (2.11) are used to study the convexity properties of the entropy functional along contraction families on graphs (see [Hil14, Section 5]).

### 2.2 The $W_1$ -orientation

It is not possible to use directly Proposition 2.13 to propose a general Benamou-Brenier condition because such a definition relies on an orientation of the graph  $G$  which has been constructed by using the fact that  $f_0$  is Dirac. As a first necessary step in the construction of general  $W_{1,+}$ -geodesics, we thus need to find a nice orientation on  $G$ , depending on the initial and final measures  $f_0$  and  $f_1$ .

The term "nice orientation" is vague, but the study of the thinning and of the contraction families suggests that, in order to have interesting consequences on the convexity of the entropy, we should at least require that  $g_t(x_1x_2) \geq 0$  for every  $x_1 \rightarrow x_2 \in E(G)$ . As we will see at the end of this paragraph, this requirement can be interpreted in the framework of optimal transportation theory.

We first recall some properties of supports of  $W_1$ -optimal couplings:

**Definition 2.15.** Given a couple  $f_0, f_1$  of finitely supported measures, we associate the set

$$\mathcal{C}(f_0, f_1) := \{(x, y) \in G \times G : \exists \pi \in \Pi_1(f_0, f_1), \pi(x, y) > 0\}. \tag{2.12}$$

Equivalently,  $\mathcal{C}(f_0, f_1)$  is the smallest subset of  $G \times G$  containing the supports of all the  $W_1$ -optimal couplings between  $f_0$  and  $f_1$ .

**Proposition 2.16.** There exists  $\pi \in \Pi_1(f_0, f_1)$  such that  $\text{Supp}(\pi) = \mathcal{C}(f_0, f_1)$ .

*Proof.* For every  $(x, y) \in \mathcal{C}(f_0, f_1)$ , there exists a coupling  $\pi_{(x,y)} \in \Pi_1(f_0, f_1)$  satisfying  $\pi_{(x,y)}(x, y) > 0$ . As  $f_0$  and  $f_1$  are finitely supported, we can consider the barycenter

$$\pi := \frac{1}{|\mathcal{C}(f_0, f_1)|} \sum_{(x,y) \in \mathcal{C}(f_0, f_1)} \pi_{(x,y)}, \tag{2.13}$$

which by convexity is in  $\Pi_1(f_0, f_1)$  and which is clearly fully supported in  $\mathcal{C}(f_0, f_1)$ .  $\square$

A tool often used when studying the support of optimal couplings is the cyclic monotonicity property:

**Lemma 2.17.** If  $(x_0, y_0), \dots, (x_p, y_p)$  are in  $\mathcal{C}(f_0, f_1)$  then

$$\sum_{i=0}^p d(x_i, y_i) \leq d(x_0, y_p) + \sum_{i=0}^{p-1} d(x_{i+1}, y_i). \tag{2.14}$$

*Proof.* We consider a coupling  $\pi \in \Pi_1(f_0, f_1)$  as constructed in Proposition 2.16 and a number  $0 < a < \inf_i(\pi(x_i, y_i))$ . We introduce the function  $h$  on  $G \times G$  defined by  $h(x_0, y_p) := a$ ,  $h(x, y) := a$  if  $(x, y) = (x_{i+1}, y_i)$  for some  $i \in \{0, \dots, p-1\}$ ,  $h(x, y) := -a$  if  $(x, y) = (x_i, y_i)$  for some  $i \in \{0, \dots, p\}$ , and  $h(x, y) := 0$  elsewhere. Then  $\pi + h$  is a coupling in  $\Pi(f_0, f_1)$  and

$$I_1(\pi + h) - I_1(\pi) = a \left( d(x_0, y_p) + \sum_{i=0}^{p-1} d(x_{i+1}, y_i) - \sum_{i=0}^p d(x_i, y_i) \right), \tag{2.15}$$

but  $\pi \in \Pi_1(f_0, f_1)$  implies  $I_1(\pi + h) \geq I_1(\pi)$ , which shows equation (2.14).  $\square$

Lemma 2.17 is used to define unambiguously an orientation on some edges of  $G$ :

**Theorem 2.18.** *Let  $f_0, f_1$  be two fixed probability distributions on  $G$ , and  $\gamma^{(1)}, \gamma^{(2)}$  be two geodesics in  $G$  such that  $(e_0(\gamma^{(i)}), e_1(\gamma^{(i)})) \in \mathcal{C}(f_0, f_1)$  for  $i = 1, 2$ . Then for any  $(k_1, k_2)$  with  $k_i \leq L(\gamma^{(i)}) - 1$  we cannot have both identities  $\gamma^{(1)}(k_1) = \gamma^{(2)}(k_2 + 1)$  and  $\gamma^{(1)}(k_1 + 1) = \gamma^{(2)}(k_2)$ .*

*Proof.* We suppose that both identities  $\gamma^{(1)}(k_1) = \gamma^{(2)}(k_2 + 1)$  and  $\gamma^{(1)}(k_1 + 1) = \gamma^{(2)}(k_2)$  hold. By considering the path  $e_0(\gamma^{(1)}), \dots, \gamma^{(1)}(k_1), \gamma^{(2)}(k_2 + 2), \dots, e_1(\gamma^{(2)})$ , we see that

$$d(e_0(\gamma^{(1)}), e_1(\gamma^{(2)})) \leq k_1 + L(\gamma^{(2)}) - k_2 - 1.$$

Similarly we have

$$d(e_0(\gamma^{(2)}), e_1(\gamma^{(1)})) \leq k_2 + L(\gamma^{(1)}) - k_1 - 1.$$

Since  $L(\gamma^{(i)}) = d(x_i, y_i)$  for  $i = 1, 2$ , we have

$$d(x_1, y_1) + d(x_2, y_2) \geq d(x_1, y_2) + d(x_2, y_1) + 2, \tag{2.16}$$

which by Lemma 2.17 is a contradiction. □

**Definition 2.19.** *Let  $f_0, f_1$  be two finitely supported probability measures on  $G$ .*

- *The  $W_1$  orientation associated to  $f_0, f_1$  is defined by orienting the edge  $(x, y) \in E(G)$  by  $x \rightarrow y$  if there exists a geodesic  $\gamma$  on  $G$  such that*
  1.  $(e_0(\gamma), e_1(\gamma)) \in \mathcal{C}(f_0, f_1)$ .
  2.  $\gamma(k) = x, \gamma(k + 1) = y$  for some  $k \in \{0, \dots, L(\gamma) - 1\}$ .
- *An oriented path on the oriented graph  $(G, \rightarrow)$  is an application  $\gamma : \{0, \dots, L\} \rightarrow G$  such that  $\gamma(i) \rightarrow \gamma(i + 1)$  for  $i = 0, \dots, L - 1$ .*
- *We define a partial order relation on the vertices of  $G$  by writing  $x \leq y$  if there exists an oriented path joining  $x$  to  $y$ .*

**Remark 2.20.** *The process described in the first item of Definition 2.19 may not orient every edge  $(x, y) \in E(G)$ . For instance, if  $G = \mathbb{Z}/3\mathbb{Z}$  is the complete graph with three vertices,  $f_0 := \delta(0)$  is the Dirac measure at 0 and  $f_1$  is any probability distribution on  $G$ , then the edge  $(1, 2)$  is not oriented for the  $W_1$ -orientation associated to  $(f_0, f_1)$ . This issue has already been encountered in the thinning case, see Remark 2.8.*

*If such edges exist, it is convenient to consider the subgraph  $G' \subset G$ , which depends on  $(f_0, f_1)$ , such that the edge set  $E(G')$  is exactly the set of edges  $(x, y) \in E(G)$  which can be oriented and whose vertices are the vertices of  $G$  that are endpoints of at least one oriented edge in  $E(G')$ . By an abuse of notation, we will denote  $(G', E(G'))$  by  $(G, E(G))$ .*

An important property of the  $W_1$ -orientation is the following:

**Theorem 2.21.** *Every oriented path on  $(G, \rightarrow)$  is a geodesic.*

*Proof.* Let  $\gamma$  be an oriented path on  $(G, \rightarrow)$  of length  $n$ . To show that  $\gamma$  is a geodesic, it suffices to prove that  $d(\gamma(0), \gamma(n)) \geq n$ . By definition of the  $W_1$  orientation, for each  $i \in \{0, \dots, n - 1\}$  there exists a geodesic  $\gamma^{(i)}$  of length  $L_i \geq 1$  and  $k_i \in \{0, \dots, L_i - 1\}$  such that

- $(e_0(\gamma^{(i)}), e_1(\gamma^{(i)})) \in \mathcal{C}(f_0, f_1)$ ,
- $\gamma^{(i)}(k_i) = \gamma(i)$ ,
- $\gamma^{(i)}(k_i + 1) = \gamma(i + 1)$ .

By Lemma 2.17, setting  $x_i := e_0(\gamma^{(i)})$  and  $y_i := e_1(\gamma^{(i)})$ , we have

$$\sum_{i=0}^{n-1} d(x_i, y_i) \leq d(x_0, y_{n-1}) + \sum_{i=0}^{n-2} d(x_{i+1}, y_i). \tag{2.17}$$

But,  $\gamma^{(i)}$  being a geodesic of  $G$ , we have  $d(x_i, y_i) = d(e_0(\gamma^{(i)}), e_1(\gamma^{(i)})) = L_i$ . Furthermore, for  $i \in \{0, \dots, n-2\}$  we have

$$\begin{aligned} d(x_{i+1}, y_i) &\leq d(x_{i+1}, \gamma^{(i+1)}) + d(\gamma^{(i+1)}, y_i) \\ &= d(\gamma^{(i+1)}(0), \gamma^{(i+1)}(k_{i+1})) + d(\gamma^{(i)}(k_i + 1), \gamma^{(i)}(L_i)) \\ &= k_{i+1} + L_i - k_i - 1. \end{aligned}$$

We also have the estimation

$$\begin{aligned} d(x_0, y_{n-1}) &\leq d(x_0, \gamma(0)) + d(\gamma(0), \gamma(n)) + d(\gamma(n), y_{n-1}) \\ &= d(\gamma^{(0)}(0), \gamma^{(0)}(k_0)) + d(\gamma(0), \gamma(n)) \\ &\quad + d(\gamma^{(n-1)}(L_{n-1}), \gamma^{(n-1)}(k_{n-1} + 1)) \\ &= k_0 + L_{n-1} - k_{n-1} + 1 + d(\gamma(0), \gamma(n)). \end{aligned}$$

We finally have

$$\sum_{i=0}^{n-1} L_i \leq k_0 + L_{n-1} - k_{n-1} + 1 + d(\gamma(0), \gamma(n)) + \sum_{i=0}^{n-2} k_{i+1} + L_i - k_i - 1, \tag{2.18}$$

which gives  $0 \leq d(\gamma(0), \gamma(n)) - n$  and proves the theorem.  $\square$

The following shows that the  $W_1$ -orientation is in some sense stable by restriction:

**Proposition 2.22.** *Let  $(f_t)_{t \in [0,1]}$  be a  $W_1$ -geodesic on  $G$ . For  $0 \leq s \leq t \leq 1$ , let  $(x, y)$  in  $E(G)$  such that  $x \rightarrow y$  for the  $W_1$ -orientation with respect to  $f_s, f_t$ . Then  $x \rightarrow y$  for the  $W_1$ -orientation with respect to  $f_0, f_1$ .*

*Proof.* It suffices to show that, if  $\tilde{\pi} \in \Pi_1(f_s, f_t)$  and  $\tilde{\pi}(b, c) > 0$  then  $b \leq c$  for the partial order coming from the  $W_1$ -orientation associated to  $f_0, f_1$ .

The proof this fact is inspired by the ‘gluing lemma’ stated and explained in [LV09]: let  $\pi^{(1)} \in \Pi_1(f_0, f_s), \pi^{(2)} \in \Pi_1(f_s, f_t), \pi^{(3)} \in \Pi_1(f_t, f_1)$ . We consider the ‘gluing’  $\pi$  of these three couplings, defined by:

$$\pi(a, d) := \sum_{b,c \in G} \frac{\pi^{(1)}(a, b)\pi^{(2)}(b, c)\pi^{(3)}(c, d)}{f_s(b)f_t(c)},$$

where the quotient is zero when  $f_s(b) = 0$  or  $f_t(c) = 0$ . It is easily shown that  $\pi \in \Pi(f_0, f_1)$ . Moreover,

$$\begin{aligned} W_1(f_0, f_1) &\leq \sum_{a,d \in G} d(a, d)\pi(a, d) \\ &\leq \sum_{a,b,c,d \in G} (d(a, b) + d(b, c) + d(c, d))\pi(a, d) \\ &= \sum_{a,b,c,d \in G} (d(a, b) + d(b, c) + d(c, d)) \frac{\pi^{(1)}(a, b)\pi^{(2)}(b, c)\pi^{(3)}(c, d)}{f_s(b)f_t(c)} \\ &= \sum_{a,b \in G} d(a, b)\pi^{(1)}(a, b) + \sum_{b,c \in G} d(b, c)\pi^{(2)}(b, c) + \sum_{c,d \in G} d(c, d)\pi^{(3)}(c, d) \\ &= W_1(f_0, f_s) + W_1(f_s, f_t) + W_1(f_t, f_1) \\ &= W_1(f_0, f_1). \end{aligned}$$

This shows the  $W_1$ -optimality of  $\pi$  and the equality

$$d(a, d)\pi(a, d) = (d(a, b) + d(b, c) + d(c, d))\pi(a, d).$$

Theorem 2.21 shows that, whenever  $\pi(a, d) > 0$ , we have  $a \leq b \leq c \leq d$ . On the other hand, if  $\pi^{(2)}(b, c) > 0$  then there exists  $a \in \text{Supp}(f_0)$  and  $d \in \text{Supp}(f_1)$  with  $\pi^{(1)}(a, b) > 0$  and  $\pi^{(3)}(c, d) > 0$ , so  $\pi(a, b) = 0$  and so  $b \leq c$ .  $\square$

We now prove:

**Theorem 2.23.** *Let  $(f_t)$  be a smooth  $W_1$ -geodesic on  $G$ . We endow this graph with the  $W_1$ -orientation associated to  $f_0, f_1$ . There exists a family of functions  $(g_t) : E(G) \rightarrow \mathbb{R}$  such that*

- $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$ .
- $\forall(xy) \in E(G), g_t(xy) \geq 0$ .

Moreover, there exists a family  $(h_t) : T(G) \rightarrow \mathbb{R}$  such that

$$\forall(xy) \in E(G), \frac{\partial}{\partial t} g_t(xy) = -\nabla \cdot h_t(xy).$$

We first prove a general result implying the existence of a family  $(g_t)$  such that  $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$ :

**Lemma 2.24.** *Let  $(G, \rightarrow)$  be an oriented graph and  $u : G \rightarrow \mathbb{R}$  finitely supported such that  $\sum_{x \in G} u(x) = 0$ . Then there exists  $g : E(G) \rightarrow \mathbb{R}$  with  $\nabla \cdot g = u$ .*

*Proof.* We consider two scalar products, for functions respectively defined on  $G$  and  $E(G)$ , defined by

$$\langle u, v \rangle_G := \sum_{x \in G} u(x)v(x), \quad \langle a, b \rangle_E := \sum_{x \rightarrow y} a(xy)b(xy).$$

The adjoint of the divergence operator  $\nabla \cdot$  is  $-\partial$ , where  $\partial$  is the linear operator defined by  $(\partial u)(xy) := u(y) - u(x)$ , in the sense that

$$\langle \nabla \cdot a, u \rangle_G = \langle a, \partial u \rangle_E \tag{2.19}$$

for any couple  $u, a$  of functions respectively defined on  $G$  and  $E(G)$ . The kernel of  $\partial$  is the one-dimensional space generated by the constant function  $v = 1$ . The condition  $\sum_{x \in G} u(x) = 0$  is thus equivalent to  $\langle u, v \rangle_G = 0$  or  $u \in (\ker(\partial))^{\perp_G}$ . We thus want to prove that  $(\ker(\partial))^{\perp_G} \subset \text{range}(\nabla \cdot)$ . As the linear spaces we are considering are finite-dimensional, this inclusion is equivalent to  $(\text{range}(\nabla \cdot))^{\perp_G} \subset \ker(\partial)$ . Let  $u \in (\text{range}(\nabla \cdot))^{\perp_G}$ . Then for any  $b : E(G) \rightarrow \mathbb{R}$  we have  $\langle \nabla \cdot b, u \rangle_G = 0$ , so  $\langle b, \partial u \rangle_E = 0$ , which proves that  $u \in \ker(\partial)$ .  $\square$

As we have  $\frac{\partial}{\partial t} f_t(x) = 0$ , Lemma 2.24 gives the existence of a family  $(g_t)$  with  $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$ . However, this result does not provide an explicit construction of  $g$  and in general nothing can be said about its sign.

*Proof of Theorem 2.23.* Let  $G'$  be a spanning tree of  $G$ , i.e. a tree having the same vertices as  $G$ , but with possibly fewer edges. We endow  $G'$  with the restriction of the orientation on  $G$ . According to Lemma 2.24, there exists a family of functions  $(g_t) : E(G') \rightarrow \mathbb{R}_+$  satisfying  $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$ . As  $G'$  is a tree, we know that removing an edge  $(x_0 y_0)$  from the graph  $G'$  will cut it into two disjoint subgraphs  $G'_1 := G'_1(x_0 y_0)$

and  $G'_2 := G'_2(x_0y_0)$ . Let  $u_{(x_0y_0)}$  be the indicator function of  $G'_1$ . This function satisfies  $(\partial u_{(x_0y_0)})(xy) = -1$  if  $(xy) = (x_0y_0)$  and  $(\partial u_{(x_0y_0)})(xy) = 0$  otherwise, which implies:

$$\begin{aligned} g_t(x_0y_0) &= - \sum_{(xy) \in (E(G'), \rightarrow)} g_t(xy) (\partial u_{(x_0y_0)})(xy) \\ &= - \langle g_t, \partial u_{(x_0y_0)} \rangle_E = \langle \nabla \cdot g_t, u_{(x_0y_0)} \rangle_G \\ &= - \langle \frac{\partial}{\partial t} f_t, u_{(x_0y_0)} \rangle = - \sum_{z \in G'_1} \frac{\partial}{\partial t} f_t(z) \end{aligned}$$

We want to prove that  $g_t(x_0y_0) \geq 0$ . Actually we will prove that the function  $t \mapsto \sum_{z \in G'_1} f_t(z)$  is strictly decreasing, so we have  $g_t(x_0y_0) > 0$ . For  $0 \leq s \leq t \leq 1$ , let  $\pi \in \Pi_1(f_s, f_t)$ . We have

$$\sum_{z \in G'_1} f_s(z) = \sum_{x \leq y \in G : x \in G'_1} \pi(x, y), \quad \sum_{z \in G'_1} f_t(z) = \sum_{x \leq y \in G : y \in G'_1} \pi(x, y)$$

By Proposition 2.22, we know that if  $\pi(x, y) > 0$  then  $x \leq y$ . In particular, we cannot have  $x \in G'_2$  and  $y \in G'_1$ . Equivalently, if  $x \leq y$ ,  $\pi(x, y) > 0$  and  $y \in G_1$  then  $x \in G_1$ . Consequently, we have:

$$\sum_{z \in G'_1} f_s(z) - \sum_{z \in G'_1} f_t(z) = - \sum_{x \leq y \in G : x \in G'_1, y \in G'_2} \pi(x, y) \leq 0. \tag{2.20}$$

Furthermore, as  $(x_0y_0)$  is an oriented edge, we know by the definition of the  $W_1$  orientation that there exists  $(x, y) \in \mathcal{C}(f_0, f_1)$  such that  $x \leq x_0 \leq y_0 \leq y$ . In particular,  $x \in G'_1$ ,  $y \in G'_2$  and  $\pi(x, y) > 0$ . This proves that the inequality (2.20) is actually strict, which shows the positivity of the family of functions  $(g_t)$  on  $E(G')$ . The first point of Theorem 2.23 is proven by extending  $g_t$  to  $E(G)$ , setting  $g_t(xy) := 0$  if  $(xy) \notin E(G')$ .

The existence of a family of functions  $(h_t)$  such that  $\frac{\partial}{\partial t} g_t = -\nabla \cdot h_t$  is proven by Lemma 2.24. We only need to check that  $\sum_{(xy) \in E(G)} \frac{\partial}{\partial t} g_t(xy) = 0$ . We are actually going to prove the stronger statement:

$$\sum_{(xy) \in (E(G), \rightarrow)} g_t(xy) = W_1(f_0, f_1).$$

To prove this fact, we consider the function  $u := \sum_{(x_0y_0) \in E(G')} u_{(x_0y_0)}$ . The function  $u$  satisfies  $(\partial u)(xy) = 1$  for every  $x \rightarrow y \in E(G')$ . We then have:

$$\begin{aligned} \int_0^t \sum_{(xy) \in (E(G), \rightarrow)} g_s(xy) ds &= \int_0^t \sum_{(xy) \in (E(G), \rightarrow)} g_s(xy) (\partial u)(x, y) ds \\ &= - \int_0^t \sum_{x \in G} (\nabla \cdot g_s)(x) u(x) dt \\ &= \int_0^t \sum_{x \in G} \frac{\partial}{\partial s} f_s(x) u(x) ds \\ &= \sum_{y \in G} f_t(y) u(y) - \sum_{x \in G} f_0(x) u(x). \end{aligned}$$

Let  $\pi \in \Pi_1(f_0, f_t)$ . We know by Proposition 2.22 that if  $\pi(x, y) > 0$  then  $x \leq y$ . On the other hand, if  $x \leq y$  then there exists a path  $x = \gamma_0 \rightarrow \dots \rightarrow \gamma_n = y$  and we have  $u(y) - u(x) = (u(\gamma_n) - u(\gamma_{n-1})) + \dots + (u(\gamma_1) - u(\gamma_0)) = n = d(x, y)$ , so we have

$$\int_0^t \sum_{(xy) \in (E(G), \rightarrow)} g_s(xy) ds = \sum_{x \leq y} \pi(x, y) d(x, y) = W_1(f_0, f_t) = tW_1(f_0, f_1).$$

Differentiating with respect to  $t$  shows that the sum  $\sum_{(xy) \in E(G)} g_t(xy)$  is constant and equal to  $W_1(f_0, f_1)$ . To finish the proof of the theorem, we extend  $(h_t)$  to  $T(G)$  by defining  $h_t(x_0x_1x_2) := 0$  if  $(x_0x_1x_2) \notin T(G')$ .  $\square$

Actually, Theorem 2.23 can be strengthened in the following way:

**Proposition 2.25.** *In Theorem 2.23, we can replace the assertion  $\forall(xy) \in E(G)$ ,  $g_t(xy) \geq 0$  by  $\forall(xy) \in E(G)$ ,  $g_t(xy) > 0$ .*

*Proof.* The proof of Theorem 2.23 allowed us to construct, given a spanning tree  $G' \subset G$ , a family of functions  $(g_t^{G'})$  such that  $g_t^{G'}(xy) > 0$  when  $(xy) \in E(G')$  and  $g_t^{G'}(xy) = 0$  when  $(xy) \notin E(G')$ . But for each edge  $(x_0y_0) \in E(G)$  there exists a spanning tree  $G' \subset G$  with  $(x_0y_0) \in E(G')$ . We define a family  $(g_t) : E(G) \rightarrow \mathbb{R}$  as the barycenter

$$\forall(xy) \in E(G), g_t(xy) := \frac{1}{|\mathcal{T}|} \sum_{G' \in \mathcal{T}} g_t^{G'}(xy),$$

where  $\mathcal{T}$  is the (finite) set of spanning trees for  $G$ . Then  $g_t > 0$  and satisfies the conditions of Theorem 2.23. We finally construct a suitable family  $(h_t)$  by defining  $h_t := \frac{1}{|\mathcal{T}|} \sum_{G' \in \mathcal{T}} h_t^{G'}$ , where  $(h_t^{G'})$  is constructed from  $(g_t^{G'})$  as in the proof of Theorem 2.23.  $\square$

### 2.3 Definition of $W_{1,+}$ -geodesics

Having now constructed an orientation of  $G$  associated to each couple of finitely supported probability distributions  $f_0, f_1 \in \mathcal{P}_1(G)$ , we propose a definition of  $W_{1,+}$ -geodesics inspired by Proposition 2.13:

**Definition 2.26.** *Let  $G$  be a graph,  $W_1$ -oriented with respect to a couple of finitely supported probability measures  $f_0, f_1$ . A family  $(f_t)_{t \in [0,1]} \in \mathcal{P}(G)$  is said to be a  $W_{1,+}$ -geodesic if:*

1. *The curve  $(f_t)_{t \in [0,1]}$  is a  $W_1$ -geodesic.*
2. *There exists two families  $(g_t)$  and  $(h_t)$  defined respectively on  $E(G)$  and  $T(G)$  such that*

$$\frac{\partial}{\partial t} f_t = -\nabla \cdot g_t, \quad \frac{\partial}{\partial t} g_t = -\nabla \cdot h_t.$$

3. *For every  $(xy) \in E(G)$  we have  $g_t(xy) > 0$ .*
4. *The triple  $(f_t, g_t, h_t)$  satisfies the Benamou-Brenier equation*

$$\forall(x_0x_1x_2) \in T(G), f_t(x_1)h_t(x_0x_1x_2) = g_t(x_0x_1)g_t(x_1x_2). \tag{2.21}$$

**Remark 2.27.** *In the sequel, the assertion ‘let  $(f_t)$  be a  $W_{1,+}$ -geodesic’ means ‘let  $((f_t), (g_t), (h_t))$  be a triple of families of functions satisfying the conditions of Definition 2.26’. This is an abuse because nothing is known about the uniqueness of the families  $(g_t)$  and  $(h_t)$  associated to a  $W_{1,+}$ -geodesic.*

**Remark 2.28.** *We can check that any contraction of measure is also a  $W_{1,+}$ -geodesic: if  $f_0 = \delta_o$  is a Dirac measure, then the set  $\Pi_1(f_0, f_1)$  has only one element, and it is easy to prove that the  $W_1$ -orientation with respect to  $f_0, f_1$  coincide with the orientation used for contraction of measures. Proposition 2.13 shows that the other points of Definition 2.26 are satisfied by contraction families.*

It is possible to state (2.21) in terms of two different velocity fields:

**Proposition 2.29.** *Let  $(f_t)_{t \in [0,1]}$  be a  $W_{1,+}$ -geodesic on  $G$ . We define the velocity fields  $v_{+,t}$  and  $v_{-,t}$  by*

$$v_{+,t}(x_0x_1) := \frac{g_t(x_0x_1)}{f_t(x_0)}, \quad v_{-,t}(x_0x_1) := \frac{g_t(x_0x_1)}{f_t(x_1)} \tag{2.22}$$

and the velocity functions  $V_{+,t}$  and  $V_{-,t}$  by

$$V_{+,t}(x_1) := \sum_{x_2 \in \mathcal{F}(x_1)} v_{+,t}(x_1x_2), \quad V_{-,t}(x_1) := \sum_{x_0 \in \mathcal{E}(x_1)} v_{-,t}(x_0x_1). \tag{2.23}$$

The following differential equations then hold:

$$\frac{\partial}{\partial t} v_{+,t}(x_0x_1) = -v_{+,t}(x_0x_1) [V_{+,t}(x_1) - V_{+,t}(x_0)], \tag{2.24}$$

$$\frac{\partial}{\partial t} v_{-,t}(x_0x_1) = -v_{-,t}(x_0x_1) [V_{-,t}(x_1) - V_{-,t}(x_0)]. \tag{2.25}$$

*Proof.* We use the definitions of  $g_t$  and  $h_t$ , and then apply the Benamou-Brenier equation (2.21) to write:

$$\begin{aligned} \frac{\partial}{\partial t} v_{+,t}(x_0x_1) &= \frac{g_t(x_0x_1)}{f_t(x_0)^2} \left[ \sum_{\tilde{x}_1 \in \mathcal{F}(x_0)} g_t(x_0\tilde{x}_1) - \sum_{x_{-1} \in \mathcal{E}(x_0)} g_t(x_{-1}x_0) \right] \\ &\quad + \frac{1}{f_t(x_0)} \left[ - \sum_{x_2 \in \mathcal{F}(x_1)} \frac{g_t(x_0x_1)g_t(x_1x_2)}{f_t(x_1)} + \sum_{x_{-1} \in \mathcal{E}(x_0)} \frac{g_t(x_{-1}x_0)g_t(x_0x_1)}{f_t(x_0)} \right] \\ &= v_{+,t}(x_0x_1) \left[ \sum_{\tilde{x}_1 \in \mathcal{F}(x_0)} \frac{g_t(x_0\tilde{x}_1)}{f_t(x_0)} - \sum_{x_2 \in \mathcal{F}(x_1)} \frac{g_t(x_1x_2)}{f_t(x_1)} \right] \\ &= v_{+,t}(x_0x_1) [V_{+,t}(x_0) - V_{+,t}(x_1)]. \end{aligned}$$

The second formula is proven by similar methods. □

**Remark 2.30.** *Proposition 2.29 is reminiscent of the continuous case described in the introduction. In particular, equation (2.22) is similar to the transport equation (1.8) (see also the proof of Proposition 1.3) and equations (2.24) and (2.25) are similar to the formal optimality condition (1.9).*

We now give some heuristic arguments explaining the terminology ‘ $W_{1,+}$ -geodesic’. Let us consider the minimization problem described by equation (1.7) of Theorem 1.2, when the parameter  $p = 1 + \varepsilon$  is close to 1. We use the expansion  $a^{1+\varepsilon} = a \exp(\varepsilon \log(a)) = a + \varepsilon a \log(a) + O(\varepsilon^2)$ , valid for  $a > 0$ , to write

$$\int_M \int_0^1 |v_t(x)|^p d\mu_t(x) dt = \int_M \int_0^1 |v_t(x)| d\mu_t(x) dt + \varepsilon \int_M \int_0^1 |v_t(x)| \log(|v_t(x)|) d\mu_t(x) dt + O(\varepsilon^2).$$

The integral  $\int_M \int_0^1 |v_t(x)| d\mu_t(x) dt$  is exactly equation (1.7) for  $p = 1$ . We thus know, by Theorem 1.2 that the minimizers of this integral over the set of families  $(f_t)$  of probability measures with  $f_0, f_1$  prescribed and  $\frac{\partial}{\partial t} f_t(x) + \nabla \cdot (v_t(x) f_t(x)) = 0$  are exactly the  $W_1$ -geodesics joining  $f_0$  to  $f_1$ . This suggests the following:

**Definition 2.31.** *We say that a curve  $(f_t)$  of probability measures on a Riemannian manifold  $M$  is a  $W_{1,+}$ -geodesic on  $M$  if it is solution to the minimization problem*

$$\inf \int_M \int_0^1 |v_t(x)| \log(|v_t(x)|) d\mu_t(x) dt,$$

where the infimum is taken over the set of all  $W_1$ -geodesics between  $f_0$  and  $f_1$  and where the velocity field  $(v_t)$  is defined by the continuity equation

$$\frac{\partial}{\partial t} f_t(x) + \nabla \cdot (v_t(x) f_t(x)) = 0.$$

The formal optimality condition on  $(v_t)$  obtained by applying Euler-Lagrange equations is the same as for  $W_p$ -geodesics:

$$\frac{\partial}{\partial t} v_t(x) = -v_t(x) \nabla v_t(x).$$

The next proposition shows that  $W_{1,+}$ -geodesics on a graph can be related to a minimization problem similar to the continuous one described in Definition 2.31:

**Proposition 2.32.** *Let  $G$  be a  $W_1$ -orientated with respect to  $f_0, f_1$  finitely supported. We consider the problem*

$$\inf \mathcal{I}_+(f, g) := \inf \int_0^1 \sum_{x \rightarrow y} v_{+,t}(xy) \log(v_{+,t}(xy)) f_t(x), \tag{2.26}$$

where the infimum is taken over the set of  $W_1$ -geodesics  $(f_t)$  between  $f_0$  and  $f_1$  such that the velocity  $v_{+,t}(xy)$  is defined by equation (2.22) from a family of non negative  $(g_t)$  with  $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$ .

We suppose that there exists a  $W_{1,+}$ -geodesic  $(f_t)$  joining  $f_0$  to  $f_1$ . Then  $(f_t)$  is a critical point for  $\mathcal{I}_+$  in the following sense: if  $(u_t)$  is a family of functions defined on  $E(G)$  satisfying the boundary conditions  $u_0(xy) = u_1(xy) = 0$ , then

$$\mathcal{I}_+ \left( f + \eta \nabla \cdot u, g - \eta \frac{\partial u}{\partial t} \right) = \mathcal{I}_+(f, g) + O(\eta^2). \tag{2.27}$$

**Remark 2.33.** Recall that, given a  $W_1$ -geodesic  $(f_t)$ , the continuity equation  $\frac{\partial}{\partial t} f_t(x) = -\nabla \cdot g_t(x)$  may be solved by a family  $(g_t)$  which is not necessarily always positive. We restrict ourselves to the families of non-negative  $(g_t)$ , which always exist by Proposition 2.25, in order to write  $|v_{+,t}(xy)| = v_{+,t}(xy)$ .

*Proof of Proposition 2.32.* When  $\eta$  is small, we have the expansion

$$\begin{aligned} & \mathcal{I}_+ \left( f + \eta \nabla \cdot u, g - \eta \frac{\partial u}{\partial t} \right) - \mathcal{I}_+(f, g) \\ &= -\eta \int_0^1 \sum_{x \rightarrow y} \frac{\partial}{\partial t} u_t(x, y) (1 + \log(v_{+,t}(xy))) + (\nabla \cdot u_t)(x) v_t(xy) dt + O(\eta^2) \end{aligned}$$

On the other hand, we use the boundary conditions  $u_0 = u_1 = 0$  to write:

$$\begin{aligned} \int_0^1 \sum_{x \rightarrow y} \frac{\partial}{\partial t} u_t(x, y) (1 + \log(v_{+,t}(xy))) &= - \int_0^1 \sum_{x \rightarrow y} u_t(x, y) \frac{\partial}{\partial t} (1 + \log(v_{+,t}(xy))) dt \\ &= - \int_0^1 \sum_{x \rightarrow y} u_t(xy) \frac{1}{v_t(xy)} \frac{\partial}{\partial t} v_t(xy) dt \\ &= \int_0^1 \sum_{x \rightarrow y} u_t(xy) [V_{+,t}(y) - V_{+,t}(x)] dt \\ &= - \int_0^1 \sum_{x \in G} (\nabla \cdot u_t)(x) V_{+,t}(x) dt \\ &= \int_0^1 \sum_{x \rightarrow y} (\nabla \cdot u_t)(x) v_t(xy) dt, \end{aligned}$$

which proves that  $\mathcal{I}_+(f + \eta \nabla \cdot u, g - \eta \frac{\partial u}{\partial t}) = \mathcal{I}_+(f, g) + O(\eta^2)$ .  $\square$

**Remark 2.34.** Similarly, it can be proven that a  $W_{1,+}$ -geodesic is also critical for the functional

$$\inf \mathcal{I}_-(f, g) := \inf \int_0^1 \sum_{x \rightarrow y} v_{-,t}(xy) \log(v_{-,t}(xy)) f_t(x), \tag{2.28}$$

### 3 $W_{1,+}$ -geodesics as mixtures of binomial distributions

$W_{1,+}$ -geodesics have been constructed as generalizations of contraction families, which have been defined as mixture of binomial distributions. In this section, we fix a  $W_{1,+}$ -geodesic  $(f_t)$  on  $G$ , joining two finitely supported probability measures  $f_0, f_1 \in \mathcal{P}(G)$ . It will always be assumed that the graph  $G$  is  $W_1$ -oriented with respect to  $f_0, f_1$  and that every path is an oriented path, thus a geodesic, by Theorem 2.21.

The main purpose of this section is to prove Theorem 3.19:  $(f_t)$  can also be expressed as a mixture of binomial measures, with respect to a coupling  $\pi \in \Pi(f_0, f_1)$  solution to a certain minimization problem. The key ingredients to the proof of this theorem are the study of the behaviour of  $(f_t)$  along particular geodesics of  $G$ , called extremal and semi-extremal geodesics, and the construction of two sub-Markov kernels  $K, K^*$  on  $G$  associated to  $(f_t)$ .

#### 3.1 Extremal geodesics

Recall that we write  $x_2 \in \mathcal{F}(x_1)$  and  $x_1 \in \mathcal{E}(x_2)$  if  $x_1 \leq x_2$  and  $d(x_1, x_2) = 1$  or equivalently if  $(x_1 x_2)$  is an oriented edge of  $G$ . If  $\gamma$  is a geodesic of  $G$ , it will be sometimes convenient to use the notation  $\gamma_i := \gamma(i)$ .

**Definition 3.1.** Let  $\gamma$  be a geodesic on  $G$ .

- If  $L(\gamma) \geq 2$ , we associate to  $\gamma$  the function

$$C_\gamma(t) := \frac{g_t(\gamma_0 \gamma_1) \cdots g_t(\gamma_{n-1} \gamma_n)}{f_t(\gamma_1) \cdots f_t(\gamma_{n-1})}, \tag{3.1}$$

- If  $L(\gamma) = 1$ , we define  $C_\gamma(t) := g_t(\gamma_0 \gamma_1)$ .
- If  $L(\gamma) = 0$ , we define  $C_\gamma(t) := f_t(\gamma_0)$ .

**Proposition 3.2.** The function  $C_\gamma(t)$  satisfy

$$\frac{\partial}{\partial t} C_\gamma(t) = \sum_{x_0 \in \mathcal{E}(\gamma_0)} C_{x_0 \cup \gamma}(t) - \sum_{x_2 \in \mathcal{F}(\gamma_n)} C_{\gamma \cup x_2}(t), \tag{3.2}$$

where  $x_0 \cup \gamma$  (resp.  $\gamma \cup x_2$ ) is the geodesic  $x_0, \gamma_0, \dots, \gamma_n$  (resp.  $\gamma_0, \dots, \gamma_n, x_2$ ).

*Proof.* If  $L(\gamma) = 0$ , equation (3.2) is equivalent to  $\frac{\partial}{\partial t} f_t(\gamma_0) = -(\nabla \cdot g_t)(x_0)$ , which is true by the definition of  $(g_t)$ . If  $L(\gamma) \geq 1$ , we notice that

$$C_\gamma(t) = f_t(\gamma_0) v_{+,t}(\gamma_0 \gamma_1) \cdots v_{+,t}(\gamma_{n-1} \gamma_n). \tag{3.3}$$

Proposition 2.29 gives:

$$\begin{aligned} \frac{1}{C_\gamma(t)} \frac{\partial}{\partial t} C_\gamma(t) &= \frac{1}{f_t(\gamma_0)} \frac{\partial}{\partial t} f_t(\gamma_0) + \sum_{i=0}^{n-1} \frac{1}{v_{+,t}(\gamma_i \gamma_{i+1})} \frac{\partial}{\partial t} v_{+,t}(\gamma_i \gamma_{i+1}) \\ &= (-V_{+,t}(\gamma_0) + V_{-,t}(\gamma_0)) - \sum_{i=0}^{n-1} [V_{+,t}(\gamma_{i+1}) - V_{+,t}(\gamma_i)] \\ &= -V_{+,t}(\gamma_n) + V_{-,t}(\gamma_0) \\ &= - \sum_{x_2 \in \mathcal{F}(\gamma_n)} v_{+,t}(\gamma_n x_2) + \sum_{x_0 \in \mathcal{E}(\gamma_0)} v_{-,t}(x_0 \gamma). \end{aligned}$$

Multiplying by  $C_\gamma(t)$  and applying equation (3.3) leads to the result.  $\square$

Equation (3.2) takes a simpler form in the case where the set  $\mathcal{E}(e_0(\gamma))$  (or  $\mathcal{F}(e_1(\gamma))$ , or both) is empty. This motivates the following:

**Definition 3.3.** We define the particular subsets of vertices of  $G$ :

- The set of initial vertices  $\mathcal{A} \subset G$  contains every  $x_1 \in G$  such that  $\mathcal{E}(x_1)$  is empty.
- The set of final vertices  $\mathcal{B} \subset G$  contains every  $x_1 \in G$  such that  $\mathcal{F}(x_1)$  is empty.

We also define the particular subsets of geodesics of  $G$ :

- The set  $\text{E}\Gamma$  of extremal geodesics contains every  $\gamma \in \Gamma(G)$  with  $e_0(\gamma) \in \mathcal{A}$ ,  $e_1(\gamma) \in \mathcal{B}$ .
- The set  $\text{SE}\Gamma_{1,x}$  contains every  $\gamma \in \Gamma(G)$  with  $e_0(\gamma) \in \mathcal{A}$ ,  $e_1(\gamma) = x$ .
- The set  $\text{SE}\Gamma_{2,x}$  contains every  $\gamma \in \Gamma(G)$  with  $e_0(\gamma) = x$ ,  $e_1(\gamma) \in \mathcal{B}$ .

If  $e_0(\gamma) \in \mathcal{A}$  or  $e_1(\gamma) \in \mathcal{B}$ , the geodesic  $\gamma$  is said to be semi-extremal.

**Remark 3.4.** The sets  $\mathcal{A}$  and  $\mathcal{B}$  are both non empty. If we suppose for instance that  $\mathcal{B}$  is empty, then we can construct an infinite sequence  $(x_n)_{n \geq 0}$  in  $G$  such that  $x_{n+1} \in \mathcal{F}(x_n)$ . But,  $f_0$  and  $f_1$  being finitely supported and  $G$  being locally finite, the set of oriented edges of  $G$  is finite so  $x_p = x_q$  for a couple of indices  $q > p$ . This means that there exists a non-trivial oriented path  $\gamma$  joining  $x_p$  to itself, which is a contradiction because  $\gamma$  is a geodesic of  $G$  by Proposition 2.21.

An immediate corollary of Proposition 3.2 is the following:

**Proposition 3.5.** Let  $\gamma$  be a geodesic of  $G$ .

- If  $\gamma \in \text{E}\Gamma$ , then  $C_\gamma(t) = C_\gamma$  is a constant function of  $t$ .
- If  $\gamma \in \text{SE}\Gamma_{1,x}$  then  $C_\gamma(t)$  is polynomial in  $t$  and  $\deg(C_\gamma(t)) \leq \sup\{L(\tilde{\gamma}) : \tilde{\gamma} \in \text{SE}\Gamma_{2,x}\}$ .
- If  $\gamma \in \text{SE}\Gamma_{2,x}$  then  $C_\gamma(t)$  is polynomial in  $t$  and  $\deg(C_\gamma(t)) \leq \sup\{L(\tilde{\gamma}) : \tilde{\gamma} \in \text{SE}\Gamma_{1,x}\}$ .

*Proof.* If  $\gamma \in \text{E}\Gamma$ , then the sets  $\mathcal{E}(e_0(\gamma))$  and  $\mathcal{F}(e_1(\gamma))$  are empty, which by Proposition 3.2 shows that  $C_\gamma$  is a constant function of  $t$ . We prove the second point by induction on  $m = m(\gamma) := \sup\{L(\tilde{\gamma}) : \tilde{\gamma} \in \text{SE}\Gamma_{2,x}\}$ , which only depends on the endpoint  $e_1(\gamma) = x$ . If  $m = 0$  then  $\gamma \in \text{E}\Gamma$  and this case has been considered in the first point. We now fix a geodesic  $\gamma \in \text{SE}\Gamma_{1,x}$  such that  $m(\gamma) \geq 1$ . We apply Proposition 3.2 and use the fact that  $e_0(\gamma) \in \mathcal{A}$  to write:

$$\frac{\partial}{\partial t} C_\gamma(t) = - \sum_{x_2 \in \mathcal{F}(x)} C_{\gamma \cup x_2}(t). \tag{3.4}$$

it is easily shown that, for  $z \in \mathcal{F}(x)$ ,  $m(\gamma \cup \{z\}) = m(\gamma) - 1$ , which proves by induction on  $m$  that  $C_\gamma(t)$  is polynomial in  $t$  of degree less than  $m(\gamma)$ .  $\square$

### 3.2 Sub-Markov kernels associated to a $W_{1,+}$ -geodesic

The fact that the function  $C_\gamma(t)$  is constant and positive on extremal geodesics allows us to introduce a useful function on ordered subsets of  $G$ :

**Definition 3.6.** Given an ordered  $p$ -uple  $z_1 \leq z_2 \leq \dots \leq z_p$  of vertices of  $(G, \rightarrow)$ , we associate

$$m(z_1, \dots, z_p) = \sum_{\gamma \in E(z_1, \dots, z_p)} C_\gamma, \tag{3.5}$$

where  $E(z_1, \dots, z_p) \subset \text{E}\Gamma$  is defined by:

$$\gamma \in E(z_1, \dots, z_p) \iff \exists k_1 \leq \dots \leq k_p, \gamma(k_i) = z_i. \tag{3.6}$$

If  $\gamma$  is a geodesic of  $G$ , we denote by  $m(\gamma)$  the number  $m(e_0(\gamma(0)), \dots, e_1(\gamma))$ .

**Proposition 3.7.** For any family of vertices  $x_0 \leq \dots \leq x_m$  we have

$$m(x_0, \dots, x_m) = \frac{m(x_0, x_1) \cdots m(x_{m-1}, x_m)}{m(x_1) \cdots m(x_{m-1})}. \tag{3.7}$$

*Proof.* There is a natural bijection between the set  $E(x_0, \dots, x_m)$  and the product set

$$\text{SE}\Gamma_{1,x_0} \times \Gamma_{x_0,x_1} \times \cdots \times \Gamma_{x_{m-1},x_m} \times \text{SE}\Gamma_{2,x_m}.$$

Indeed, let  $\gamma \in E(x_0, \dots, x_m)$  be a geodesic of  $G$  of length  $n$  and  $0 \leq k_0 \leq \dots \leq k_m \leq n$  such that  $\gamma(k_i) = x_i$  for  $i = 0, \dots, m$ . The projection of  $\gamma$  onto  $\Gamma_{x_i,x_{i+1}}$  is given by the geodesic  $(\gamma(k_i), \dots, \gamma(k_{i+1}))$ . The inverse bijection is given by the concatenation map. We denote by  $\gamma \mapsto (p_0(\gamma) \times p_{0,1}(\gamma) \times \cdots \times p_{m-1,m}(\gamma) \times p_m(\gamma))$  this bijection. Moreover, given some  $\gamma \in E(x_0, \dots, x_m)$  of length  $n$  we have:

$$\begin{aligned} C_\gamma &= \frac{g_t(\gamma_0\gamma_1) \cdots g_t(\gamma_{n-1}\gamma_n)}{f_t(\gamma_1) \cdots f_t(\gamma_{n-1})} \\ &= \frac{g_t(\gamma_0\gamma_1) \cdots g_t(\gamma_{k_0-1}\gamma_{k_0})}{f_t(\gamma_1) \cdots f_t(\gamma_{k_0-1})} \frac{1}{f_t(\gamma_{k_0})} \frac{g_t(\gamma_{k_0}\gamma_{k_0+1}) \cdots g_t(\gamma_{k_1-1}\gamma_{k_1})}{f_t(\gamma_{k_0+1}) \cdots f_t(\gamma_{k_1-1})} \cdots \\ &\quad \cdots \frac{1}{f_t(\gamma_{k_m})} \frac{g_t(\gamma_{k_m}\gamma_{k_m+1}) \cdots g_t(\gamma_{n-1}\gamma_n)}{f_t(\gamma_{k_m+1}) \cdots f_t(\gamma_{n-1})} \\ &= \frac{C_{p_0(\gamma)}(t) C_{p_{0,1}(\gamma)}(t) \cdots C_{p_{m-1,m}(\gamma)}(t) C_{p_m(\gamma)}(t)}{f_t(x_0) \cdots f_t(x_m)}. \end{aligned}$$

We thus have:

$$\begin{aligned} m(x_0, \dots, x_m) &= \frac{\left(\sum_{\gamma^{(0)} \in \text{SE}\Gamma_{1,x_0}} C_{\gamma^{(0)}}(t)\right) \left(\sum_{\gamma^{(0,1)} \in \Gamma_{x_0,x_1}} C_{\gamma^{(0,1)}}(t)\right) \cdots \left(\sum_{\gamma^{(m)} \in \text{SE}\Gamma_{2,x_m}} C_{\gamma^{(m)}}(t)\right)}{f_t(x_0) \cdots f_t(x_m)} \\ &=: \frac{A_{1,x_0}(t) A_{x_0,x_1}(t) \cdots A_{x_{m-1},x_m}(t) A_{2,x_m}(t)}{f_t(x_0) \cdots f_t(x_m)}. \end{aligned}$$

With the same notations we have, for  $i = 0, \dots, m$ ,

$$m(x_i) = \frac{A(1, x_i) A(2, x_i)}{f_t(x_i)},$$

and for  $i = 0, \dots, m - 1$ ,

$$m(x_i, x_{i+1}) = \frac{A_{1,x_i}(t) A_{x_i,x_{i+1}}(t) A_{2,x_{i+1}}(t)}{f_t(x_i) f_t(x_{i+1})}.$$

Equation (3.7) then follows from a direct calculation. □

**Definition 3.8.** The sub-Markov kernels  $K$  and  $K^*$  associated to a  $W_{1,+}$ -geodesic  $(f_t)$  on  $G$  are defined by

$$\forall x_1 \in G, \forall x_0 \in \mathcal{E}(x_1), K(x_1, x_0) := \frac{m(x_1, x_0)}{m(x_1)}, \tag{3.8}$$

$$\forall x_0 \in G, \forall x_1 \in \mathcal{F}(x_0), K^*(x_0, x_1) := \frac{m(x_0, x_1)}{m(x_0)}. \tag{3.9}$$

If  $(x_0 x_1) \notin E(G, \rightarrow)$ , we set  $K(x_1, x_0) = K^*(x_0, x_1) = 0$ . We also define

$$Kf(x_1) := \sum_{x_0} K(x_1, x_0) f(x_0), \quad K^*f(x_0) := \sum_{x_1} K^*(x_0, x_1) f(x_1). \tag{3.10}$$

**Remark 3.9.** If  $x_1 \in \mathcal{A}$  is an initial vertex of  $G$ , then  $\mathcal{E}(x_1) = \emptyset$  and  $Kf(x_1)$ , defined as a sum over an empty set, is thus set to 0. Similarly, we set  $K^*f(x_0) = 0$  if  $x_0 \in \mathcal{B}$  is a final vertex of  $G$ .

**Proposition 3.10.** The kernels  $K$  and  $K^*$  satisfy the following:

- If  $x_1 \notin \mathcal{A}$  then  $\sum_{x_0 \in \mathcal{E}(x_1)} K(x_1, x_0) = 1$ .
- If  $x_0 \notin \mathcal{B}$  then  $\sum_{x_1 \in \mathcal{F}(x_0)} K^*(x_0, x_1) = 1$ .
- The operators  $K$  and  $K^*$  are adjoint for the scalar product  $\langle f, g \rangle := \sum_{x \in G} f(x)g(x)m(x)$ .
- The iterated kernel  $K^n$  is supported on the set of couples  $(x_0, x_n)$  such that  $x_n \in \mathcal{E}^n(x_0)$ , i.e. such that  $x_0 \leq x_n$  and  $d(x_n, x_0) = n$ . For such a couple we have

$$K^n(x_n, x_0) = \frac{m(x_n, x_0)}{m(x_n)}.$$

- Similarly, for  $x_n \in \mathcal{F}^n(x_0)$ , i.e. for  $x_n \leq x_0$  such that  $d(x_n, x_0) = n$  we have

$$(K^*)^n(x_0, x_n) = \frac{m(x_0, x_n)}{m(x_0)}.$$

- The operators  $K$  and  $K^*$  are nilpotent.

*Proof.* The first point comes from the fact that, if  $x_0 \notin \mathcal{B}$ , there exists a bijection between the set  $E(x_0)$  and the disjoint union  $\bigcup_{x_1 \in \mathcal{F}(x_0)} E(x_0, x_1)$ . The second point is proven similarly. The third point is proven by noticing that both scalar products  $\langle Kf, g \rangle$  and  $\langle f, K^*g \rangle$  are equal to

$$\sum_{x_0 \rightarrow x_1} m(x_0, x_1)f(x_0)g(x_1).$$

To prove the fourth point, we write the general formula for the iterated kernel for some  $n \geq 2$ :

$$\forall x_0, x_n \in G, K^n(x_n, x_0) := \sum_{x_{n-1}, \dots, x_1} K(x_n, x_{n-1}) \cdots K(x_1, x_0).$$

The product  $K(x_n, x_{n-1}) \cdots K(x_1, x_0)$  is non-zero if and only if  $x_0 \rightarrow \cdots \rightarrow x_n$ , i.e.  $(x_0, \dots, x_n)$  is a geodesic. This proves that  $K^n(x_n, x_0) > 0$  implies that  $x_0 \in \mathcal{E}^n(x_n)$ . Moreover we have:

$$K^n(x_n, x_0) = \sum_{\gamma \in \Gamma_{x_0, x_n}} \frac{m(x_n, \gamma_{n-1})}{m(x_n)} \cdots \frac{m(\gamma_1, x_0)}{m(\gamma_1)} = \frac{m(x_n, x_0)}{m(x_n)}$$

by Proposition 3.7. The fifth point is proven similarly. The nilpotency of  $K$  and  $K^*$  comes from the fact that  $(G, \rightarrow)$  has a finite diameter: if  $n > \text{Diam}(G)$  then  $K^n = 0$  and  $(K^*)^n = 0$ .  $\square$

**Remark 3.11.** The first point of Proposition 3.10 shows that  $K$  can easily be transformed into a Markov kernel: it suffices to add a vertex  $\omega$  (often called 'cemetery') to  $G$  and oriented edges  $\omega \rightarrow x$  for every  $x \in \mathcal{A}$ . The sub-Markov kernel  $K$  is extended into a Markov kernel on  $G \cup \omega$  by defining  $K(\omega, \omega) = 1$  and  $K(\omega, x) = 1$  for every  $x \in \mathcal{A}$ . The kernel  $K^*$  can be treated similarly, by considering the oriented edges  $(x, \omega)$  for  $x \in \mathcal{B}$ .

### 3.3 Polynomial structure of $W_{1,+}$ -geodesics

In this paragraph we use properties of the functions  $C_\gamma(t)$  and of the sub-Markovian kernels  $K, K^*$  to give expression of  $(f_t)$  as a mixture of binomial measures on geodesics  $G$ .

**Proposition 3.12.** *Let  $x \in G$  be a vertex and  $\gamma, \tilde{\gamma}$  be two geodesics on  $G$  with  $\gamma \in \text{SE}\Gamma_1(G, x)$  and  $\tilde{\gamma} \in \text{SE}\Gamma_2(G, x)$ . Then*

$$f_t(x) = \frac{C_\gamma(t)C_{\tilde{\gamma}}(t)}{C_{\gamma \cup \tilde{\gamma}}}, \tag{3.11}$$

where  $\gamma \cup \tilde{\gamma}$  is the concatenation of  $\gamma$  and  $\tilde{\gamma}$ .

**Remark 3.13.** *A first consequence of Propositions 3.5 and 3.12 is the fact that, for any  $x \in G$ ,  $f_t(x)$  is a polynomial function of  $t$  such that  $\deg(f_t(x)) \leq \text{Diam}(G)$ .*

We also use Proposition 3.12 to show the following:

**Proposition 3.14.** *For  $x \in G$ , we consider two semi-extremal curves  $\gamma^{(1)}, \gamma^{(2)} \in \text{SE}\Gamma_{1,x}(G)$ . The quotient  $\frac{C_{\gamma^{(1)}}(t)}{C_{\gamma^{(2)}}(t)}$  does not depend on  $t$  and is equal to  $\frac{m(\gamma^{(1)})}{m(\gamma^{(2)})}$ . Furthermore, we have*

$$C_{\gamma^{(1)}}(t) = \frac{m(\gamma^{(1)})}{m(x)} \sum_{\gamma \in \text{SE}\Gamma_{1,x}(G)} C_\gamma(t). \tag{3.12}$$

*Proof.* Let  $\tilde{\gamma}$  be in  $\text{SE}\Gamma_{2,x}(G)$ . Then Proposition (3.12) shows that

$$\frac{C_{\gamma^{(1)}}(t)}{C_{\gamma^{(2)}}(t)} = \frac{C(\gamma^{(1)} \cup \tilde{\gamma})}{C(\gamma^{(2)} \cup \tilde{\gamma})}.$$

We use the fact that this quotient does not depend on  $\tilde{\gamma}$  to write

$$\frac{C_{\gamma^{(1)}}(t)}{C_{\gamma^{(2)}}(t)} = \frac{\sum_{\tilde{\gamma} \in \text{SE}\Gamma_{2,x}(G)} C(\gamma^{(1)} \cup \tilde{\gamma})}{\sum_{\tilde{\gamma} \in \text{SE}\Gamma_{2,x}(G)} C(\gamma^{(2)} \cup \tilde{\gamma})} = \frac{m(\gamma^{(1)})}{m(\gamma^{(2)})}.$$

The second point is proven by writing

$$\sum_{\gamma \in \text{SE}\Gamma_{1,x}(G)} \frac{C_\gamma(t)}{C_{\gamma^{(1)}}(t)} = \sum_{\gamma \in \text{SE}\Gamma_{1,x}(G)} \frac{m(\gamma)}{m(\gamma^{(1)})} = \frac{m(x)}{m(\gamma^{(1)})}. \tag{3.13}$$

□

We now introduce two families of functions which play the same role as  $(u_t)_{t \in [0,1]}$  and  $(v_t)_{t \in [0,1]}$  in the case of contraction of measures:

**Definition 3.15.** *We define the functions  $P_t(x)$  and  $Q_t(x)$  by*

$$P_t(x) := \frac{1}{m(x)} \sum_{\gamma^{(2)} \in \text{SE}\Gamma_{2,x}} C_t(\gamma^{(2)}), \quad Q_t(x) := \frac{1}{m(x)} \sum_{\gamma^{(1)} \in \text{SE}\Gamma_{1,x}} C_t(\gamma^{(1)}), \tag{3.14}$$

if  $x \notin \mathcal{A}$  (resp.  $x \notin \mathcal{B}$ ), and by  $P_t(x) := f_t(x)$ , resp.  $Q_t(x) := f_t(x)$ , if  $x \in \mathcal{A}$  (resp.  $x \in \mathcal{B}$ ).

**Proposition 3.16.** *The functions  $f_t, g_t$  and  $h_t$  are related to  $P_t, Q_t$  and  $m$  by*

1.  $f_t(x_0) = m(x_0)P_t(x_0)Q_t(x_0)$ ,
2.  $g_t(x_0x_1) = m(x_0x_1)P_t(x_0)Q_t(x_1)$ ,

3.  $h_t(x_0x_1x_2) = m(x_0x_1x_2)P_t(x_0)Q_t(x_2)$ .

*Proof.* To prove the first point, we notice that the concatenation map  $\gamma^{(1)}, \gamma^{(2)} \mapsto \gamma^{(1)} \cup \gamma^{(2)}$  is a bijection between the sets  $SE\Gamma_{1,x_0} \times SE\Gamma_{2,x_0}$  and  $E(x_0)$ . We then use Proposition 3.12 to write:

$$\begin{aligned} \sum_{(\gamma^{(1)}, \gamma^{(2)}) \in SE\Gamma_{1,x_0} \times SE\Gamma_{2,x_0}} C_{\gamma^{(1)}}(t)C_{\gamma^{(2)}}(t) &= \sum_{\gamma \in E(x_0)} C_{\gamma}f_t(x_0) \\ &= f_t(x_0)m(x_0). \end{aligned}$$

To prove the second point, given of vertices  $x_0 \rightarrow x_1$  we consider the bijection between the sets  $SE\Gamma_{1,x_0} \times SE\Gamma_{2,x_1}$  and  $E(x_0, x_1)$  given by the concatenation  $\gamma^{(1)}, \gamma^{(2)} \rightarrow \gamma^{(1)} \cup \gamma^{(2)}$ . Moreover, if  $\gamma^{(1)} \in SE\Gamma_{1,x_0}$  and  $\gamma^{(2)} \in SE\Gamma_{2,x_1}$  have length  $L_1 \geq 2$  and  $L_2 \geq 2$  we have:

$$\begin{aligned} C_{\gamma^{(1)}}(t)C_{\gamma^{(2)}}(t) &= \frac{g(\gamma_0^{(1)}\gamma_1^{(1)}) \cdots g(\gamma_{L_1-1}^{(1)}x_0) g(x_1\gamma_1^{(2)}) \cdots g(\gamma_{L_2-1}^{(2)}\gamma_{L_2}^{(2)})}{f(\gamma_1^{(1)}) \cdots f(\gamma_{L_1-1}^{(1)}) f(\gamma_1^{(2)}) \cdots f(\gamma_{L_2-1}^{(2)})} \\ &= C_{\gamma^{(1)} \cup \gamma^{(2)}}(t) \frac{f_t(x_0)f_t(x_1)}{g_t(x_0x_1)}. \end{aligned}$$

Summing over all  $\gamma^{(1)}, \gamma^{(2)}$  gives

$$\frac{1}{m(x_0)}P_t(x_1) \frac{1}{m(x_1)}Q_t(x_0) = m(x_0, x_1) \frac{f_t(x_0)f_t(x_1)}{g_t(x_0x_1)}.$$

Replacing  $f_t(x_0)$  and  $f_t(x_1)$  by their expressions in terms of  $P_t, Q_t$  proves the second point. The third point is simply proven by using the Benamou-Brenier equation:

$$\begin{aligned} h_t(x_0x_1x_2) &= \frac{g_t(x_0x_1)g_t(x_1x_2)}{f_t(x_1)} = \frac{m(x_0, x_1)m(x_1, x_2)}{m(x_1)}P_t(x_0)Q_t(x_2) \\ &= m(x_0, x_1, x_2)P_t(x_0)Q_t(x_2). \end{aligned}$$

□

**Proposition 3.17.** *The functions  $P_t$  and  $Q_t$  satisfy the differential equations*

$$\frac{\partial}{\partial t}P_t(x) = KP_t(x), \quad \frac{\partial}{\partial t}Q_t(x) = -K^*Q_t(x). \tag{3.15}$$

**Proof:** When applied to semi-extremal geodesics, Proposition 3.2 takes a simpler form. More precisely, if  $\gamma^{(2)} \in SE\Gamma_{2,x_0}$ , we have

$$\frac{\partial}{\partial t}C_{\gamma^{(2)}}(t) = \sum_{x_{-1} \in \mathcal{E}(x_0)} C_{x_{-1} \cup \gamma^{(2)}}(t). \tag{3.16}$$

On the other hand, by Proposition 3.14, we have:

$$\begin{aligned} \sum_{\gamma^{(2)} \in SE\Gamma_{2,x_0}} C_t(x_{-1} \cup \gamma^{(2)}) &= \sum_{\gamma^{(2)} \in SE\Gamma_{2,x_0}} \frac{m(x_{-1} \cup \gamma^{(2)})}{m(x_{-1})} \sum_{\tilde{\gamma}_2 \in SE\Gamma_{2,x_{-1}}} C_{\tilde{\gamma}_2}(t) \\ &= \frac{m(x_{-1}, x_0)}{m(x_{-1})}P_t(x_{-1}). \end{aligned}$$

Summing this last equation over  $x_{-1} \in \mathcal{E}(x_0)$  gives the result. The differential equation for  $Q_t(x_0)$  is proven similarly. □

**Proposition 3.18.** *There exist two functions  $a, b : G \rightarrow \mathbb{R}$  such that*

$$P_t(z) = \frac{1}{m(z)} \sum_{x \leq z} m(x, z) a(x) \frac{t^{d(x,z)}}{d(x, z)!}, \quad Q_t(z) = \frac{1}{m(z)} \sum_{y \geq z} m(z, y) b(y) \frac{(1-t)^{d(z,y)}}{d(z, y)!}. \quad (3.17)$$

*Proof.* For  $x \in G$ , let  $a(x) := P_0(x)$  be the constant term of the polynomial  $t \mapsto P_t(x)$ . Using Proposition 3.17 and Proposition 3.10, we have

$$\begin{aligned} P_t(z) &= [\exp(tK)P_0](x) = [\exp(tK)a](z) \\ &= \sum_{l \geq 0} \frac{t^l}{l!} (K^l a)(z) \\ &= \sum_{l \geq 0} \sum_{x \in \mathcal{E}^l(z)} \frac{t^l}{l!} \frac{m(x, z)}{m(z)} a(x) \\ &= \frac{1}{m(z)} \sum_{x \leq z} m(x, z) a(x) \frac{t^{d(x,z)}}{d(x, z)!}. \end{aligned}$$

The proof of the second point is quite similar: define  $\tilde{Q}_t(z) := Q_{1-t}(z)$  and  $b(y) := \tilde{Q}_0(y) = Q_1(y)$ . As we have  $\frac{\partial \tilde{Q}_t(z)}{\partial t} = (K^* \tilde{Q}_t)(z)$ , we use again Proposition 3.10 to conclude.  $\square$

We are now ready to write the  $W_{1,+}$ -geodesic  $(f_t)$  as a mixture of binomial measures:

**Theorem 3.19.** *For any couple of vertices  $x \leq y \in G$  we define the binomial probability distribution  $\text{bin}_{(x,y),t}$  on  $G$ , associated to the application  $m$ , supported on the set of vertices  $z \in G$  such that  $x \leq z \leq y$ , by*

$$\text{bin}_{(x,y),t}(z) := \frac{m(x, z, y)}{m(x, y)} \frac{d(x, y)!}{d(x, z)! d(z, y)!} t^{d(x,z)} (1-t)^{d(z,y)}. \quad (3.18)$$

The  $W_{1,+}$ -geodesic  $(f_t)_{t \in [0,1]}$  is a mixture of such binomial measures:

$$f_t(\cdot) = \sum_{x \leq y} \frac{m(x, y)}{d(x, y)!} a(x) b(y) \text{bin}_{(x,y),t}(\cdot). \quad (3.19)$$

*Proof.* The theorem follows from the calculation:

$$\begin{aligned} f_t(z) &= m(z) P_t(z) Q_t(z) \\ &= \frac{1}{m(z)} \sum_{x, y: x \leq z \leq y} m(x, z) a(x) \frac{t^{d(x,z)}}{d(x, z)!} m(z, y) b(y) \frac{(1-t)^{d(z,y)}}{d(z, y)!} \\ &= \sum_{x, y: x \leq z \leq y} \frac{m(x, z) m(z, y)}{m(z)} \frac{m(x, y)}{d(x, y)!} a(x) b(y) \text{bin}_{(x,y),t}(z), \end{aligned}$$

and from the fact that  $\frac{m(x,z)m(z,y)}{m(z)} = m(x, z, y)$  (by Proposition 3.7).  $\square$

## 4 Existence of $W_{1,+}$ -geodesics

In the previous section, we showed that any  $W_{1,+}$ -geodesic  $(f_t)$  can be expressed a mixture of binomial distributions with respect to a certain coupling between  $f_0$  and  $f_1$ . We now turn to the question of the existence of a  $W_{1,+}$ -geodesic  $(f_t)$  joining two fixed probability distributions  $f_0, f_1$ . Through this section, we fix such a couple of initial and final measures and endow the underlying graph  $G$  with the  $W_1$ -orientation associated to  $f_0, f_1$ .

**Definition 4.1.** Let  $m : E(G) \rightarrow \mathbb{R}_+^*$  be satisfying  $\nabla \cdot m(x) = 0$  for every  $x \notin \mathcal{A}, \mathcal{B}$ . Let  $p \geq 0$  be an integer. We extend  $m$  as a function on ordered families in  $(G, \rightarrow)$  by defining:

- If  $p = 0$ ,  $m(x) := \sum_{y \in \mathcal{F}(x)} m(x, y)$ .
- If  $p \geq 2$  and  $\gamma : \{0, \dots, p\} \rightarrow (G, \rightarrow)$  is a geodesic, then

$$m(\gamma) := m(\gamma_0, \dots, \gamma_p) := \frac{\prod_{i=0}^{p-1} m(x_i, x_{i+1})}{\prod_{j=1}^{p-1} m(x_j)} \tag{4.1}$$

- If  $p \geq 2$  and  $x_0 \leq \dots \leq x_p$  then

$$m(x_0, \dots, x_p) = \frac{1}{\prod_{j=1}^{p-1} m(x_j)} \prod_{i=1}^{p-1} \sum_{\gamma \in \Gamma_{x_i, x_{i+1}}} m(\gamma).$$

**Remark 4.2.** The assumption  $\nabla \cdot m(x) = 0$  for  $x \notin \mathcal{A}, \mathcal{B}$  allows us to write

$$\sum_{y \in \mathcal{F}(x)} m(x, y) = m(x) = \sum_{y' \in \mathcal{E}(x)} m(y', x).$$

**Remark 4.3.** An equivalent way to define the extension of  $m$  is to define  $m(\gamma)$  on extremal geodesics using equation (4.1) and to extend it to general  $p$ -uples as in Definition 3.6, the quantity  $m(\gamma)$  playing the role of  $C_\gamma$ .

**Theorem 4.4.** A  $W_1$ -geodesic  $(f_t)$  is a  $W_{1,+}$ -geodesic if and only if there exist:

- A function  $m : E(G) \rightarrow \mathbb{R}_+^*$  satisfying  $\nabla \cdot m(x) = 0$  for  $x \notin \mathcal{A}, \mathcal{B}$ , extended to ordered families of  $G$
- A couple of non-negative functions  $a, b : G \rightarrow \mathbb{R}_+$ ,

such that equations (3.18) and (3.19) hold.

*Proof.* The 'only if' part of Theorem 3.19 is exactly Theorem 3.19. Indeed, the restriction to  $E(G)$  of the function  $m$  constructed from a  $W_{1,+}$ -geodesic  $(f_t)$  satisfies  $\nabla \cdot m = 0$  outside of  $\mathcal{A} \cup \mathcal{B}$ , and using Definition 4.1 to extend this restriction to ordered families allows us to recover the original  $m$ . Moreover, the functions  $a$  and  $b$  introduced in Proposition 3.18 are non-negative: indeed  $a(x)$  is the constant term of the polynomial  $P_t(x)$ , which is non-negative for every  $t \in [0, 1]$ , and the same goes for  $b(x)$ .

Conversely, let  $(f_t)$  be a curve satisfying the assumptions of Theorem 4.4. We define the polynomial functions

$$P_t(z) := \frac{1}{m(z)} \sum_{x \leq z} m(x, z) a(x) \frac{t^{d(x,z)}}{d(x,z)!}, \quad Q_t(z) := \frac{1}{m(z)} \sum_{y \geq z} m(z, y) b(y) \frac{t^{d(z,y)}}{d(z,y)!}.$$

Direct calculations show that  $f_t(z) = m(z)P_t(z)Q_{1-t}(z)$ . Moreover, using the definitions of  $m(x, z)$  and  $m(z, y)$ , one can prove easily that  $P_t$  and  $Q_t$  satisfy the differential equations

$$\frac{\partial}{\partial t} P_t(z) = \sum_{z_0 \in \mathcal{E}(z)} \frac{m(z_0, z)}{m(z_0)} P_t(z_0), \quad \frac{\partial}{\partial t} Q_t(z) = \sum_{z_1 \in \mathcal{F}(z)} \frac{m(z, z_1)}{m(z_1)} Q_t(z_1).$$

This allows us to write  $\frac{\partial}{\partial t} f_t(z) = -\nabla \cdot g_t(z)$  where we define

$$g_t(x_0 x_1) := m(x_0, x_1) P_t(x_0) Q_{1-t}(x_1).$$

Similarly, defining  $h_t(x_0x_1x_2) := m(x_0, x_{1,2})P_t(x_0)Q_{1-t}(x_2)$  we have  $\frac{\partial}{\partial t}g_t(x_0x_1) = -\nabla \cdot h_t(x_0x_1)$ . The positivity of  $P_t$  and  $Q_{1-t}$  implies the positivity of  $g_t(x_0x_1)$ . Moreover, the formula

$$m(x_1)m(x_0, x_1, x_2) = m(x_0, x_1)m(x_1, x_2)$$

implies

$$f_t(x_1)h_t(x_0x_1x_2) = g_t(x_0x_1)g_t(x_1x_2),$$

which shows that  $(f_t)$  is a  $W_{1,+}$ -geodesic. □

The task of finding a  $W_{1,+}$ -geodesic joining  $f_0$  to  $f_1$  is simplified by Theorem 4.4 because it turns it into the static problem of finding a coupling  $\pi$  between  $f_0$  and  $f_1$  such that  $\pi(x, y) := \frac{m(x,y)}{d(x,y)!}a(x)b(y)1_{x \leq y}$  for a couple of functions  $a(x), b(y)$  defined on  $G$  and for a function  $m$  constructed in Definition 4.1.

Theorem 4.4 can be used to construct explicitly  $W_{1,+}$ -geodesics, as shown in the following two examples:

- On the graph  $G = \mathbb{Z}$ , consider two probability distributions  $f_0$  and  $f_1$  defined by  $f_0(0) = f_0(1) = 1/2$  and  $f_1(1) = f_1(2) = 1/2$ . The  $W_1$ -orientation associated to  $f_0, f_1$  is obtained by orienting the edges  $0 \rightarrow 1$  and  $1 \rightarrow 2$ , the other edges being discarded. The only oriented triple is  $0 \rightarrow 1 \rightarrow 2$ . As there is only one extremal geodesic, the function  $m(x, y)$  is necessarily a constant which can be set to 1. By Theorem 4.4, we want to find two functions  $a, b : \{0, 1\} \rightarrow \mathbb{R}$  such that the measure  $\pi$  on  $\mathbb{Z} \times \mathbb{Z}$  defined by  $\pi(i, j) := \frac{a(i)b(j)}{d(i,j)!}$  for  $0 \leq i \leq j \leq 2$  and  $\pi(i, j) := 0$  elsewhere is a coupling between  $f_0$  and  $f_1$ . The only solutions are

$$((a(0), a(1), a(2))) = \lambda \left( \frac{1}{2 + \sqrt{2}}, \frac{1}{2 + \sqrt{2}}, 0 \right), \quad (b(0), b(1), b(2)) = \frac{1}{\lambda} (0, 1, \sqrt{2})$$

for any  $\lambda > 0$ . The associated coupling then satisfies

$$\pi(0, 1) = \frac{1}{2 + \sqrt{2}}, \quad \pi(0, 2) = \frac{1}{2 + 2\sqrt{2}}, \quad \pi(1, 1) = \frac{1}{2 + 2\sqrt{2}}, \quad \pi(1, 2) = \frac{1}{2 + \sqrt{2}}.$$

The only  $W_{1,+}$ -geodesic joining  $f_0$  to  $f_1$  is finally obtained by considering binomial mixtures with respect to  $\pi$ :

$$(f_t(0), f_t(1), f_t(2)) = \frac{1}{2 + 2\sqrt{2}} \left( (1-t)^2 + \sqrt{2}(1-t), 2t(1-t) + 1 + \sqrt{2}, t^2 + \sqrt{2}t \right).$$

It is then possible to compute  $g_t(01) = \frac{1+\sqrt{2}(1-t)}{2+\sqrt{2}}$ ,  $g_t(12) = \frac{1+\sqrt{2}t}{2+\sqrt{2}}$ ,  $h_t(012) = \frac{1}{1+\sqrt{2}}$  and check that we have  $g_t(01)g_t(12) = f_t(1)h_t(012)$ .

- Let  $G = \{0, 1\}^2$  be the square graph. We denote  $a = (0, 0)$ ,  $b = (0, 1)$ ,  $c = (1, 0)$  and  $d = (1, 1)$ . We define the probability distributions  $f_0, f_1$  by  $f_0(a) = f_0(b) = 1/2$  and  $f_1(b) = f_1(d) = 1/2$ . The  $W_1$ -orientation is now obtained by orienting the edges

$$a \rightarrow b, \quad a \rightarrow c, \quad b \rightarrow d, \quad c \rightarrow d.$$

There are now two extremal geodesics, which are  $a \rightarrow b \rightarrow d$  and  $a \rightarrow c \rightarrow d$ . The functions  $m : E(G) \rightarrow \mathbb{R}_+^*$  satisfying  $\nabla \cdot m(x) = 0$  are exactly the functions such that  $m(ab) = m(bd) = A$  and  $m(ac) = m(cd) = B$  for two constants  $A, B > 0$ . The function  $m$  is extended by  $m(a) = m(d) = A + B$ ,  $m(b) = A$ ,  $m(c) = B$  and

$$m(a, d) = m(a, b, d) + m(a, c, d) = \frac{m(a, b)m(b, d)}{m(b)} + \frac{m(a, c)m(c, d)}{m(c)} = \frac{A^2}{A} + \frac{B^2}{B} = A + B.$$

As in the first example, we use Theorem 4.4 to associate to the function  $m$  a coupling  $\pi$  between  $f_0$  and  $f_1$ . After calculations, and setting  $\theta := \frac{A}{A+B}$ , we find that  $\pi$  satisfies

$$\pi(a, b) = \sqrt{\frac{\theta}{2}} \frac{1}{1 + \sqrt{2\theta}} = \pi(b, d), \quad \pi(a, d) = \frac{1}{2} \frac{1}{1 + \sqrt{2\theta}}.$$

We now use equation (3.19) to write:

$$(f_t(a), f_t(b), f_t(c), f_t(d)) = \left( \frac{(1-t)^2 + \sqrt{2\theta}(1-t)}{2(1 + \sqrt{2\theta})}, \frac{2\theta t(1-t) + 1 + \sqrt{2\theta}}{2(1 + \sqrt{2\theta})}, \frac{2(1-\theta)t(1-t)}{2(1 + \sqrt{2\theta})}, \frac{t^2 + \sqrt{2\theta}t}{2(1 + \sqrt{2\theta})} \right).$$

From this we calculate:

$$(g_t(ab), g_t(bd), g_t(ac), g_t(cd)) = \left( \frac{2\theta(1-t) + \sqrt{2\theta}}{2(1 + \sqrt{2\theta})}, \frac{2\theta t + \sqrt{2\theta}}{2(1 + \sqrt{2\theta})}, \frac{2(1-\theta)(1-t)}{2(1 + \sqrt{2\theta})}, \frac{2(1-\theta)t}{2(1 + \sqrt{2\theta})} \right)$$

and:

$$h_t(abd) = \frac{\theta}{1 + \sqrt{2\theta}}, \quad h_t(acd) = \frac{1-\theta}{1 + \sqrt{2\theta}},$$

and we can check that both identities hold:

$$h_t(abd)f_t(b) = g_t(ab)g_t(bd), \quad h_t(acd)f_t(c) = g_t(ac)g_t(cd).$$

Theorem 4.4 is also used to prove the existence of  $W_{1,+}$ -geodesics with prescribed initial and final distributions:

**Theorem 4.5.** *Let  $f_0, f_1 \in \mathcal{P}(G)$  be finitely supported. Then there exists a  $W_{1,+}$ -geodesic between  $f_0$  and  $f_1$ .*

*Proof.* Let  $m : E(G) \rightarrow \mathbb{R}_+^*$  be a positive function with  $\nabla \cdot m(x) = 0$  for  $x \notin \mathcal{A}, \mathcal{B}$ , and extended to ordered families of  $G$ . We set  $c(x, y) := \frac{m(x, y)}{d(x, y)}$ . By Theorem 4.4, it suffices to prove the existence of a coupling  $\pi \in \Pi_1(f_0, f_1)$  such that  $\pi(x, y) = c(x, y)a(x)b(y)1_{x \leq y}$  for a couple of positive  $a, b : G \rightarrow \mathbb{R}$ .

We will adopt the following point of view on the set  $\Pi_1(f_0, f_1)$ :

Let  $\mathcal{D} := \{(x, y) \in G \times G \mid x \leq y\}$ . In the Euclidean space  $\mathbb{R}^{\mathcal{D}}$ , we consider the particular families of vectors  $(j_{0,x})_{x \in G}$  and  $(j_{1,y})_{y \in G}$  defined by

$$\forall (x, y) \in \mathcal{D}, \quad j_{0,x_0}(x, y) := 1_{x=x_0}, \quad j_{1,y_0}(x, y) := 1_{y=y_0}.$$

If for every  $(x, y) \in \mathcal{D}$  we have  $x_0 \neq x$  then  $j_{0,x_0} = 0$ .

If  $\pi \in \mathbb{R}^{\mathcal{D}}$ , we have

$$\pi \cdot j_{0,x_0} := \sum_{y \geq x_0} \pi(x_0, y), \quad \pi \cdot j_{1,y_0} := \sum_{x \leq y_0} \pi(x, y_0).$$

In particular we have

$$\Pi_+(f_0, f_1) := \mathbb{R}_+^{\mathcal{D}} \cap \left( \bigcap_{x_0 \in G} \{\pi : \pi \cdot j_{0,x_0} = f_0(x_0)\} \right) \cap \left( \bigcap_{y_0 \in G} \{\pi : \pi \cdot j_{1,y_0} = f_1(y_0)\} \right).$$

In other words,  $\Pi_1(f_0, f_1)$  is seen as the intersection of the “quadrant”  $\mathbb{R}_+^{\mathcal{D}}$  with an affine subspace of  $\mathbb{R}^{\mathcal{D}}$  directed by the vector subspace  $V^\perp$ , where  $V$  is the vector space generated by the families  $(j_{0,x})_{x \in G}$  and  $(j_{1,y})_{y \in G}$ .

Depending on the dimension of  $\Pi_1(f_0, f_1)$  as a subset of an affine subspace of  $\mathbb{R}^{\mathcal{D}}$ , we will consider two cases:

1. The dimension of  $\Pi_1(f_0, f_1)$  is zero. In this case, the vector space  $V$  is  $\mathbb{R}^{\mathcal{D}}$ . In particular, the vector  $l \in \mathbb{R}^{\mathcal{D}}$ , with components  $l(x, y) := \frac{\pi(x, y)}{m(x, y)}$  for every couple  $x \leq y \in \mathcal{D}$ , can be written under the form

$$l(x, y) = \sum_{x \in G} A(x)j_{0,x} + \sum_{y \in G} B(y)j_{1,y}$$

for a unique couple of functions  $A, B$  defined on  $G$ . Considering the exponential of each side proves that  $\pi$  can be written under the form  $\pi(x, y) := c(x, y)a(x)b(y)1_{x \leq y}$  with  $a(x) := \exp(A(x))$  and  $b(y) := \exp(B(y))$ .

2. The dimension of  $\Pi_1(f_0, f_1)$  is positive. In this case we will use the fact that the interior  $\Pi_1(f_0, f_1)$  is non-empty and equal to the set of fully supported  $W_1$ -couplings:

$$\Pi_1(f_0, f_1)^\circ = \{\pi \in \Pi_1(f_0, f_1) : \forall (x, y) \in \mathcal{D}, \pi(x, y) > 0\}.$$

The boundary of  $\Pi_1(f_0, f_1)$  is thus described by:

$$\partial\Pi_1(f_0, f_1) = \{\pi \in \Pi_1(f_0, f_1) : \exists (x, y) \in \mathcal{D}, \pi(x, y) = 0\}.$$

We consider the mapping  $J : \mathbb{R}_+^{\mathcal{D}} \rightarrow \mathbb{R}$  defined by

$$J(\pi) := \sum_{(x,y) \in \mathcal{D}} \pi(x, y) \log \left( \pi(x, y) \frac{d(x, y)!}{c(x, y)} - \pi(x, y) \right), \tag{4.2}$$

where the variables are denoted by  $\pi(x, y)$ , for  $x \leq y$ . The function  $J$  is clearly continuous on  $\mathbb{R}_+^{\mathcal{D}}$  and smooth on  $(\mathbb{R}_+^*)^{\mathcal{D}}$ . Moreover we have

$$\frac{\partial J}{\partial \pi(x, y)} = \log \left( \pi(x, y) \frac{d(x, y)!}{m(x, y)} \right). \tag{4.3}$$

The Hessian of  $J$  is thus a diagonal matrix with coefficients  $\left( \frac{1}{\pi(x, y)} \right)_{(x,y) \in \mathcal{D}}$ , so  $J$  is strictly convex on  $(\mathbb{R}_+^*)^{\mathcal{D}}$ .

The set  $\Pi_1(f_0, f_1)$  being compact, the infimum of  $J$  on  $\Pi_1(f_0, f_1)$  is attained for some coupling  $\tilde{\pi}$ . As  $J$  is strictly convex and  $\Pi_1(f_0, f_1)$  is a convex subset of  $\mathbb{R}^{\mathcal{D}}$ , we know that  $\tilde{\pi}$  is unique and that we have either  $\tilde{\pi} \in \partial\Pi_1(f_0, f_1)$  or  $\tilde{\pi} \in \Pi_1(f_0, f_1)^\circ$  and in this second case  $\tilde{\pi}$  is a critical point for the restriction to  $\Pi_1(f_0, f_1)$  of the application  $J$ .

Let us prove that  $\tilde{\pi} \in \Pi_1(f_0, f_1)^\circ$ : we consider a segment  $\pi_t := (1 - t)\pi_0 + t\pi_1$ , where  $\pi_0 \in \partial\Pi_1(f_0, f_1)$  and  $\pi_1 \in \Pi_1(f_0, f_1)^\circ$ . Each  $\pi_t$  is in  $\Pi_1(f_0, f_1)$ , by convexity. The function  $J(t) := J(\pi_t)$  is continuous on  $[0, 1]$ , smooth on  $]0, 1[$  and we have:

$$J'(t) = \sum_{(x,y) \in \mathcal{D}} (\pi_1(x, y) - \pi_0(x, y)) \log \left( \pi_t(x, y) \frac{d(x, y)!}{m(x, y)} \right).$$

As  $\pi_0 \in \partial\Pi_1(f_0, f_1)$ , there exists  $(x_0, y_0) \in \mathcal{D}$  such that  $\pi_0(x_0, y_0) = 0$  and we have

$$\lim_{t \rightarrow 0} (\pi_1(x_0, y_0) - \pi_0(x_0, y_0)) \log \left( \pi_t(x_0, y_0) \frac{d(x_0, y_0)!}{m(x_0, y_0)} \right) = -\infty,$$

so we have  $\lim_{t \rightarrow 0} J'(t) = -\infty$ . The infimum of  $J$  on  $\Pi_1(f_0, f_1)$  is thus not attained on  $\partial\Pi_1(f_0, f_1)$ .

We have proven the existence of a unique critical point  $\tilde{\pi} \in \Pi_1(f_0, f_1)^\circ$  for the restriction to  $\Pi_1(f_0, f_1)$  of  $J$ . As  $\Pi_1(f_0, f_1)$  is a subset of an affine space directed by the vector subspace  $V^\perp$ , we know that

$$\text{grad}_{\tilde{\pi}} J \in V.$$

In other terms,

$$\text{grad}_{\tilde{\pi}} J = \sum_{x \in G} A(x)j_{0,x} + \sum_{y \in G} B(y)j_{1,y}$$

for a couple of functions  $A, B : G \rightarrow \mathbb{R}$ . Due to the particular form taken by  $j_{0,x}$  and  $j_{1,y}$ , equation (4) can be written in a simple way:

$$\forall (x, y) \in \mathcal{D}, \text{grad}_{\tilde{\pi}}(J)(x, y) = A(x) + B(y).$$

But equation (4.3) gives an explicit formula for  $\text{grad}_{\tilde{\pi}}(J)(x, y)$ , which allows us to write, for  $(x, y) \in \mathcal{D}$ :

$$\begin{aligned} \frac{\tilde{\pi}(x, y)}{c(x, y)} &= \exp(\text{grad}_{\tilde{\pi}}(J)(x, y)) \\ &= \exp(A(x) + B(y)) = a(x)b(y), \end{aligned}$$

where  $a(x) := \exp(A(x))$  and  $b(y) := \exp(B(y))$ . Theorem 4.4 then gives the existence of a  $W_{1,+}$ -geodesic  $(f_t)$  between  $f_0$  and  $f_1$  constructed from the function  $m$  and the coupling  $\tilde{\pi}$ . □

**Remark 4.6.** *The particular form taken by  $W_{1,+}$ -geodesics (see equation (3.19)) and the minimisation problems associated by the functionals (4.2) and (2.26), are reminiscent of the theory of Entropic Interpolations, constructed in a recent series of articles by Léonard. A survey of the main results of this theory is found in [Leo14]. A construction of entropic interpolations and a discussion of the cases where they can be described as mixtures of binomials is found in [Leo13a]. Another paper, see [Leo13b], addresses the question of the convexity of entropy along such interpolations.*

*A major difference between these two kinds of interpolations lies in their construction: in order to define an entropic interpolation on a graph  $G$ , one requires an underlying Markov chain to which is canonically associated a positive measure  $R^{01}$  on the set of couples of vertices  $(x, y) \in G$ . On the other hand, the definition of a  $W_{1,+}$ -interpolation does not require an underlying Markov chain. It only relies on the "metric-measure" properties of the graph  $G$ , endowed with its counting measure. However, to each  $W_{1,+}$ -geodesic is associated a function  $m$  on the ordered subsets of  $G$ , which is used to construct sub-Markov kernels.*

*A complete understanding of the links between entropic interpolations and  $W_{1,+}$ -geodesics, and more especially between the measure  $R^{01}$  of entropic interpolations and the function  $m$  of  $W_{1,+}$ -geodesics, is still under investigation.*

## References

- [AGS] Luigi Ambrosio, Nicola Gigli, and Giuseppe Savaré. Gradient flows: in metric spaces and in the space of probability measures. *Lectures in Mathematics ETH Zürich*. Birkhäuser Verlag, Basel, second edition, 2008. MR-2401600
- [AGS12] Luigi Ambrosio, Nicola Gigli, and Giuseppe Savaré. Heat flow and calculus on metric measure spaces with Ricci curvature bounded below—the compact case. *Boll. Unione Mat. Ital. (9)*, 5(3):575–629, 2012. MR-3051737

- [BB99] Jean-David Benamou and Yann Brenier. A numerical method for the optimal time-continuous mass transport problem and related problems. In *Monge Ampère equation: applications to geometry and optimization (Deerfield Beach, FL, 1997)*, volume 226 of *Contemp. Math.*, pages 1–11. Amer. Math. Soc., Providence, RI, 1999. MR-1660739
- [BB00] Jean-David Benamou and Yann Brenier. A computational fluid mechanics solution to the Monge-Kantorovich mass transfer problem. *Numerische Mathematik*, 84(3):375–393, 2000. MR-1738163
- [EKS13] Matthias Erbar, Kazumasa Kuwada, and Karl-Theodor Sturm. On the equivalence of the entropic curvature-dimension condition and bochner’s inequality on metric measure spaces. *arXiv preprint arXiv:1303.4382*, 2013.
- [EM12] Matthias Erbar and Jan Maas. Ricci curvature of finite Markov chains via convexity of the entropy. *Arch. Ration. Mech. Anal.*, 206(3):997–1038, 2012. MR-2989449
- [GRST12] Nathael Gozlan, Cyril Roberto, Paul-Marie Samson, and Prasad Tetali. Displacement convexity of entropy and related inequalities on graphs. *Probability Theory and Related Fields*, 1–48, 2012. MR-3256809
- [Hil14] Erwan Hillion. Contraction of measures on graphs. *Potential Analysis*, 1–20, 2012.
- [HJK10] Peter Harremoës, Oliver Johnson, and Ioannis Kontoyiannis. Thinning, entropy, and the law of thin numbers. *IEEE Trans. Inform. Theory*, 56(9):4228–4244, 2010. MR-2807322
- [Leo13a] Christian Léonard. On the convexity of the entropy along entropic interpolations. *arXiv preprint*, 1310.1274.
- [Leo13b] Christian Léonard. Lazy random walks and optimal transport on graphs. *arXiv preprint*, 1308.0226.
- [Leo14] Christian Léonard. A survey of the Schrödinger problem and some of its connections with optimal transport. *Discret Contin. Dyn. Syst.*, 34(2014), no.4, 15331574. MR-3121631
- [LV09] John Lott and Cédric Villani. Ricci curvature for metric-measure spaces via optimal transport. *Ann. of Math. (2)*, 169(3):903–991, 2009. MR-2480619
- [Oll09] Yann Ollivier. Ricci curvature of Markov chains on metric spaces. *Journal of Functional Analysis*, 256(3), 810–864. MR-2484937
- [OV00] Felix Otto and Cédric Villani. generalization of an inequality by Talagrand and links with the logarithmic Sobolev inequality. *Journal of Functional Analysis*, 173(2), 361–400. MR-1760620
- [Stu06a] Karl-Theodor Sturm. On the geometry of metric measure spaces. I. *Acta Math.*, 196(1):65–131, 2006. MR-2237206
- [Stu06b] Karl-Theodor Sturm. On the geometry of metric measure spaces. II. *Acta Math.*, 196(1):133–177, 2006. MR-2237207
- [Vil03] Cédric Villani Topics in optimal transportation. *American Math. Soc.*, vol. 58. MR-1964483
- [Vil08] Cédric Villani Optimal transport, old and new. *Springer*, vol. 338. MR-2459454
- [YJ09] Yaming Yu and Oliver Johnson. Concavity of entropy under thinning. In *Information Theory, 2009. ISIT 2009. IEEE International Symposium on*, pages 144–148. IEEE, 2009.

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