

Gossip in $CAT(\kappa)$ metric spaces

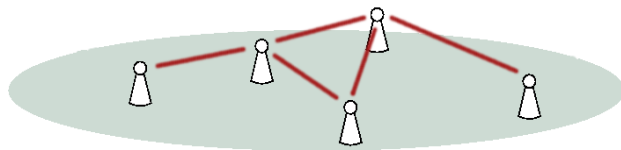
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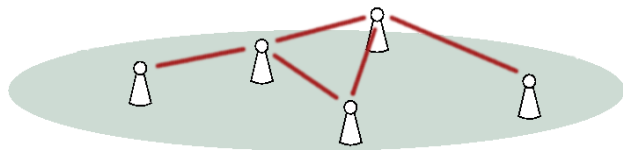
Problem

We consider a network of N agents such that:



- ▶ The network is represented by a connected, undirected graph $G = (V, E)$, where $V = \{1, \dots, N\}$ stands for the set of agents and E denotes the set of available communication links between agents.
- ▶ At any given time t an agent v stores data represented as an element $x_v(t)$ of a data space \mathcal{M} .
- ▶ $X_t = (x_1(t), \dots, x_N(t))$ is the tuple of data values of the whole network at instant t .

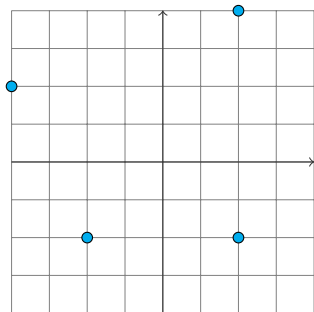
Problem (cont'd)



- ▶ Each agent has its own Poisson clock that ticks with a common intensity λ (the clocks are identically made) independently of other clocks.
- ▶ When an agent clock ticks, the agent is able to perform some computations and wake up some neighboring agents.

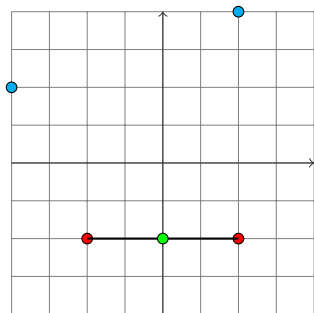
The goal is to take the system from an initial state $X(0)$ to a **consensus state**; meaning a state of the form $X_\infty = (x_\infty, \dots, x_\infty)$ with: $x_\infty \in \mathcal{M}$.

Random Pairwise Gossip (Xiao & Boyd'04)



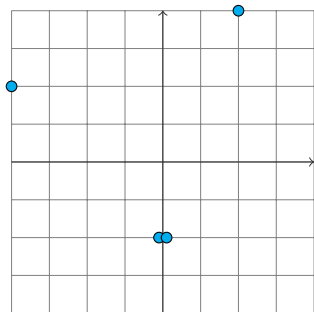
$$x_0 = \begin{pmatrix} -1 & -1 \\ 1 & -1 \\ -2 & 1 \\ 1 & 2 \end{pmatrix}$$

Random Pairwise Gossip (Xiao & Boyd'04)



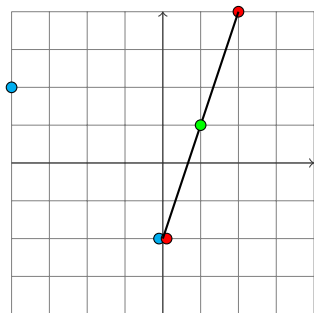
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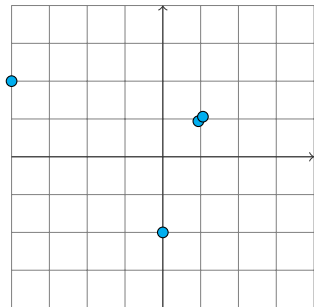
$$x_1 = \begin{pmatrix} 0 & -1 \\ 0 & -1 \\ -2 & 1 \\ 1 & 2 \end{pmatrix}$$

Random Pairwise Gossip (Xiao & Boyd'04)



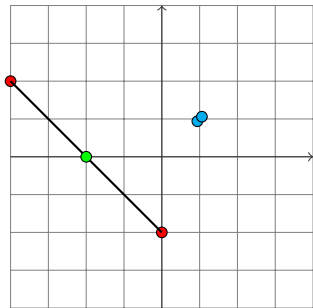
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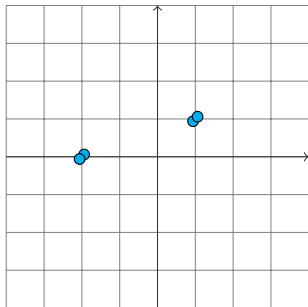
$$x_1 = \begin{pmatrix} 0.5 & 0.5 \\ 0 & -1 \\ -2 & 1 \\ 0.5 & 0.5 \end{pmatrix}$$

Random Pairwise Gossip (Xiao & Boyd'04)



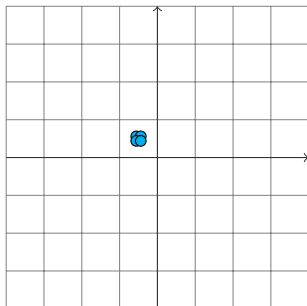
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Random Pairwise Gossip (Xiao & Boyd'04)



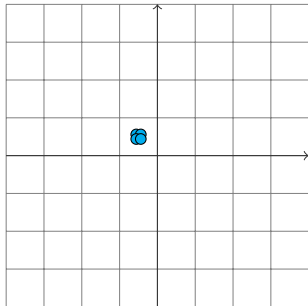
$$x_2 = \begin{pmatrix} 0.5 & 0.5 \\ -1 & 0 \\ -1 & 0 \\ 0.5 & 0.5 \end{pmatrix}$$

Random Pairwise Gossip (Xiao & Boyd'04)



$$x_{\infty} = \begin{pmatrix} -0.25 & 0.25 \\ -0.25 & 0.25 \\ -0.25 & 0.25 \\ -0.25 & 0.25 \end{pmatrix}$$

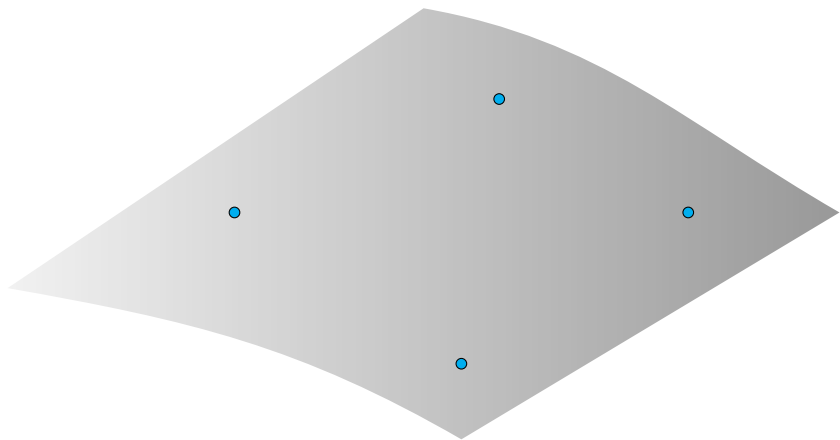
Random Pairwise Gossip (Xiao & Boyd'04)



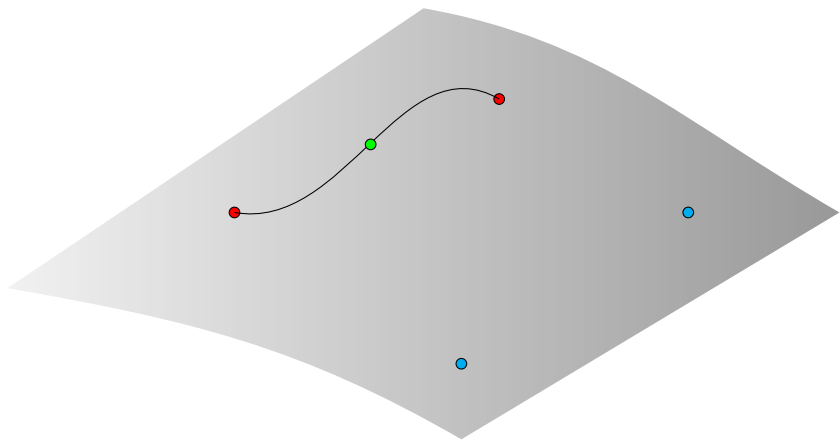
$$x_{\infty} = \begin{pmatrix} -0.25 & 0.25 \\ -0.25 & 0.25 \\ -0.25 & 0.25 \\ -0.25 & 0.25 \end{pmatrix}$$

$$x_n = \left(I - \frac{1}{2}(\delta_{i_n} - \delta_{j_n})(\delta_{i_n} - \delta_{j_n})^T \right) x_{n-1}$$

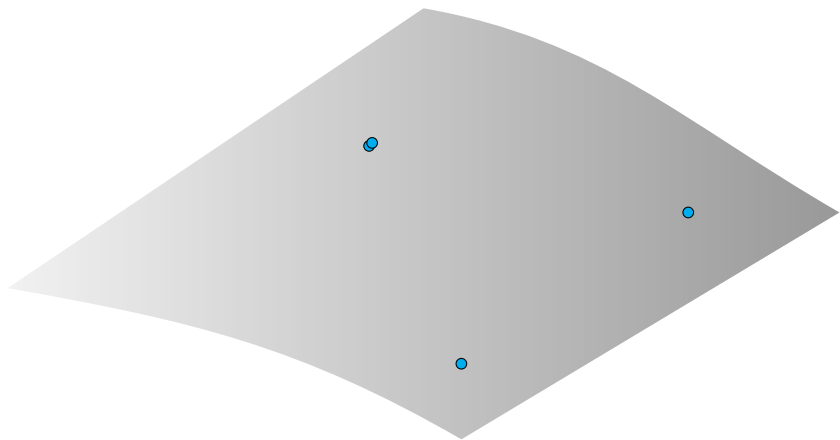
A natural extension in a metric setting



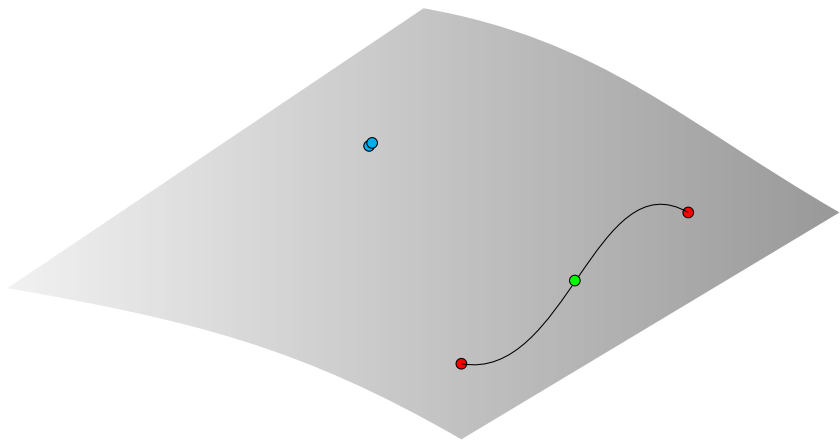
A natural extension in a metric setting



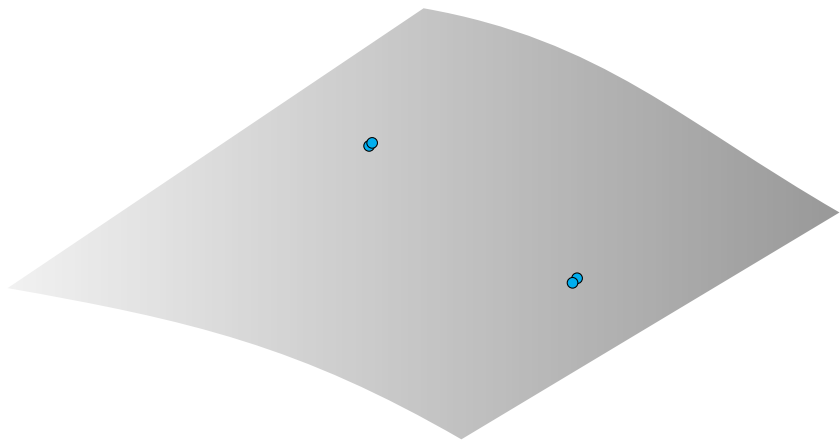
A natural extension in a metric setting



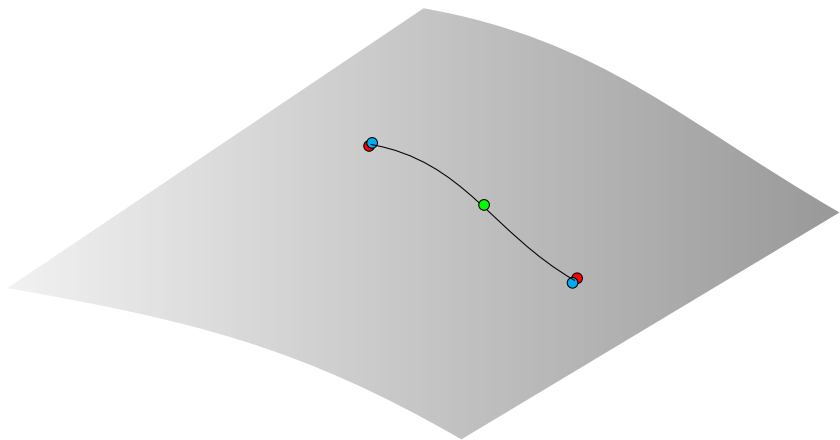
A natural extension in a metric setting



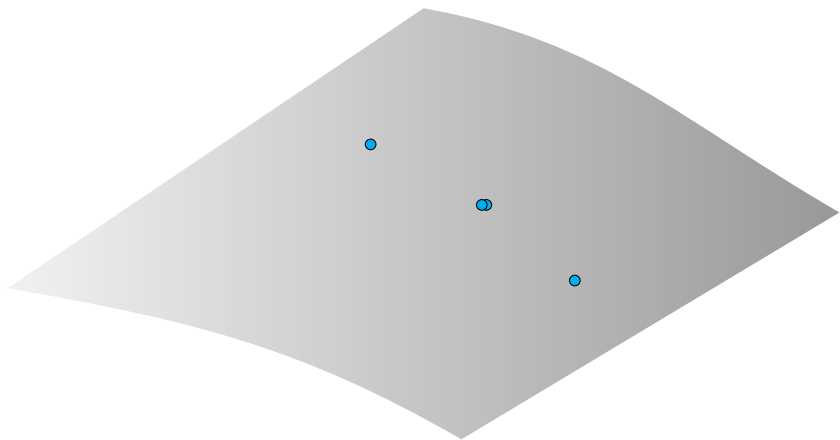
A natural extension in a metric setting



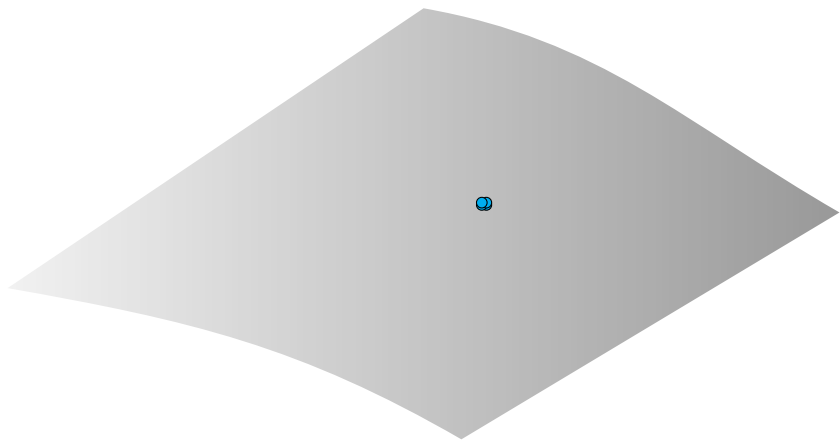
A natural extension in a metric setting



A natural extension in a metric setting



A natural extension in a metric setting



Outline

1. Motivation
2. State of the art
3. $\text{CAT}(\kappa)$ spaces
4. Previous result for $\kappa = 0$
5. Why the $\kappa > 0$ case is more complex
6. Our result

Motivation

In its Euclidean setting, Random Pairwise Midpoint cannot address several useful type of data:

- ▶ Sphere positions (Sphere)
- ▶ Line orientations (Projective space)
- ▶ Solid orientations (Rotations)
- ▶ Subspaces (Grassmanians)
- ▶ Phylogenetic Trees (Metric space)
- ▶ Cayley graphs (Metric space)
- ▶ Reconfigurable systems (Metric space)

State of the art

- ▶ Consensus optimization on manifolds :
[Sarlette-Sepulchre'08],[Tron *et al.*'12],[Bonnabel'13]
- ▶ Synchronization on the circle : [Sarlette *et al.*'08]
- ▶ Synchronization on $SO(3)$: [Tron *et al.*'12]
- ▶ Our previous work: Distributed pairwise gossip on $CAT(0)$ spaces

Caveat: In this work, we deal the problem of **synchronization**, *i.e.* attaining a consensus, whatever its value; **contrarily to the Euclidean case** where it is known that random pairwise midpoints converges to \bar{x}_0 .

CAT(κ) spaces

Model spaces

Consider a model surface \mathcal{M}_κ with constant sectional curvature κ :

- ▶ $\kappa < 0$ corresponds to a *hyperbolic space*
- ▶ $\kappa = 0$ corresponds to a *Euclidean space*
- ▶ $\kappa > 0$ corresponds to a *sphere*

Geodesics

Assume \mathcal{M} is a metric space equipped with metric d . A map $\gamma : [0, l] \rightarrow \mathcal{M}$ such that:

$$\forall 0 \leq t, t' \leq l, \quad d(\gamma(t), \gamma(t')) = |t - t'|$$

is called a *geodesic* in \mathcal{M} ; $a = \gamma(0)$ and $b = \gamma(l)$ are its endpoints. If there exists one and only one geodesic linking a to b , it is denoted $[a, b]$.

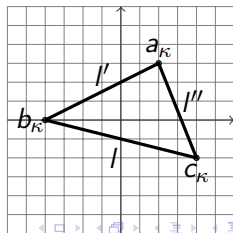
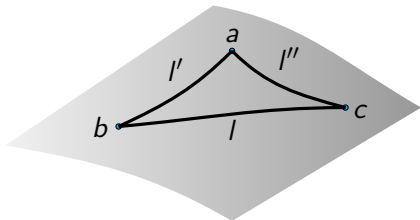
CAT(κ) spaces (cont'd)

Triangles

A triple of geodesics γ , γ' and γ'' with respective endpoints a , b and c is called a *triangle* and is denoted $\Delta(\gamma, \gamma', \gamma'')$ or $\Delta(a, b, c)$ when there is no ambiguity.

Comparison triangles

When $\kappa \leq 0$, given a triangle $\Delta(\gamma, \gamma', \gamma'')$, there always exist a triangle $\Delta(a_\kappa, b_\kappa, c_\kappa)$ in \mathcal{M}_κ such that $d(a, b) = d(a_\kappa, b_\kappa)$, $d(b, c) = d(b_\kappa, c_\kappa)$ and $d(c, a) = d(c_\kappa, a_\kappa)$ with $a = \gamma(0)$, $b = \gamma'(0)$ and $c = \gamma''(0)$.



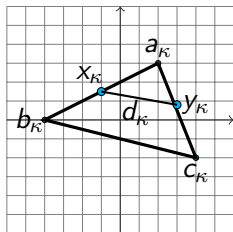
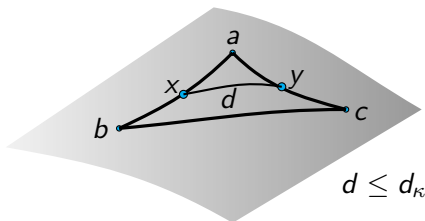
CAT(κ) spaces (cont'd)

CAT(κ) inequality

A triangle $\Delta(\gamma, \gamma', \gamma'')$ in a metric space \mathcal{M} satisfies the CAT(κ) inequality if for any $x \in [a, b]$ and $y \in [a, c]$ one has:

$$d(x, y) \leq d(x_{\kappa}, y_{\kappa})$$

where $x_{\kappa} \in [a_{\kappa}, b_{\kappa}]$ is such that $d(a_{\kappa}, x_{\kappa}) = d(a, x)$ and $y_{\kappa} \in [a_{\kappa}, c_{\kappa}]$ is such that $d(a_{\kappa}, y_{\kappa}) = d(a, y)$.



A metric space is said CAT(κ) if every pair of points can be joined by a geodesic and every triangle with perimeter less than $2D_{\kappa} = \frac{2\pi}{\sqrt{\kappa}}$ satisfy the CAT(κ) inequality.

Formal setting

Assumptions

1. Time is *discrete* $t = 0, 1, \dots$
2. At each time each agent holds a “value” $x_{t,v}$ in a $CAT(\kappa)$ metric space \mathcal{M}
3. At each time t , an agent V_t randomly wakes up and wakes up a neighbor W_t , according to the probability distribution:

$$\mathbb{P}[\{V_k, W_k\} = \{v, w\}] = \begin{cases} P_{v,w} > 0 & \text{if } v \sim w \\ 0 & \text{otherwise} \end{cases}$$

Algorithm description

$$x_{t,v} = \begin{cases} \text{Midpoint}(x_{t-1,V_t}, x_{t-1,W_t}) & \text{if } v \in \{V_t, W_t\} \\ x_{t-1,v} & \text{otherwise} \end{cases}$$

Previous result

The algorithm is sound

Because geodesics exist and are unique in CAT(0) spaces.

Convergence

The algorithm converges to a consensus with probability 1, whatever the initial state x_0 .

Rate of convergence

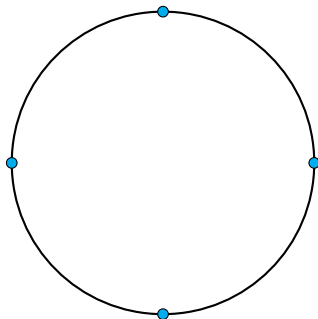
Convergence occur at a *linear rate*: define

$$\sigma^2(x) = \sum_{v \sim w} d^2(x_v, x_w) ;$$

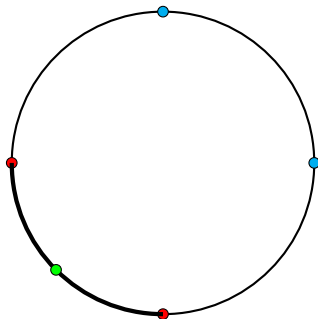
then, there exists a constant $L < 0$ such that

$$\mathbb{E}\sigma^2(X_k) \leq C_0 \exp(Lk)$$

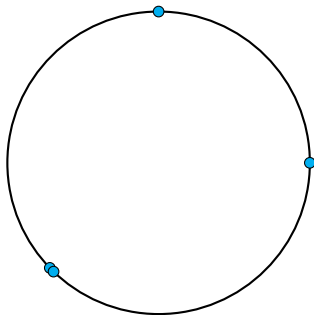
What changes for the $\kappa > 0$ (the case of the sphere)



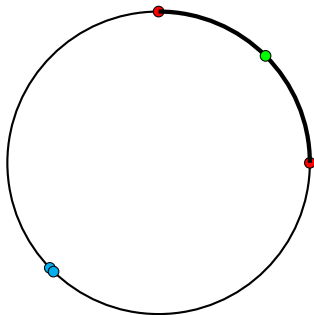
What changes for the $\kappa > 0$ (the case of the sphere)



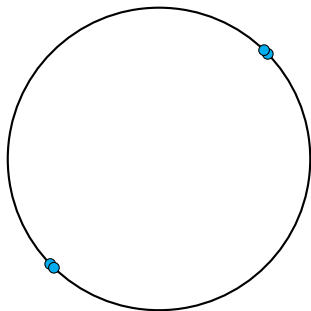
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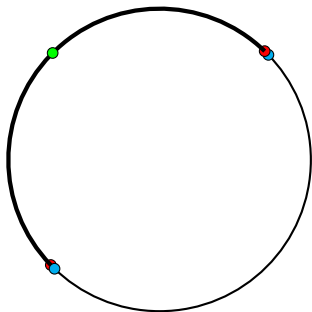
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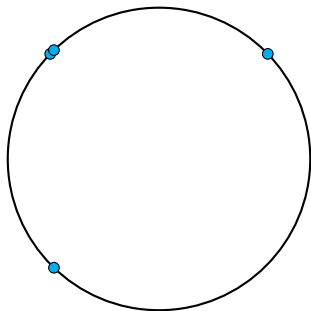
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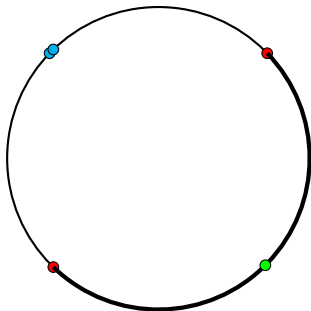
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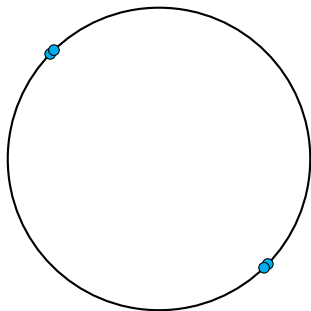
What changes for the $\kappa > 0$ (the case of the sphere)



What changes for the $\kappa > 0$ (the case of the sphere)



What changes for the $\kappa > 0$ (the case of the sphere)



Our result

Provided the diameter of the initial set of values is less than $D_\kappa/2$,

The algorithm is sound

Because geodesics exist and are unique using this restriction.

Convergence

The algorithm converges to a consensus with probability 1.

Rate of convergence

Convergence occur at a *linear rate*: define

$$\sigma^2(x) = \sum_{v \sim w} \chi_\kappa(d(x_v, x_w)) ;$$

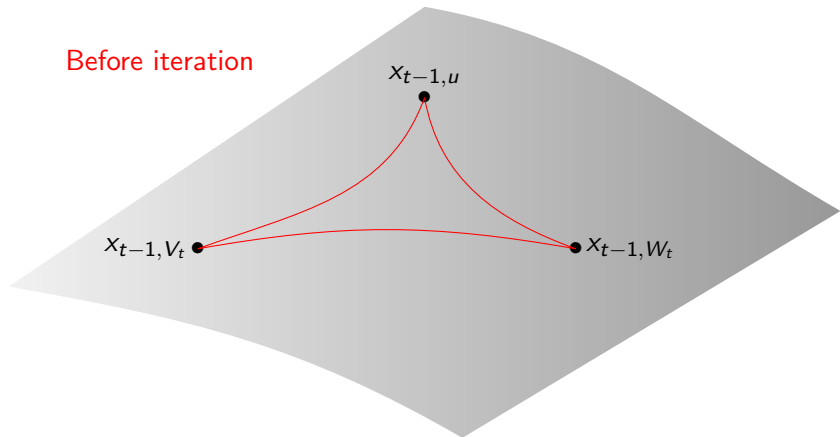
with:

$$\chi_\kappa(x) = 1 - \cos(\sqrt{\kappa}x)$$

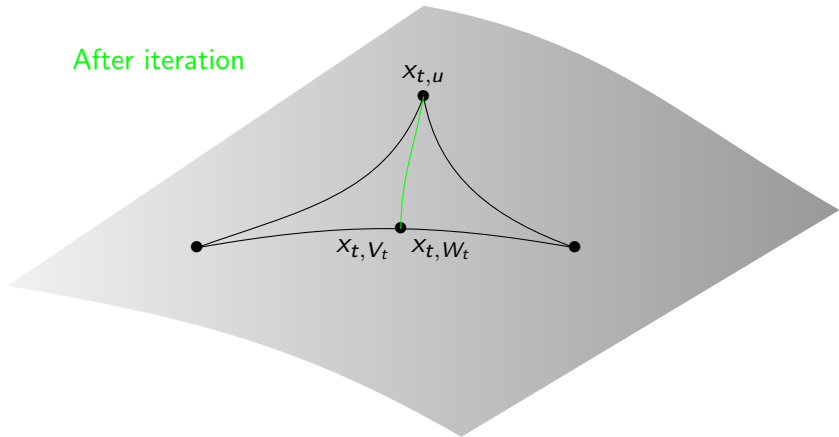
then, there exists a constant $L \in (-1, 0)$ such that:

$$\mathbb{E}\sigma^2(X_k) \leq C_0 \exp(Lk)$$

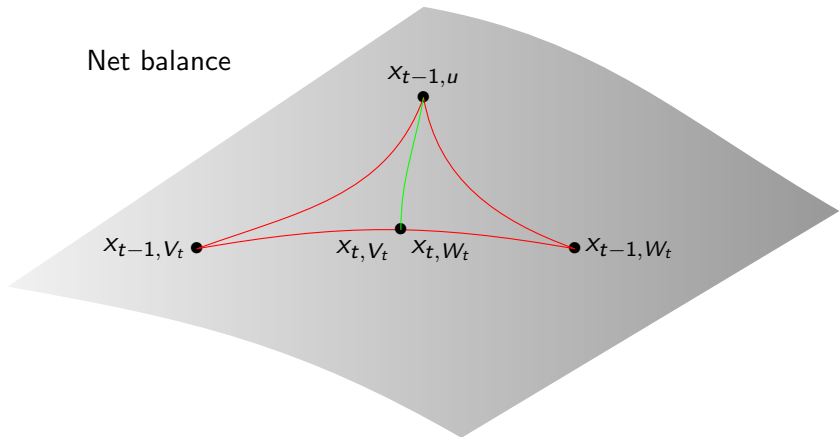
Before iteration



After iteration



Net balance



Sketch of proof (Net balance)

Let us look at the increments:

$$N(\sigma_{\kappa}^2(X_t) - \sigma_{\kappa}^2(X_{t-1})) = -\chi_{\kappa}(d(X_{V_t}(t-1), X_{W_t}(t-1))) \\ + \sum_{\substack{u \in V \\ u \neq V_t, u \neq W_t}} T_{\kappa}(V_t, W_t, u)$$

with:

$$T_{\kappa}(V_t, W_t, u) = 2\chi_{\kappa}(d(X_u(t), M_t)) - \chi_{\kappa}(d(X_u(t), X_{V_t}(t-1))) \\ - \chi_{\kappa}(d(X_u(t), X_{W_t}(t-1)))$$

Using the inequality:

$$\chi_{\kappa} \left(d \left(\left\langle \frac{p+q}{2} \right\rangle, r \right) \right) \leq \frac{\chi_{\kappa}(d(p, r)) + \chi_{\kappa}(d(q, r))}{2}$$

Sketch of proof (Two propositions)

We can prove the a first proposition:

$$\mathbb{E}[\sigma_{\kappa}^2(X_{k+1}) - \sigma_{\kappa}^2(X_k)] \leq -\frac{1}{N}\mathbb{E}\Delta_{\kappa}(X_k)$$

with:

$$\Delta_{\kappa}(x) = \frac{1}{2N} \sum_{\substack{v \sim w \\ \{v,w\} \in E}} P_{v,w} \chi_{\kappa}(d(x_v, x_w))$$

Using graph connectedness we prove a second proposition:

Assume $G = (V, E)$ is an undirected connected graph, there exists a constant $C_G \geq 1$ depending on the graph only such that:

$$\forall x \in \mathcal{M}^N, \quad \frac{1}{2}\Delta_{\kappa}(x) \leq \sigma_{\kappa}^2(x) \leq C_G \Delta_{\kappa}(x)$$

Sketch of proof (cont'd)

The following lemma

Assume a_n is a sequence of nonnegative numbers such that $a_{n+1} - a_n \leq -\beta a_n$ with $\beta \in (0, 1)$. Then,

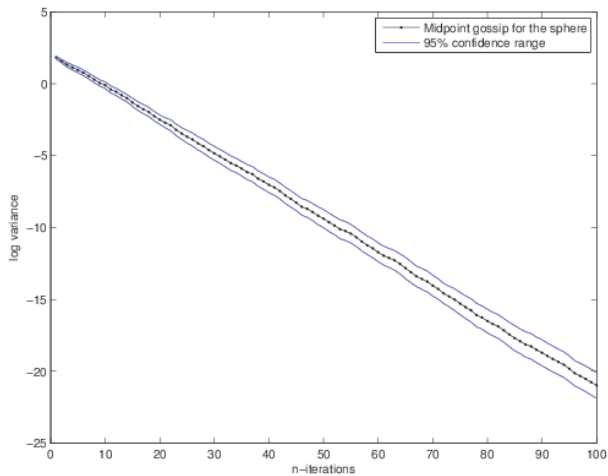
$$\forall n \geq 0, \quad a_n \leq a_0 \exp(-\beta n)$$

Combined with the two propositions, gives the desired result.

$$\mathbb{E}\sigma^2(X_k) \leq \exp(Lk)$$

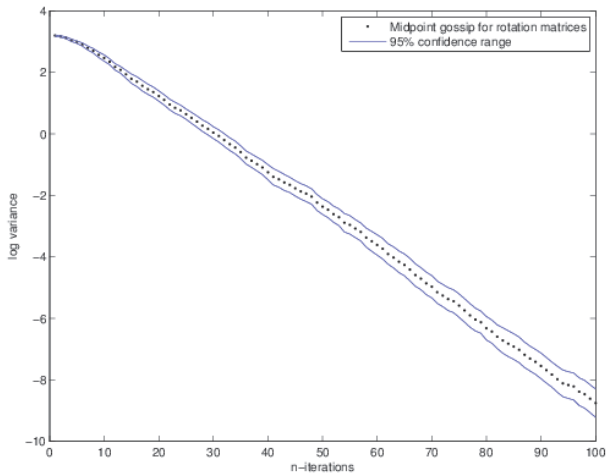
Simulation results

► Sphere



Simulation results

► Rotations



Summary

- ▶ We have proved that, when the data belong to complete $\text{CAT}(\kappa)$ metric space, *provided the initial values are close enough*, the same algorithm makes sense and also converge linearly.
- ▶ We have checked that our results are consistent with simulations.