

Coupling of Brownian motions associated with a time-dependent metric

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1. Introduction

M : m -dim. manifold, $0 \leq T_1 < T_2 \leq \infty$,
 $(g(t))_{t \in [T_1, T_2]}$: smooth complete
Riemannian metrics on M .

Examples

- $\partial_t g(t) = 2 \operatorname{Ric}_{g(t)}$ (backward Ricci flow)
- $\partial_t g(t) \leq 2 \operatorname{Ric}_{g(t)} - 2K g(t)$ (*)
(time-dependent extension of “ $\operatorname{Ric} \geq K$ ”)
- Given g_0 with $\operatorname{Ric}_{g_0} \geq 0$,
 $g(t) := e^{-2K(t-T_1)} g_0$ satisfies (*)

Q. Does (*) work as an analogue of $\operatorname{Ric} \geq K$?

$(X_t)_{t \in [T_1, T_2]}$: $g(t)$ -Brownian motion on M , i.e.

$$P_{T_1 \rightarrow t} f(x) := \mathbb{E}[f(X_t) | X_{T_1} = x]$$

solves the heat equation

$$\begin{cases} \partial_t u = \Delta_{g(t)} u, & (t > T_1), \\ u(T_1, \cdot) = f \end{cases}$$

[Arnaudon, Coulibaly & Thalmaier '08/Coulibaly]:

constructions via SDE on the frame bundle

Rem X_t cannot explode under (*) [K.-Philipowski]

Coupling:

A pair of particles (X_t, Y_t) each of which moves as an $g(t)$ -Brownian motion on M

- ★ Behavior of Y_t can depend on that of X_t
 - ↪ Useful for studying variation of the sol. to the heat eq.
- ★ When $\partial_t g(t) \equiv 0$,
 - $\text{Ric} \geq K$ yields “nice” couplings

What we will consider:

- (i) Coupling by parallel transport**
- (ii) Coupling by reflection**
- (iii) Coupling by spacetime parallel transport**

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Goal

A nice control of “distance” between X_t and Y_t

⇒ (Sharper) monotonicity of transportation costs

⇒ Functional inequalities (gradient estimates)

2. Coupling by parallel transport

Transportation cost

$c : M \times M \rightarrow \mathbb{R}$: cost function

($c(x, y)$: cost of bringing a unit mass from x to y)

For $\mu, \nu \in \mathcal{P}(M)$,

$$\Pi(\mu, \nu) := \left\{ \pi \left| \begin{array}{l} \pi(E \times M) = \mu(E), \\ \pi(M \times E) = \nu(E) \end{array} \right. \right\}$$

(set of all couplings between μ and ν),

$$\mathcal{I}_c(\mu, \nu) := \inf_{\pi \in \Pi(\mu, \nu)} \int_{M \times M} c(x, y) \pi(dx dy)$$

(Minimal total transportation cost from μ to ν)

Equivalent conditions for $\text{Ric} \geq K$

when $\partial_t g(t) \equiv 0, T_1 = 0$

[von Renesse & Sturm '05, etc.]

$P_t := P_{0 \rightarrow t} = e^{t\Delta}$: the heat semigroup

- (i) $\text{Ric} \geq K$
- (ii) $\mathcal{I}_{(e^{Kt}d)^p}(P_t^* \mu, P_t^* \nu) \searrow$
for some $p \in [1, \infty]$
- (iii) $|\nabla P_t f|(x)^q \leq e^{-qKt} P_t(|\nabla f|^q)(x)$
for some $q \in [1, \infty]$

The case $\partial_t g(t) \neq 0$

[McCann & Topping '10]:

Suppose M : cpt.

\Rightarrow The following are equivalent:

- (i) $\partial_t g(t) \leq 2 \operatorname{Ric}_{g(t)}$
- (ii) $\forall \mu_t, \nu_t$: heat distributions, $\mathcal{T}_{d_{g(t)}^2}(\mu_t, \nu_t) \searrow$
- (iii) $\operatorname{Lip}_{g(s)}(P_{s \rightarrow t} f) \leq \operatorname{Lip}_{g(t)}(f)$

★ They used techniques in optimal transport

An extension via stochastic analysis

[Arnaudon & Coulibaly & Thalmaier '09]:

Suppose

$$\partial_t g(t) \leq 2 \operatorname{Ric}_{g(t)} - 2K g(t)$$

\Rightarrow For $\forall \mu, \nu \in \mathcal{P}(M)$, $\forall \pi \in \Pi(\mu, \nu)$,
 $\exists (X_t, Y_t)$: coupled $g(t)$ -BMs
with the initial distribution π s.t.

$$e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow \text{ a.s.}$$

Rem

Heuristically,

$$\partial_t \left(d_{g(t)}(X_t, Y_t) \right) \leq -K$$



$$e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow$$

Why ACT is an extension of MT?

$$\star e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow$$

$$\Rightarrow \boxed{\forall \varphi \nearrow, \mathcal{I}_{\varphi}(e^{K(t-T_1)} d_{g(t)}) (\mu_t, \nu_t) \searrow}$$

Why ACT is an extension of MT?

$$\star e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow$$

$$\Rightarrow \boxed{\forall \varphi \nearrow, \mathcal{I}_{\varphi}(e^{K(t-T_1)} d_{g(t)}) (\mu_t, \nu_t) \searrow}$$

\therefore Let π be a minimizer of $\mathcal{I}_{\varphi}(d_{T_1})(\mu_{T_1}, \nu_{T_1})$

\Downarrow

$$\mathcal{I}_{\varphi}(e^{K(t-T_1)} d_{g(t)}) (\mu_t, \nu_t)$$

$$\leq \mathbb{E}[\varphi(e^{K(t-T_1)} d_{g(t)}(X_t, Y_t))]]$$

$$\leq \mathbb{E}[\varphi(d_{g(T_1)}(X_{T_1}, Y_{T_1}))]$$

$$= \mathcal{I}_{\varphi}(d_{g(T_1)}) (\mu_{T_1}, \nu_{T_1})$$

Bakry-Émery's gradient estimate

$$\star e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow$$

$$\Rightarrow |\nabla P_{s \rightarrow t} f|_{g(s)}(x)$$

$$\leq e^{-K(t-s)} P_{s \rightarrow t}(|\nabla f|_{g(t)})(x)$$

Bakry-Émery's gradient estimate

$$\star e^{K(t-T_1)} d_{g(t)}(X_t, Y_t) \searrow$$

$$\begin{aligned} \Rightarrow |\nabla P_{s \rightarrow t} f|_{g(s)}(x) \\ \leq e^{-K(t-s)} P_{s \rightarrow t}(|\nabla f|_{g(t)})(x) \end{aligned}$$

$$\therefore \text{Let } \mu_{T_1} = \delta_x \text{ and } \nu_{T_1} = \delta_y$$

$$|P_{s \rightarrow t} f(x) - P_{s \rightarrow t} f(y)| \leq \mathbb{E}[|f(X_t) - f(Y_t)|]$$

$$\leq \mathbb{E} \left[\left| \frac{f(X_t) - f(Y_t)}{d_{g(t)}(X_t, Y_t)} \right| \right] e^{-K(t-T_1)} d_{g(T_1)}(x, y)$$

3. Coupling by reflection

Thm 1 [K.]

Suppose $\exists K \in \mathbb{R}$ s.t.

$$\partial_t g(t) \leq 2 \operatorname{Ric}_{g(t)} - 2K g(t)$$

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$\Rightarrow \forall x, y \in M, \exists (X_t, Y_t)$: Markovian coupling of $g(t)$ -BMs from (x, y) s.t.

$$\begin{aligned} \mathbb{P} \left[\inf_{T_1 \leq s \leq t} d_{g(s)}(X_s, Y_s) > 0 \right] \\ \leq \mathbb{P} \left[\inf_{T_1 \leq s \leq t} \rho_s > 0 \right] \end{aligned}$$

where ρ_t solves $\rho_{T_1} = d_{g(T_1)}(x, y)$ and

$$d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$$

What is ρ_t ?

- Heuristically, “ $d_{g(t)}(X_t, Y_t) \leq \rho_t$ ” \Rightarrow Thm 1
- ρ_t can be realized as $\rho_t := |\hat{X}_t - \hat{Y}_t|$,
where \hat{X}_t solves $\hat{X}_{T_1} = d_{g(T_1)}(x, y)/2$ and

$$d\hat{X}_t = \sqrt{2}d\beta_t - K\hat{X}_tdt$$

(Ornstein-Uhlenbeck process)

and $\hat{Y}_t = -\hat{X}_t$

$((\hat{X}_t, \hat{Y}_t)$: coupling by reflection of O-U proc.)

Rem (Coalescence)

- We may assume

$$Y_t = X_t \text{ when } t > \inf\{s > T_1 \mid X_s = Y_s\}$$

- The same is true for (\hat{X}_t, \hat{Y}_t)

Rem (Maximality)

$$\mathbb{P} \left[\inf_{T_1 \leq s \leq t} |\hat{X}_s - \hat{Y}_s| > 0 \right] = \varphi_{t-T_1} (|\hat{X}_{T_1} - \hat{Y}_{T_1}|)$$

where

$$\varphi_{s-T_1}(a) := \|\mathbb{P}_{a/2} \hat{X}_s^{-1} - \mathbb{P}_{-a/2} \hat{X}_s^{-1}\|_{\text{var}}$$

$$\left(\begin{array}{l} \varphi_s(a) = \sqrt{\frac{2}{\pi}} \int_0^{\frac{a}{2\sqrt{2}\sqrt{\beta(s)}}} e^{-x^2/2} dx, \\ \beta(s) = \frac{e^{Ks} - 1}{K} \end{array} \right)$$

$$\star \mathbf{E}[\varphi_s(|\hat{X}_t - \hat{Y}_t|)] = \varphi_{s+t-T_1} (|\hat{X}_{T_1} - \hat{Y}_{T_1}|)$$

Thm 2 [K. & Sturm]

Let $T_1 < T \leq T_2$. $\forall \mu_t, \nu_t$: heat distributions,

$$\mathcal{I}_{\varphi_{T-t} \circ d_g(t)}(\mu_t, \nu_t) \searrow$$

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Let $T_1 < T \leq T_2$. $\forall \mu_t, \nu_t$: heat distributions,

$$\mathcal{I}_{\varphi_{T-t} \circ d_{g(t)}}(\mu_t, \nu_t) \searrow$$

\therefore Suppose $\mu_{T_1} = \delta_x, \nu_{T_1} = \delta_y$

$$d_{g(t)}(X_t, Y_t) \leq |\hat{X}_t - \hat{Y}_t| \text{ \& } \varphi_{T-t} \nearrow$$

$$\Downarrow$$

$$\mathbb{E}[\varphi_{T-t}(d_{g(t)}(X_t, Y_t))] \leq \mathbb{E}[\varphi_{T-t}(|\hat{X}_t - \hat{Y}_t|)]$$

$$\leq \mathbb{E}[\varphi_{T-T_1}(|\hat{X}_{T_1} - \hat{Y}_{T_1}|)]$$

$$= \mathcal{I}_{\varphi_{T-T_1} \circ d_{g(T_1)}}(\delta_x, \delta_y)$$

Cor 1 [K.]

$$\left\| \left\| \nabla P_{T_1 \rightarrow t} f \right\|_{g(T_1)} \right\|_{\infty} \leq \frac{1}{2\sqrt{\pi\beta(t - T_1)}} \text{osc } f$$

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$$\begin{aligned} \therefore \lim_{y \rightarrow x} \frac{P_{T_1 \rightarrow t} f(x) - P_{T_1 \rightarrow t} f(y)}{d_{g(T_1)}(x, y)} &= \lim_{y \rightarrow x} \frac{\mathbb{E}[f(X_t) - f(Y_t)]}{d_{g(T_1)}(x, y)} \\ &= \text{osc } f \lim_{y \rightarrow x} \frac{\mathbb{P}[\inf_{T_1 \leq s \leq t} d_{g(s)}(X_s, Y_s) > 0]}{d_{g(T_1)}(x, y)} \\ &\leq \varphi'_{t-T_1}(0) \text{osc } f \end{aligned}$$

4. Sketch of the proof of Thm 1

(Suppose $T_1 = 0$ here, for simplicity)

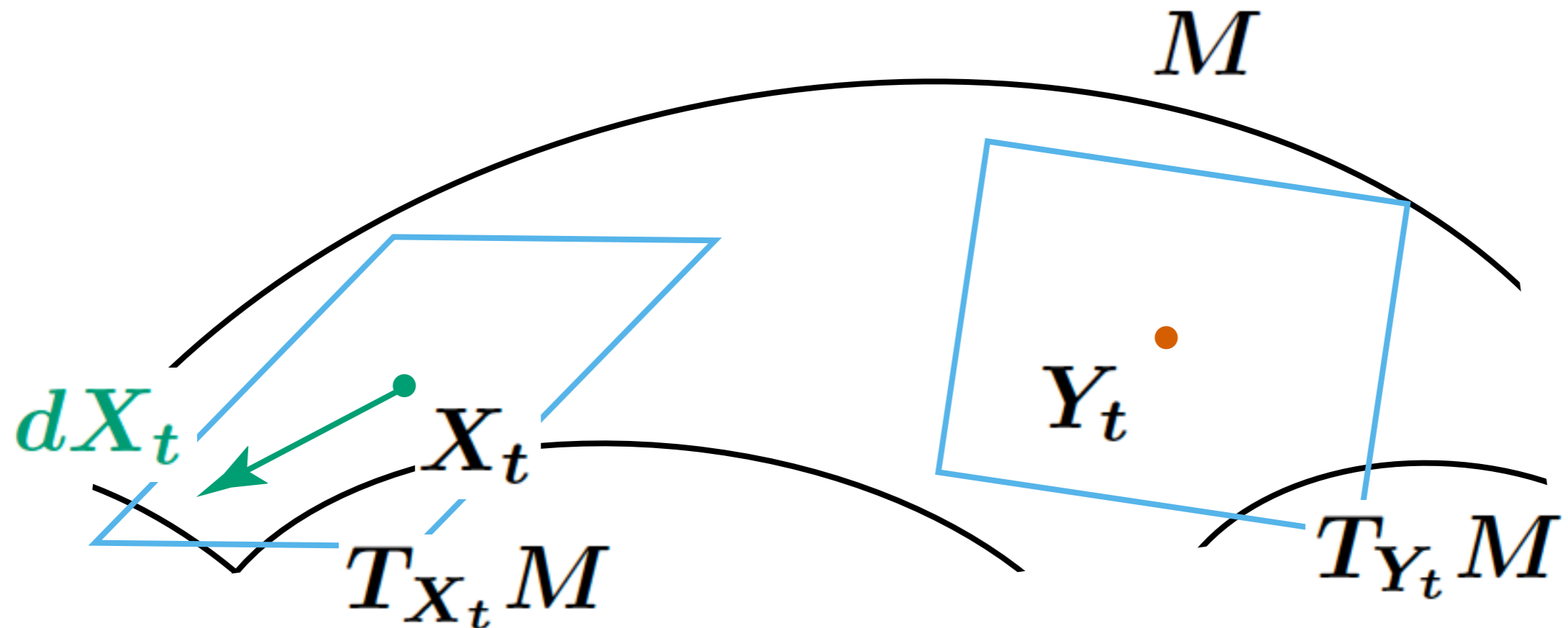
4.1. Heuristic idea

Construct (X_t, Y_t)

where $dY_t = \text{"(local) reflection" of } dX_t$

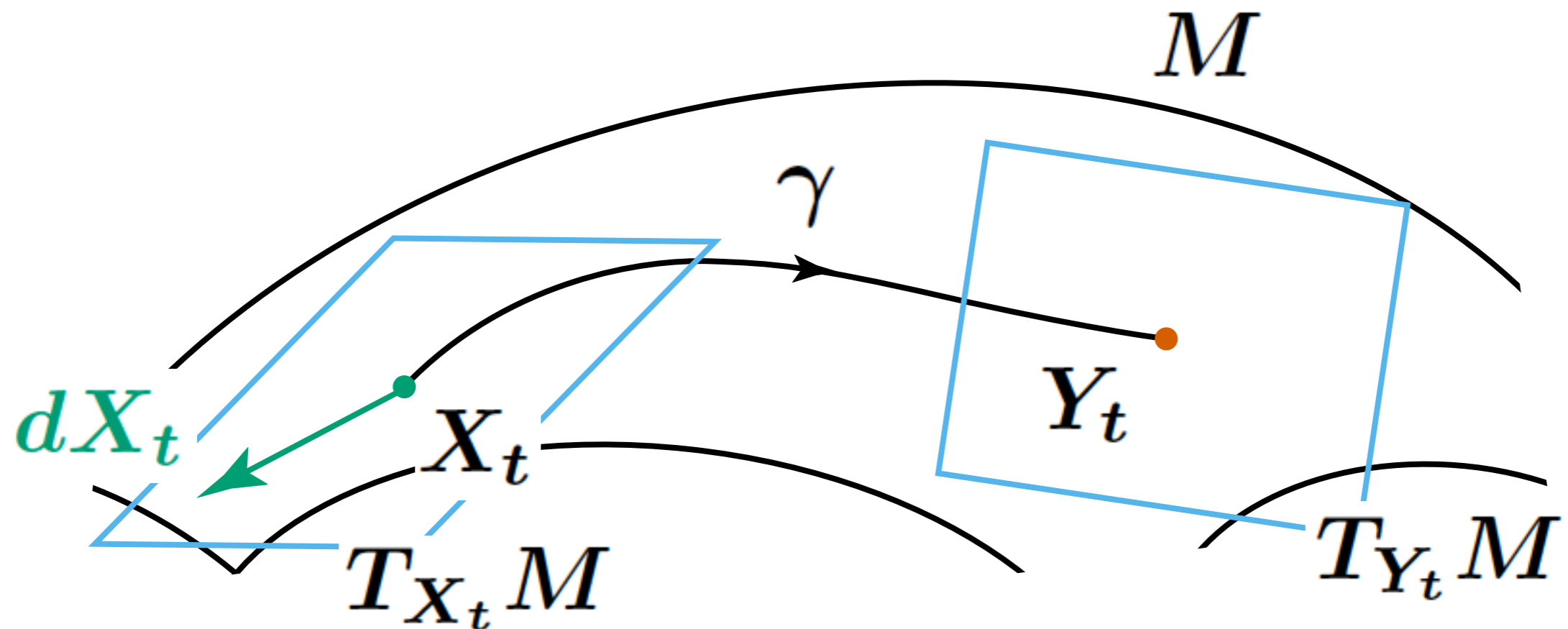
Construct (X_t, Y_t)

where $dY_t =$ “(local) reflection” of dX_t



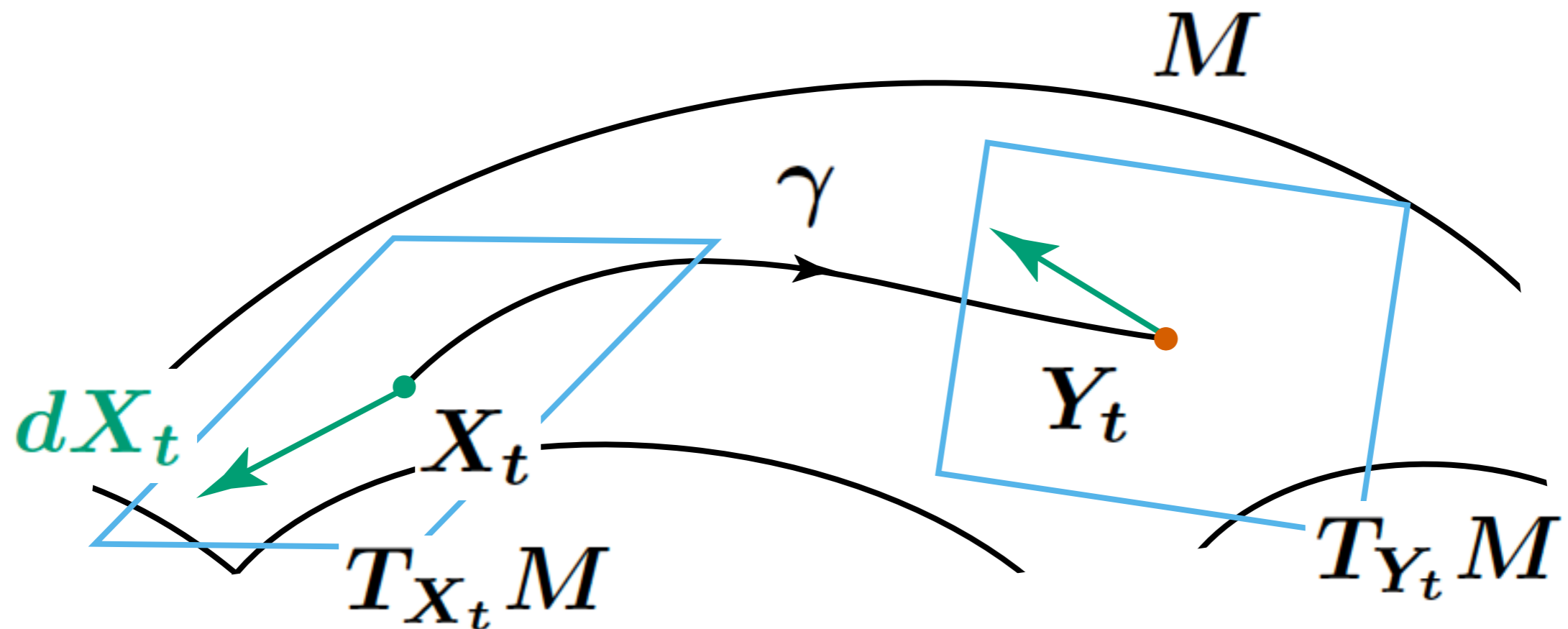
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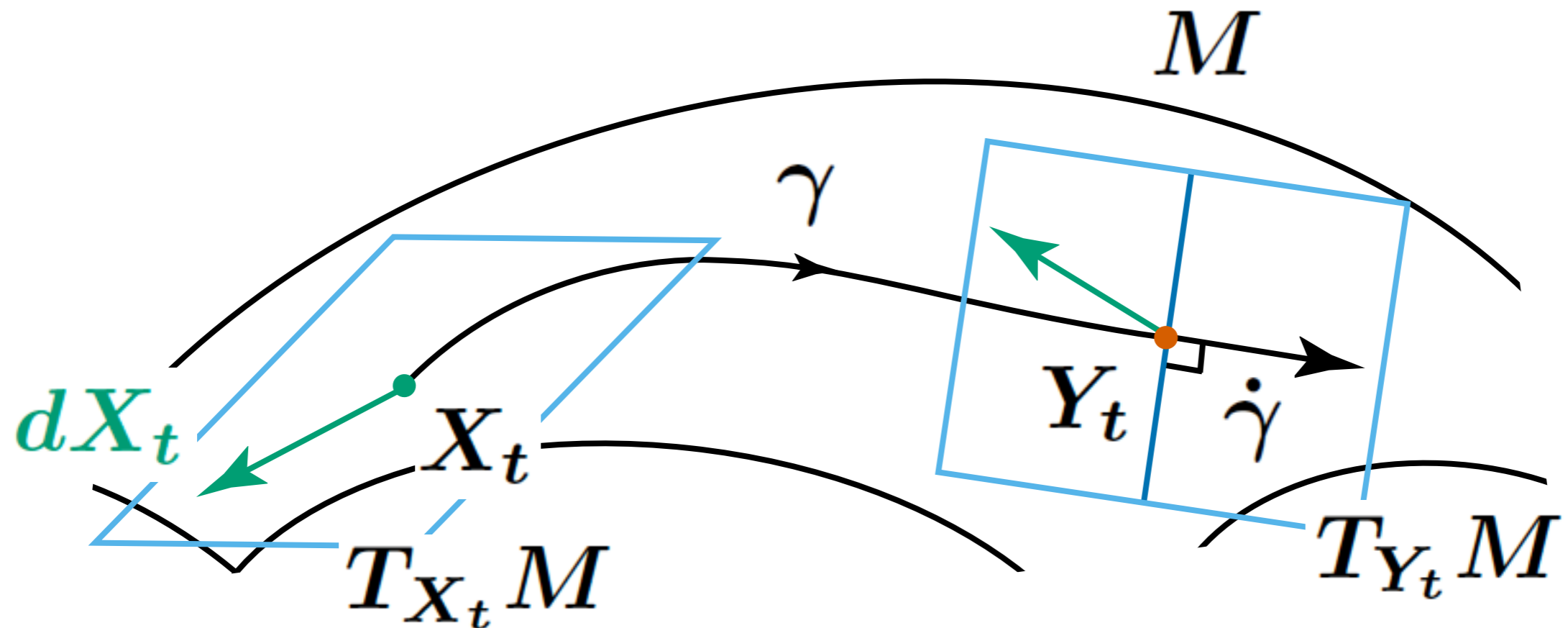
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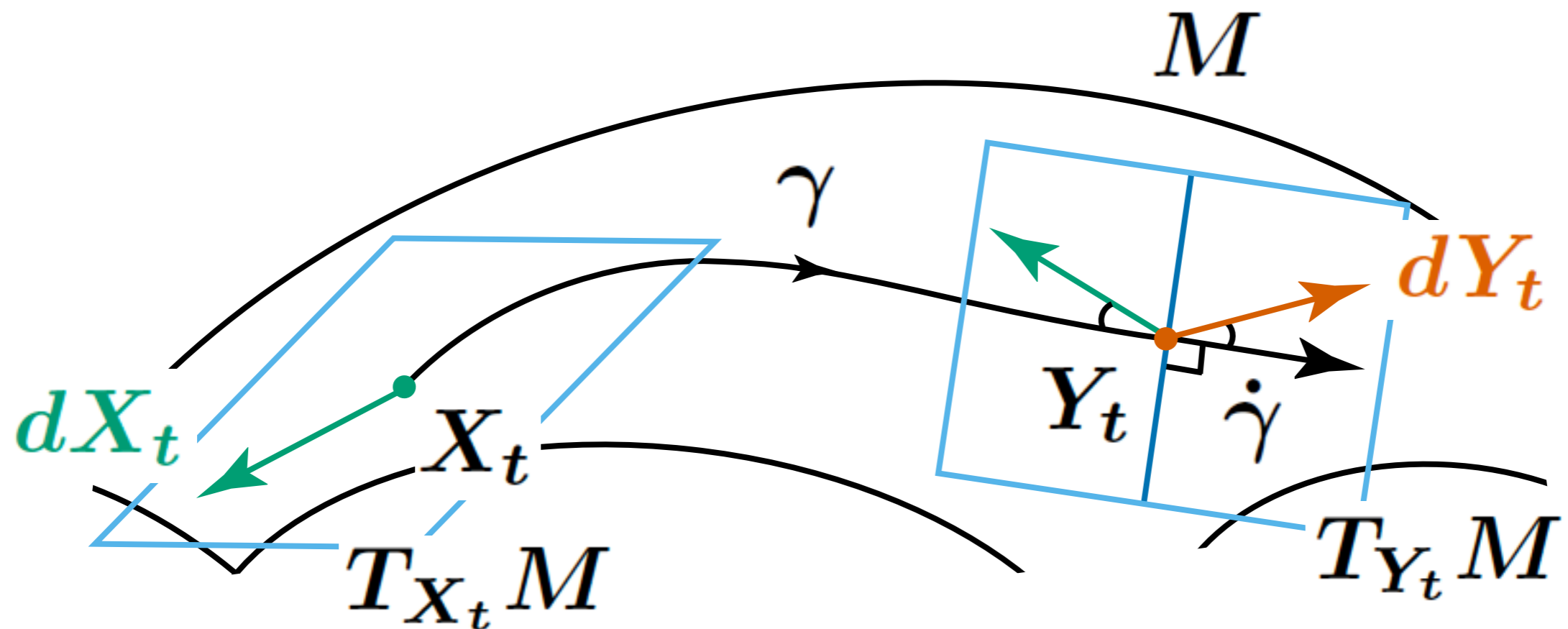
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$$\sigma_t := d_{g(t)}(X_t, Y_t)$$

↓ the “Itô formula”

$$\begin{aligned} d\sigma_t &= \sqrt{2} \langle \nabla d_{g(t)}(X_t, Y_t), dX_t \otimes dY_t \rangle \\ &\quad + (\partial_t d_{g(t)})(X_t, Y_t) dt \\ &\quad + \sum_{i=2}^m \langle \text{Hess } d_{g(t)}(X_t, Y_t), e_i \otimes \parallel_{\gamma} e_i \rangle dt \\ &\quad - L_t \\ &= (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL}) \end{aligned}$$

$((e_i)_{i=1}^m)$: ONB of $T_{X_t}M$, $e_1 = \dot{\gamma}$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$

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1st order:

$$\sqrt{2} \langle \nabla d_{g(t)}(X_t, Y_t), dX_t \otimes dY_t \rangle_{g(t)}$$

$$= \sqrt{2} (\langle \dot{\gamma}, dY_t \rangle - \langle \dot{\gamma}, dX_t \rangle)$$

$$= -2\sqrt{2} \langle \dot{\gamma}, dX_t \rangle =: 2\sqrt{2} \beta_t$$

($\Rightarrow \beta_t$: 1-dim. BM)

$$\text{Recall: } d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$



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(T):

$$\partial_t d_{g(t)}(X_t, Y_t)$$

$$= \frac{1}{2} \int_{\gamma} \partial_t g(t)(\dot{\gamma}(s), \dot{\gamma}(s)) ds$$

$$\text{Recall: } d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$



2nd order:

$$\sum_{i=2}^m \langle \text{Hess } d_{g(t)}(X_t, Y_t), e_i \otimes \parallel_{\gamma} e_i \rangle$$

$$\leq - \int_{\gamma} \text{Ric}_{g(t)}(\dot{\gamma}(s), \dot{\gamma}(s)) ds$$

by the index lemma

$$\text{Recall: } d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$



$$\Rightarrow (\text{T}) + (\text{2nd})$$

$$\leq \int_{\gamma} (\partial_t g(t) - \frac{1}{2} \text{Ric}_{g(t)}(\dot{\gamma}(s), \dot{\gamma}(s))) ds dt$$

$$\leq -K\sigma_t dt$$

by our assumption

$$\text{Recall: } d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$



(CL) (= $-L_t$):

L_t comes from the effect of singularity of $d_{g(t)}$ at $g(t)$ -cut locus

$$\Rightarrow L_t \geq 0$$

Recall: $d\rho_t = 2\sqrt{2}d\beta_t - K\rho_t dt$

$$d\sigma_t = (\text{1st}) + (\text{T}) + (\text{2nd}) + (\text{CL})$$



$$d\sigma_t \leq 2\sqrt{2}\beta_t - K\sigma_t dt$$



$$\sigma_t \leq \rho_t$$

by a comparison argument

4.2. Toward a rigorous argument

Difficulty: $\left\{ \begin{array}{l} \text{Solvability of SDE} \\ \text{Extraction of } L_t \\ \{t \mid (X_t, Y_t) \in \text{Cut}_{g(t)}\}: \text{ small?} \end{array} \right.$

When $\partial_t g(t) \equiv 0$,

[Kendall '86, Cranston '91, F.-Y. Wang '94/'05]

Difficulty: $\left\{ \begin{array}{l} \text{Solvability of SDE} \\ \text{Extraction of } L_t \\ \{t \mid (X_t, Y_t) \in \text{Cut}_{g(t)}\}: \text{ small?} \end{array} \right.$

$\left(\begin{array}{l} \text{When } \partial_t g(t) \equiv 0, \\ \text{[Kendall '86, Cranston '91, F.-Y. Wang '94/'05]} \end{array} \right)$

Our method: Random walk approximation

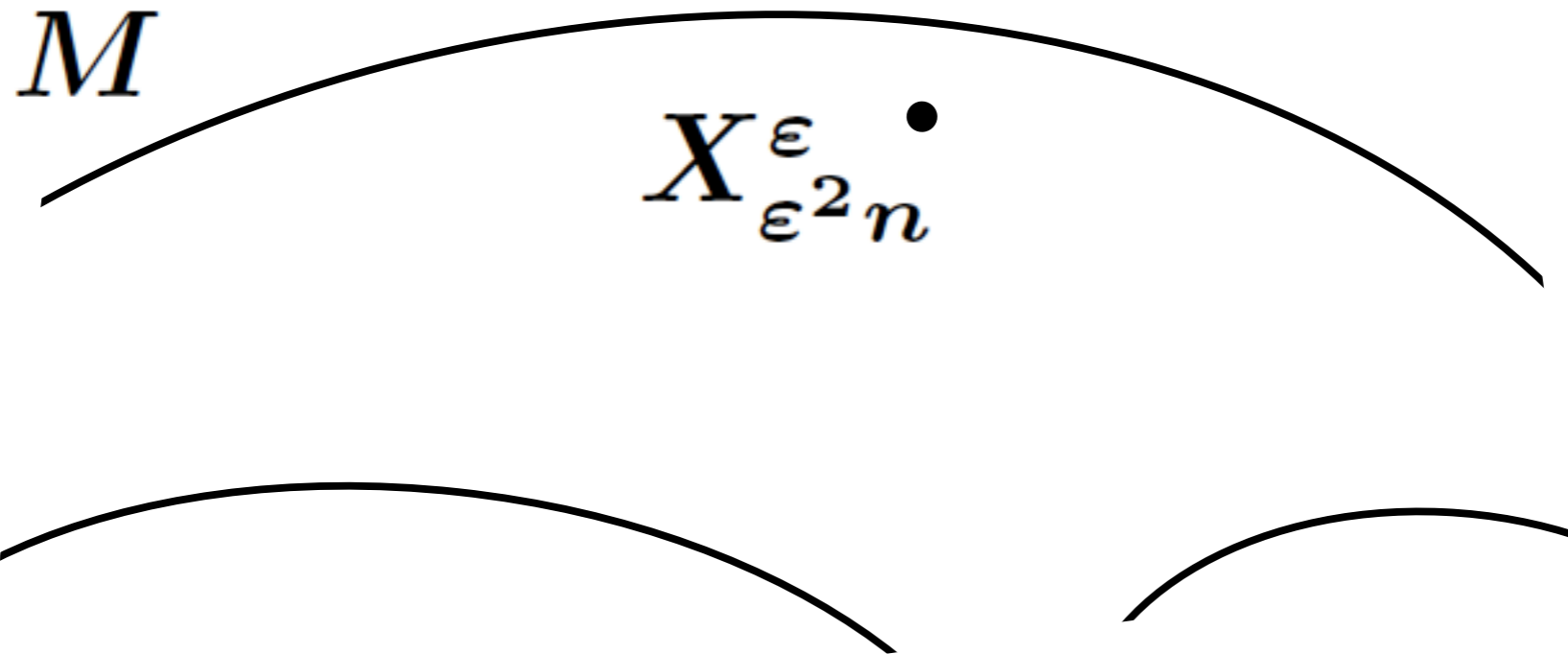
Show " $\sigma_t \leq \rho_t$ " in a weak sense

without extracting L_t

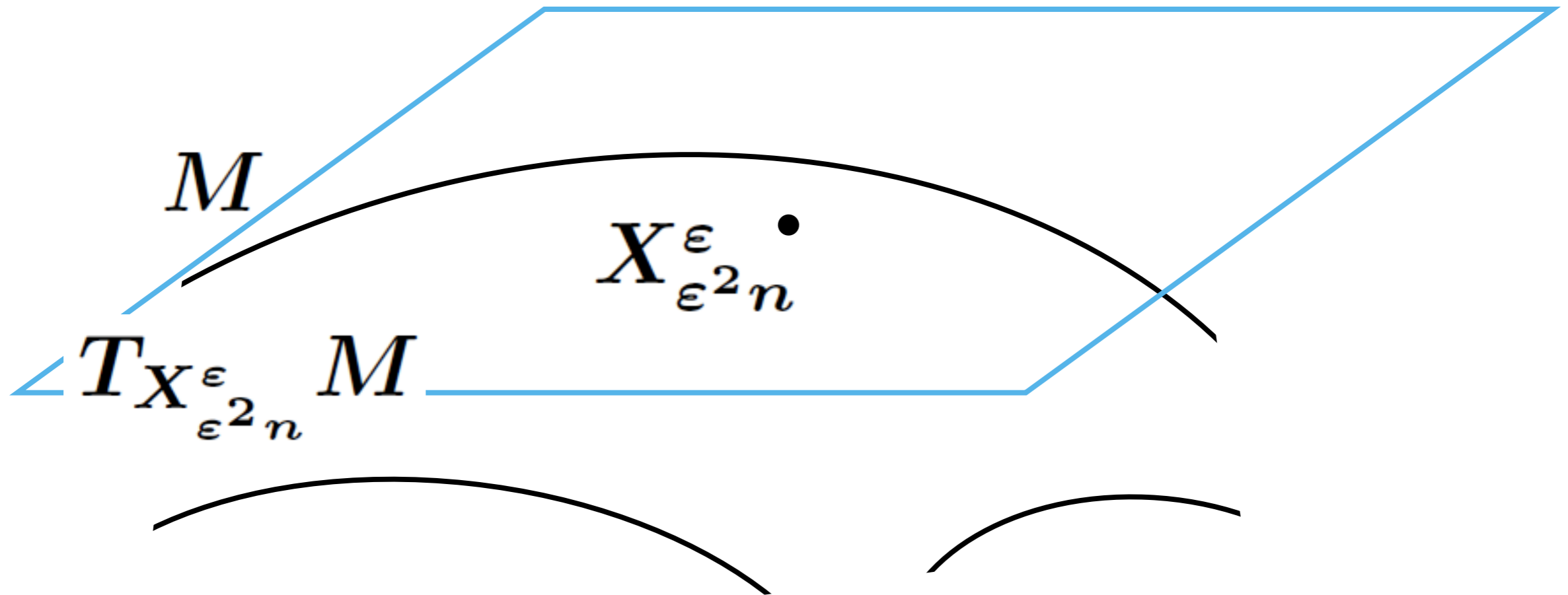
(When $\partial_t g(t) \equiv 0$, [von Renesse '04, K.'10])

Approximation by coupled RWs $(X_t^\varepsilon, Y_t^\varepsilon)$

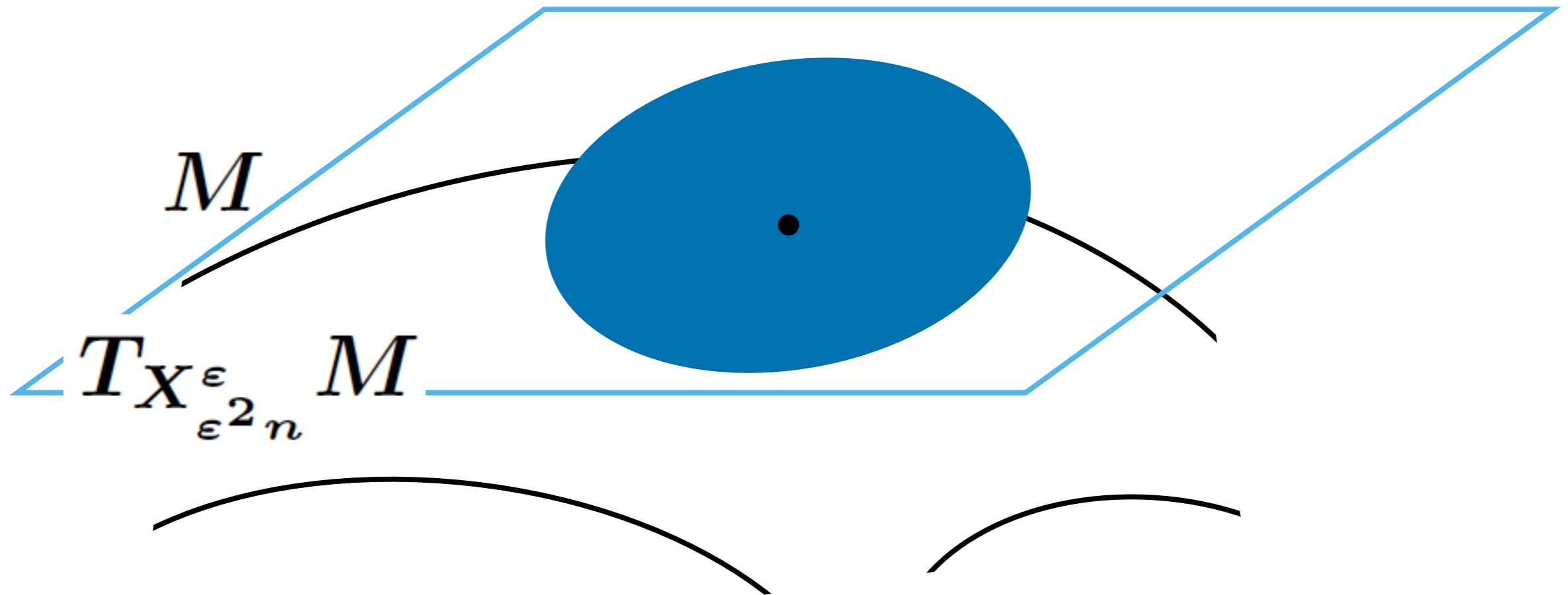
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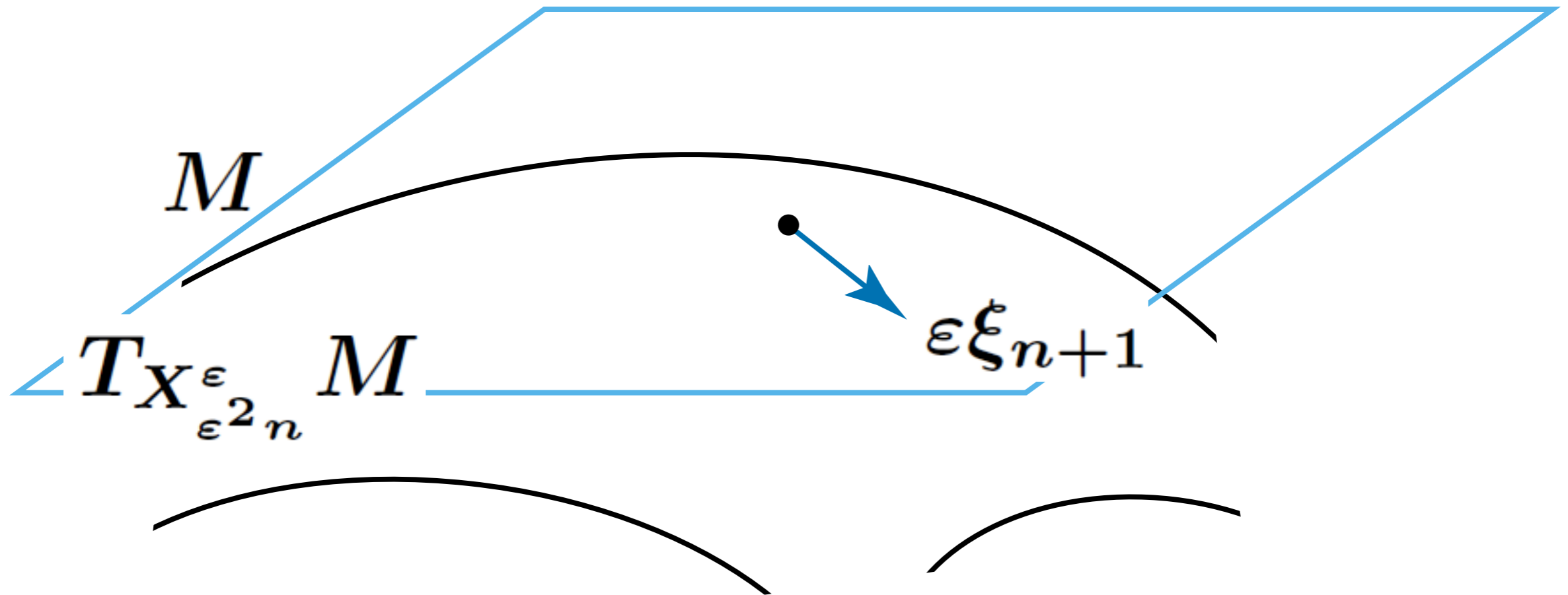
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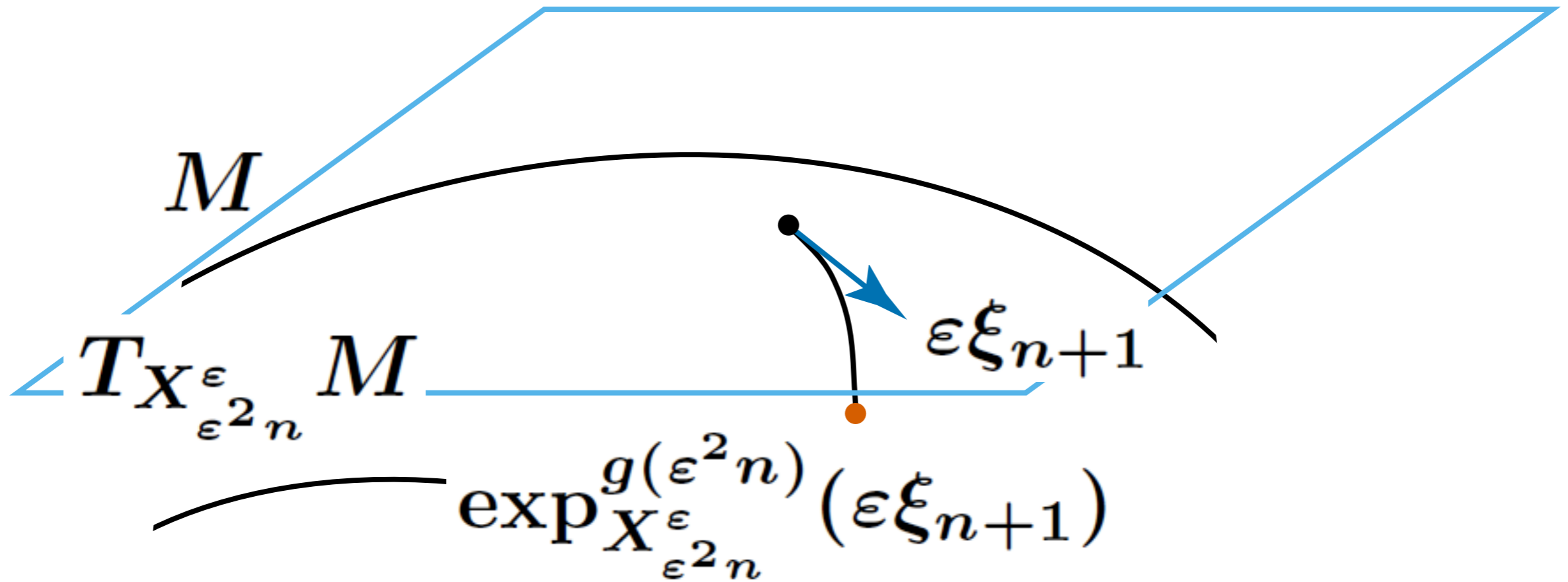
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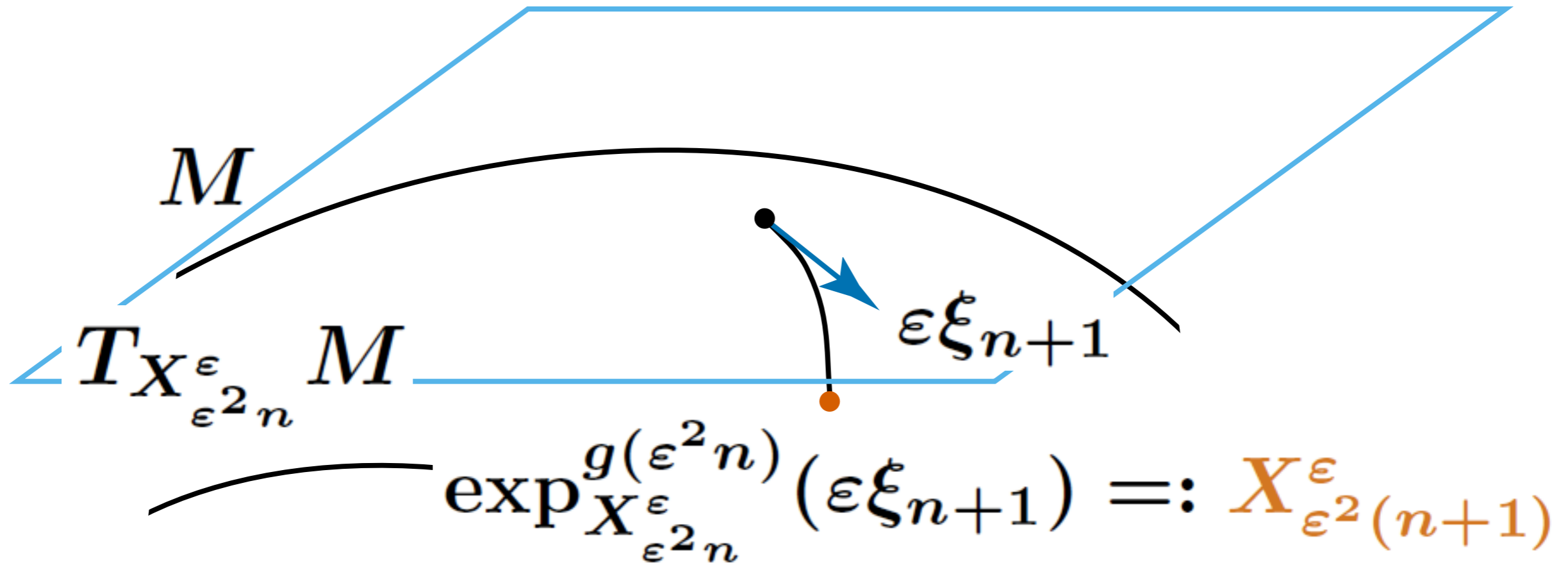
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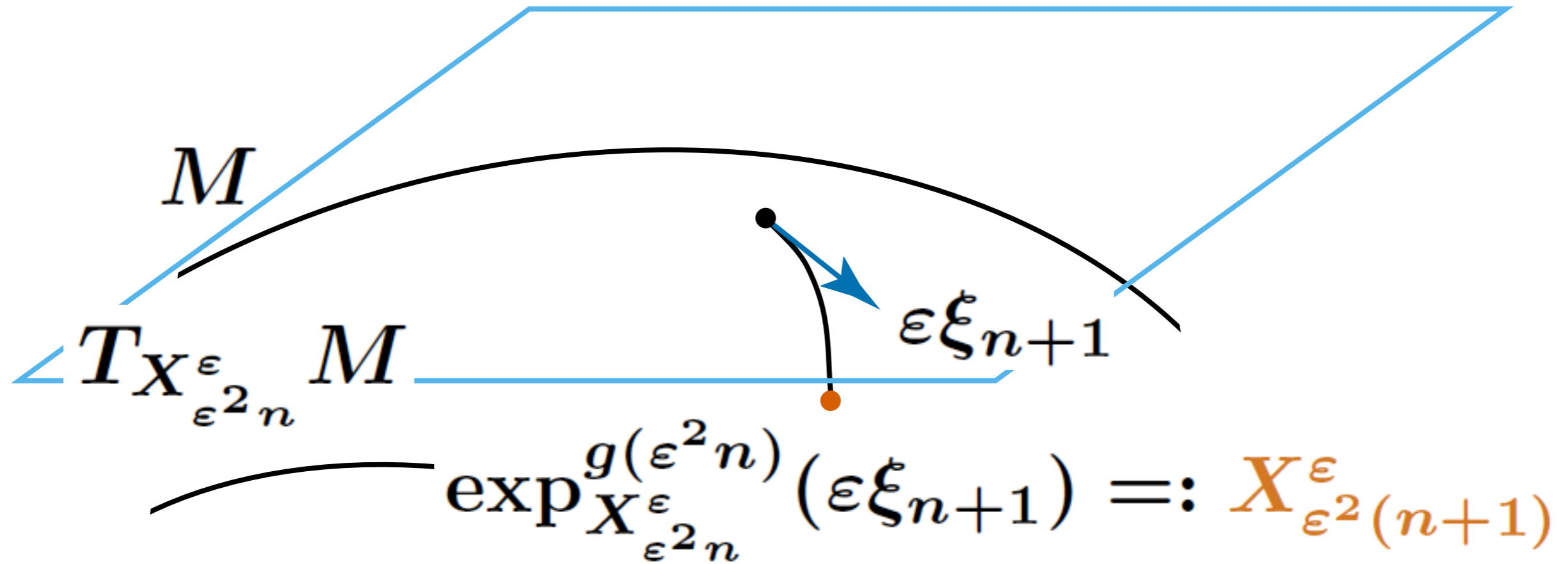
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Thm 3 [K.] (invariance principle)

$$X^\varepsilon \xrightarrow{d} X \text{ as } \varepsilon \rightarrow 0.$$

Why does it work?

Discrete Itô formula (Taylor expansion):

$$\sigma_{\varepsilon^2(n+1)}^\varepsilon = \sigma_{\varepsilon^2 n}^\varepsilon + \varepsilon \lambda_{n+1}^\varepsilon + \varepsilon^2 \Lambda_{n+1}^\varepsilon + o(\varepsilon^2)$$

When $(X_{\varepsilon^2 n}^\varepsilon, Y_{\varepsilon^2 n}^\varepsilon) \in \text{Cut}_{g(\varepsilon^2 n)}$,

Dividing a min. geod. into two pieces:

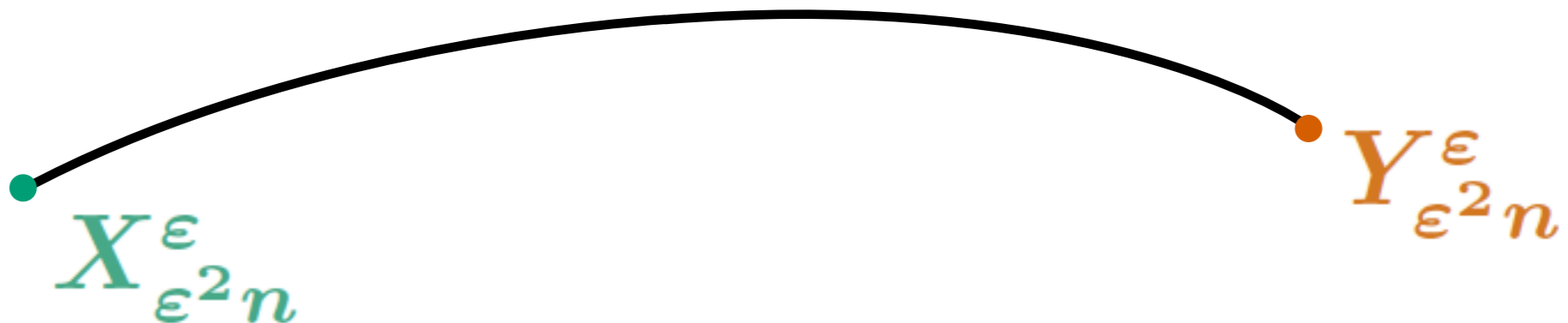
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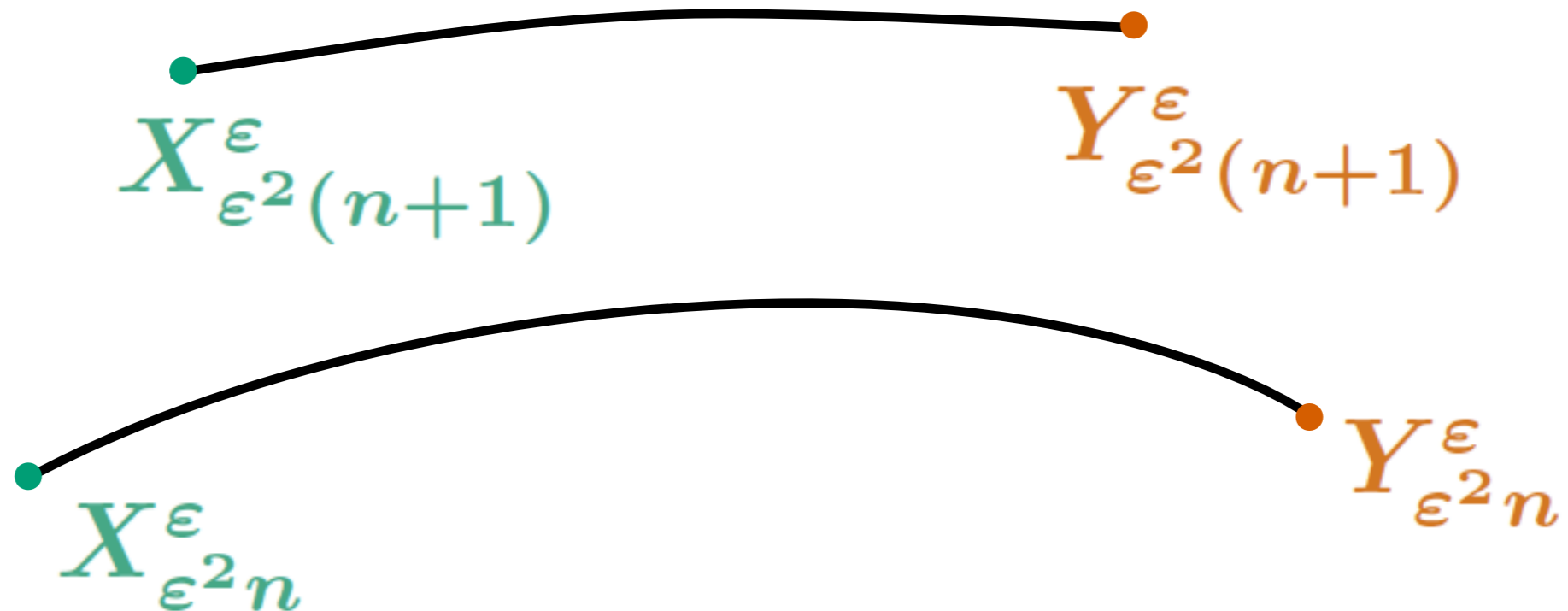
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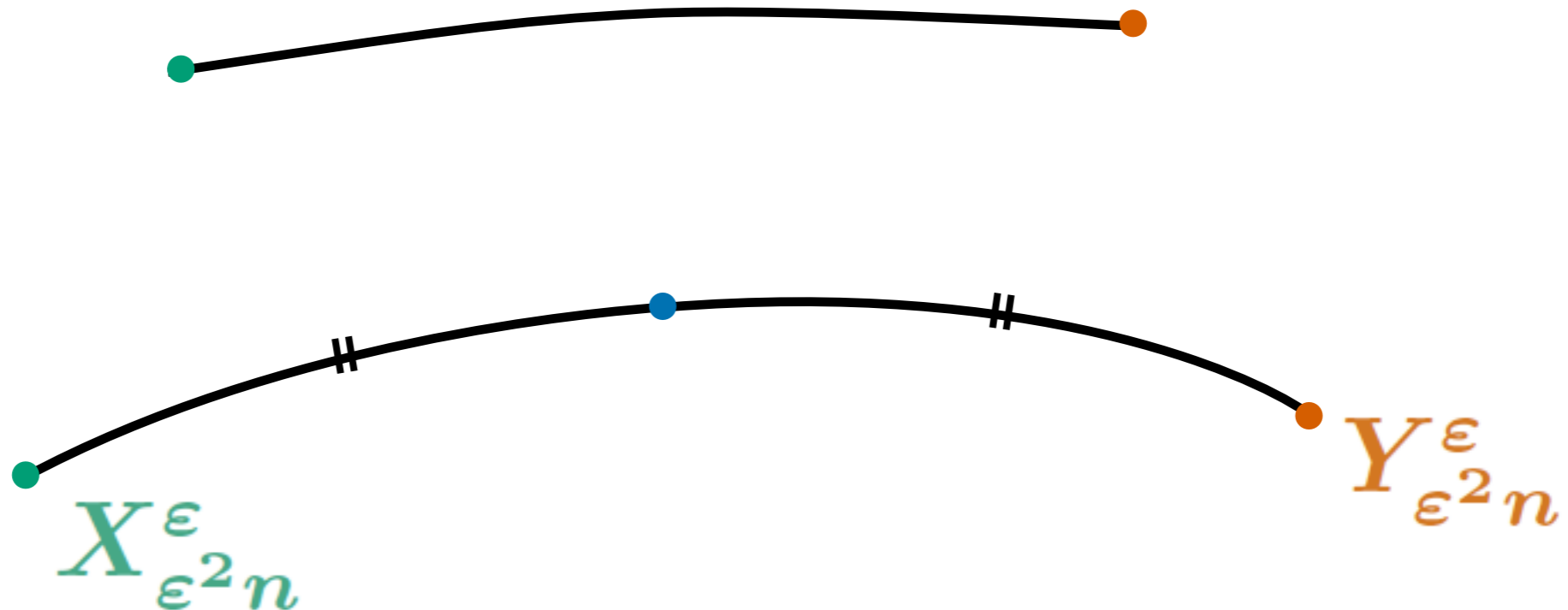
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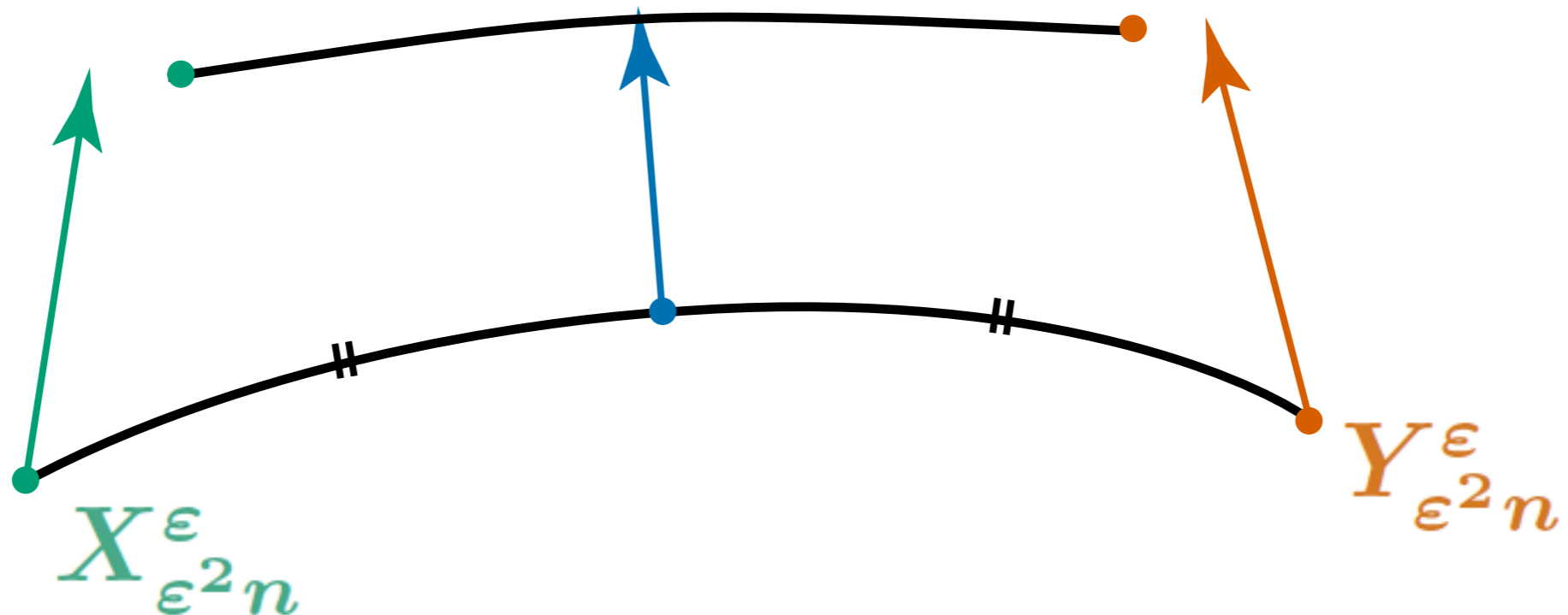
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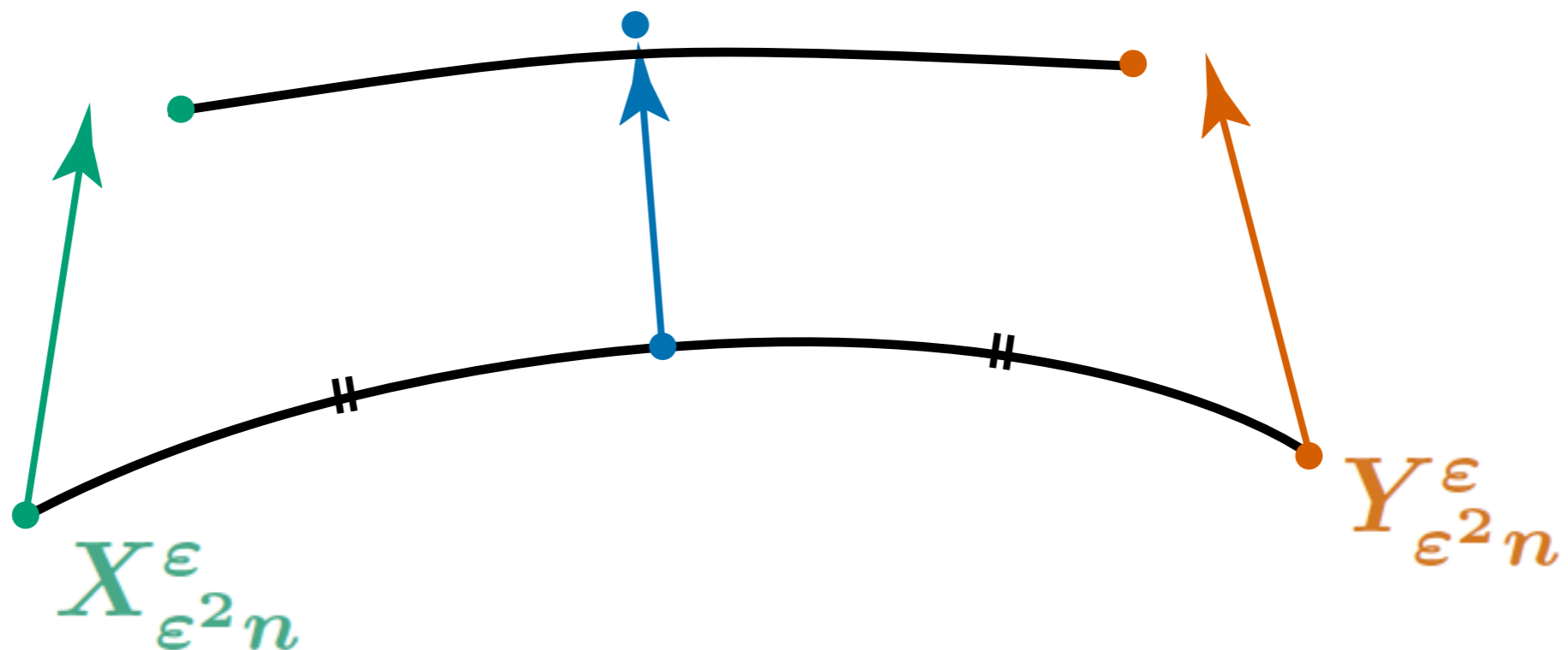
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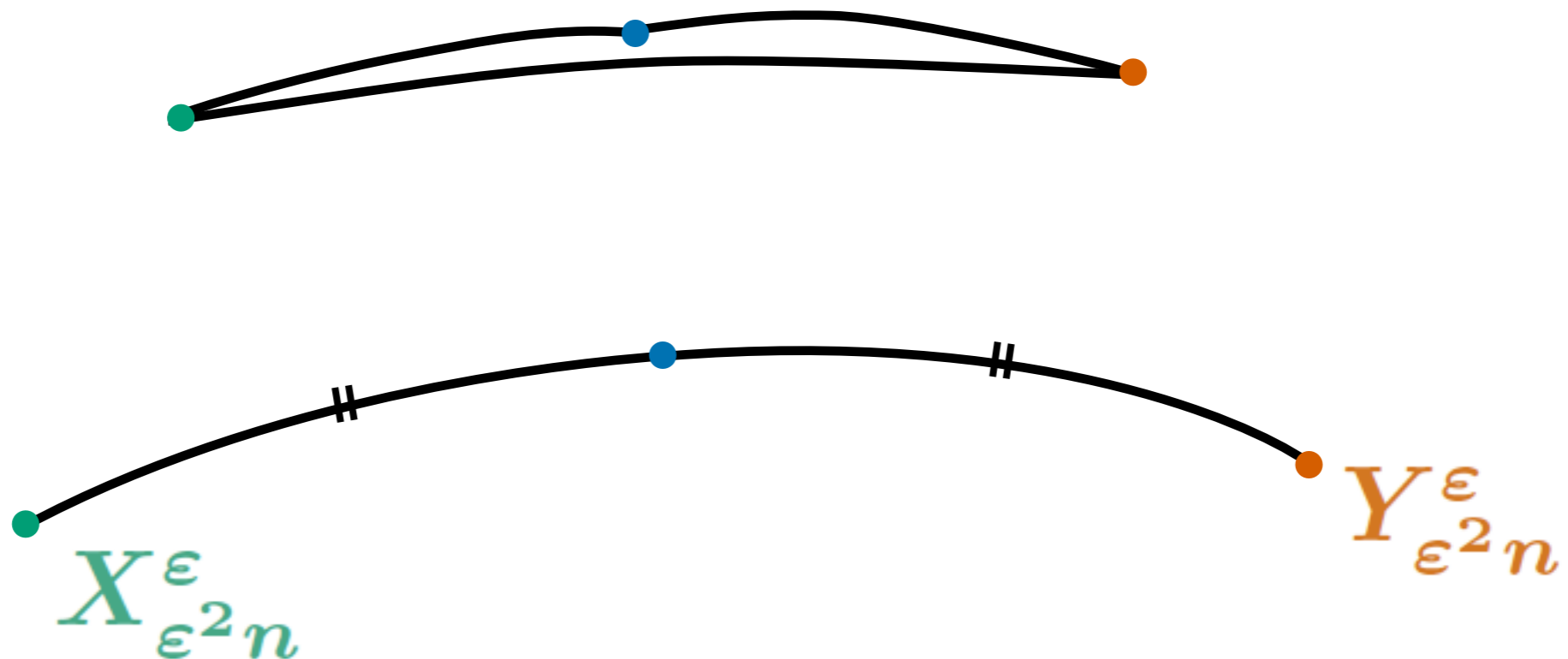
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$$\sigma_{\varepsilon^2(n+1)}^\varepsilon = \sigma_{\varepsilon^2 n}^\varepsilon + \varepsilon \lambda_{n+1}^\varepsilon + \varepsilon^2 \Lambda_{n+1}^\varepsilon + o(\varepsilon^2)$$

When $(X_{\varepsilon^2 n}^\varepsilon, Y_{\varepsilon^2 n}^\varepsilon) \in \text{Cut}_{g(\varepsilon^2 n)}$,

Dividing a min. geod. into two pieces:



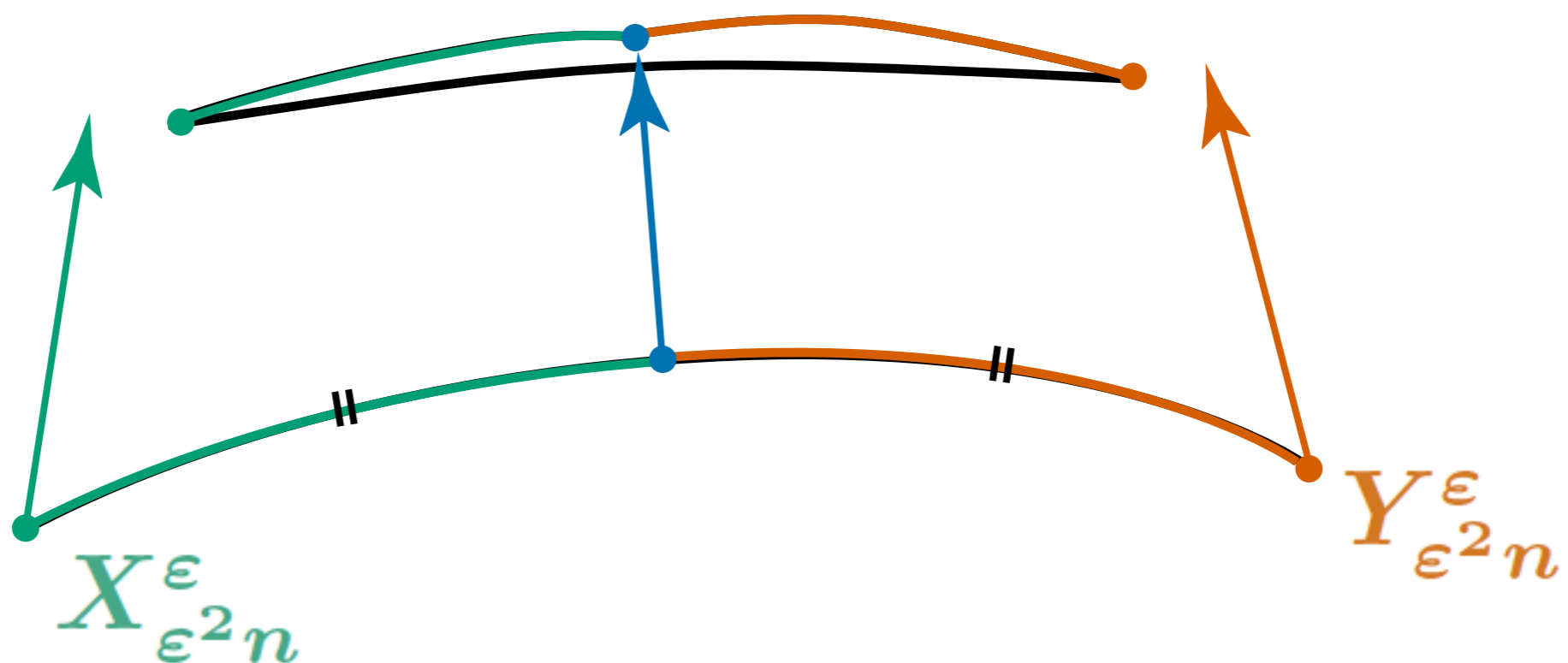
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Obstructions: Discreteness of the Itô formula

- (Invariance principle)

$$\varepsilon \sum_n \lambda_n^\varepsilon \rightarrow 2\sqrt{2}\beta. \text{ in law}$$

- (Law of large numbers)

$$\overline{\lim}_{\varepsilon \rightarrow 0} \varepsilon^2 \sum_n \Lambda_n^\varepsilon \leq \overline{\lim}_{\varepsilon \rightarrow 0} \left(-K \varepsilon^2 \sum_n \sigma_{\varepsilon^2 n}^\varepsilon \right)$$

(!) Λ_n^ε depends on λ_n^ε

(!) $\Lambda_{n+1}^\varepsilon \leq -K \sigma_{\varepsilon^2 n}^\varepsilon$ a.s. is NOT true

(!) Need a uniform bound for the error term $o(\varepsilon^2)$

Thm 4 [K.] (unif. nonexplosion/localization)

$$\sup_{\varepsilon} \mathbb{P}_x \left[\sup_{0 \leq s \leq t} d_{g(s)}(o, X^\varepsilon(s)) > R \right] \rightarrow 0$$

as $R \rightarrow \infty$

\Rightarrow Local uniform control of $o(\varepsilon^2)$ is sufficient

$$\Rightarrow \varepsilon^2 \sum_n \Lambda_n^\varepsilon \approx \varepsilon^2 \sum_n \mathbb{E}[\Lambda_n^\varepsilon | \mathcal{F}_{n-1}]$$

with arbitrary high probability (as $\varepsilon \rightarrow 0$)

$$\star \mathbb{E}[\Lambda_n^\varepsilon | \mathcal{F}_{n-1}] \leq -K \sigma_{\varepsilon^2(n-1)}^\varepsilon$$

$\Rightarrow \forall \delta > 0,$

$$\sigma_{\varepsilon^2 n}^{\varepsilon} \leq \sigma_0^{\varepsilon} + \varepsilon \sum_{j \leq n} \lambda_j^{\varepsilon} - K \varepsilon^2 \sum_{j \leq n} \sigma_{\varepsilon^2 j}^{\varepsilon} + \delta$$

with arbitrary high probability (as $\varepsilon \rightarrow 0$).

\Downarrow

$$\mathbb{P} \left[\inf_{n \leq \varepsilon^{-2} T} \sigma_{\varepsilon^2 n}^{\varepsilon} > \delta \right]$$

$$\leq \mathbb{P} \left[\inf_{n \leq \varepsilon^{-2} T} \rho_{\varepsilon^2 n}^{\varepsilon} > \delta' \right] + (\text{error})$$

\Rightarrow Thm 1 ($\varepsilon \rightarrow 0, \delta \rightarrow 0$)

**5. Coupling by spacetime parallel transport
(joint work with R. Philipowski)**

Perelman's \mathcal{L} -distance: Suppose $T_1 = 0$

$$\gamma : [\tau_1, \tau_2] \rightarrow M, [\tau_1, \tau_2] \subset [0, T_2]$$

$$\mathcal{L}(\gamma) := \int_{\tau_1}^{\tau_2} \sqrt{\tau} \left(|\dot{\gamma}(\tau)|_{g(\tau)}^2 + R_{g(\tau)}(\gamma(\tau)) \right) d\tau$$

$$L(\tau_1, x; \tau_2, y) := \inf \left\{ \mathcal{L}(\gamma) \mid \begin{array}{l} \gamma(\tau_1) = x, \\ \gamma(\tau_2) = y \end{array} \right\}$$

Normalization

Given $0 \leq \bar{\tau}_1 < \bar{\tau}_2 \leq T_2$,

$$\Theta_t(x, y) := 2(\sqrt{\bar{\tau}_2 t} - \sqrt{\bar{\tau}_1 t})L(\bar{\tau}_1 t, x; \bar{\tau}_2 t, y) \\ - 2m(\sqrt{\bar{\tau}_2 t} - \sqrt{\bar{\tau}_1 t})^2$$

Thm 5 [K. & Philipowski]

Suppose

$$\left\{ \begin{array}{l} \partial_t g(t) = 2 \operatorname{Ric}_{g(t)}, \\ \inf_{\substack{X \in TM \\ t \in [T_1, T_2]}} \frac{\operatorname{Ric}_{g(t)}(X, X)}{g(t)(X, X)} > -\infty \end{array} \right.$$

$\Rightarrow \exists (X_\tau, Y_\tau)$: coupling of $g(\tau)$ -BMs

s.t. $(\Theta_t(X_{\bar{\tau}_1 t}, Y_{\bar{\tau}_2 t}))_{t \in [1, T_2/\bar{\tau}_2]}$

is a **supermartingale**

Cor 2 [K. & Philipowski]

$\forall \varphi: \nearrow$, concave & $\forall \mu_t, \nu_t$: heat distributions,
 $\mathcal{I}_{\varphi}(\Theta_t)(\mu_{\bar{\tau}_1 t}, \nu_{\bar{\tau}_2 t}) \searrow$

- [Topping '09]: $\mathcal{I}_{\Theta_t}(\mu_{\bar{\tau}_1 t}, \nu_{\bar{\tau}_2 t}) \searrow$
when M :cpt, via optimal transport techniques
(\Rightarrow Monotonicity of Perelman's \mathcal{W} -entropy)

Strategy of the Proof

- Properties of \mathcal{L} -distance
being analogous to the Riem. distance
 - \mathcal{L} -geodesic, 1st & 2nd variation of \mathcal{L} -length,
 \mathcal{L} -index lemma, \mathcal{L} -cut locus
- Approximation by random walks
- Coupling of $dX_{\bar{\tau}_1 t}^\varepsilon$ and $dY_{\bar{\tau}_2 t}^\varepsilon$ by
spacetime-parallel transport along \mathcal{L} -geodesic

Spacetime parallel transport

For $\gamma : [s, t] \rightarrow M$ & V : vector field along γ ,

V : spacetime parallel

$$\text{def } \Leftrightarrow \nabla_{\dot{\gamma}(u)}^{g(u)} V(u) = -\frac{1}{2} \partial_u g(u)^\# V(u)$$

\mathcal{L} -geodesic

$\gamma : [s, t] \rightarrow M$: \mathcal{L} -geodesic

$$\text{def } \Leftrightarrow \nabla_{\dot{\gamma}_u}^{g(u)} \dot{\gamma}_u = \frac{1}{2} \nabla^{g(u)} R_{g(u)} - 2 \text{Ric}_{g(u)}^\#(\dot{\gamma}_u) - \frac{1}{2u} \dot{\gamma}_u$$

$\sqrt{u} \dot{\gamma}_u$ is **NOT** spacetime parallel to γ !