

Rates of convergence for the Krasnoselskii-Mann fixed point iteration

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Based on joint work with
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Outline

- 1 Introduction and examples
- 2 Sharp recursive bounds by optimal transport
- 3 Upper bounds by suboptimal transports
- 4 The constant $\kappa = 1/\sqrt{\pi}$ is tight
- 5 KM iterations with errors
- 6 Some final comments...

Krasnoselskii-Mann sequential averaging process

$T : C \rightarrow C$ non-expansive / C convex bounded in $(X, \|\cdot\|)$ normed space

$$(KM) \quad x^{n+1} = (1 - \alpha_{n+1}) x^n + \alpha_{n+1} T x^n$$

- ▷ algorithm to compute & prove existence of fixed points
- ▷ **convex optimization:** Gradient, Prox, Douglas-Rachford, ADMM, POCS...
- ▷ **stochastic processes:** stochastic shortest path, Q-learning, random walks
- ▷ **evolution equations:** discretization of $\frac{dx}{dt} + [I - T](x) = 0$

Questions: $\left\{ \begin{array}{l} \text{a) } \|x^n - T x^n\| \rightarrow 0 \text{ ? (Asymptotic Regularity)} \\ \text{b) How fast ? (Rate of Convergence)} \end{array} \right.$

Example: θ -rotation in \mathbb{R}^2

$$T(x, y) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow \|x^n - Tx^n\| = 2 \sin\left(\frac{\theta}{2}\right) \cos^n\left(\frac{\theta}{2}\right) \|x^0\|$$

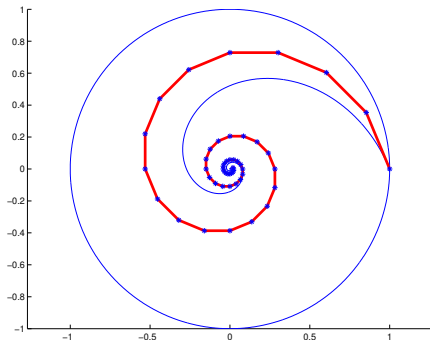
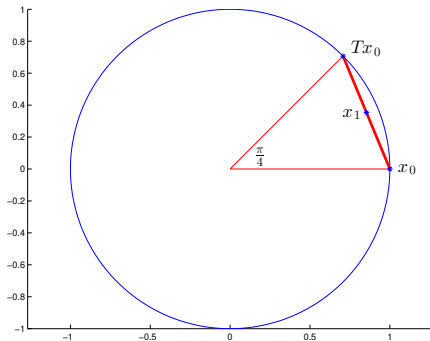


Figure: KM iterates for $\theta = \frac{\pi}{4}$ with $\alpha_n \equiv \frac{1}{2}$

a) If $\|x^n - Tx^n\| \rightarrow 0$ then...

- ▷ every strong/weak cluster point is a fixed point of T
- ▷ if C is strong/weak compact \Rightarrow existence of fixed points (Browder-Göhde-Kirk'65)
- ▷ moreover $\|x^n - \bar{x}\|$ decreases for all $\bar{x} \in \text{Fix}T$, hence x^n converges strong/weak to a fixed point (Krasnoselskii'55, Shaefer'57, Browder-Petryshyn'66, Edelstein'70, Groetsch'72, Ishikawa'76, Edelstein-O'Brien'78, Reich'79...)

b) How fast?

- ▷ convergence rates
- ▷ non-asymptotic error bounds

Example: Gradient descent

$f : \mathcal{H} \rightarrow \mathbb{R}$ convex with L -Lipschitz gradient, \mathcal{H} Hilbert

$$(G) \quad x^{n+1} = x^n - \gamma_{n+1} \nabla f(x^n)$$

From Baillon-Haddad's Theorem

$$\nabla f \text{ is } L\text{-Lipschitz} \Leftrightarrow Tx \triangleq x - \frac{2}{L} \nabla f(x) \text{ is non-expansive}$$

and (G) can be written as

$$x^{n+1} = \left(1 - \frac{\gamma_{n+1}L}{2}\right)x^n + \frac{\gamma_{n+1}L}{2}Tx^n$$

Remarks:

- $\text{Fix}(T) = \text{Argmin}_{x \in \mathcal{H}} f(x)$
- Residuals $|x^n - Tx^n| = \frac{2}{L} |\nabla f(x^n)|$

Example: Proximal point method

$\min_{x \in \mathcal{H}} f(x)$ where $f \in \Gamma_0(\mathcal{H})$ with \mathcal{H} a Hilbert space

$$(Prox) \quad x^{n+1} = \text{Prox}_{\lambda f}(x^n) = \operatorname{argmin}_{y \in \mathcal{H}} f(y) + \frac{1}{2\lambda} |y - x^n|^2$$

Theorem (Moreau 1965)

$f_\lambda(x) \triangleq \min_{y \in \mathcal{H}} f(y) + \frac{1}{2\lambda} |y - x|^2$ is a smooth convex minorant of f

$\nabla f_\lambda(x) = \frac{1}{\lambda} [x - \text{Prox}_{\lambda f}(x)]$ is $\frac{1}{\lambda}$ -Lipschitz.

(Prox) can be rewritten as a Gradient and/or a (KM) iteration

$$x^{n+1} = x^n - \lambda \nabla f_\lambda(x^n) = \frac{1}{2} x^n + \frac{1}{2} R_{\lambda f}(x^n)$$

for the non-expansive *reflection operator* $R_{\lambda f}(x) = 2 \text{Prox}_{\lambda f}(x) - x$.

Remark: $\text{Fix}(R_{\lambda f}) = \text{Fix}(\text{Prox}_{\lambda f}) = \text{Argmin} f_\lambda = \text{Argmin} f$.

Example: Douglas-Rachford

$\min_{x \in \mathcal{H}} f(x) + g(x)$ with $f, g \in \Gamma_0(\mathcal{H})$ and \mathcal{H} Hilbert

$$(DR) \quad x^{n+1} = (1 - \alpha)x^n + \alpha R_{\lambda f} \circ R_{\lambda g}(x^n)$$

Special cases:

- Alternating Direction Method of Multipliers (ADMM)
- Spingarn's partial inverse method
- Decomposition of separable problems

Example: Forward-Backward

$\min_{x \in \mathcal{H}} f(x) + g(x)$ with $f : \mathcal{H} \rightarrow \mathbb{R}$ convex with L -Lipschitz gradient, $g \in \Gamma_0(\mathcal{H})$

(FB)
$$x^{n+1} = \text{Prox}_{\lambda g}(x^n - \gamma \nabla f(x^n)).$$

Recall: $S : \mathcal{H} \rightarrow \mathcal{H}$ is α -averaged if $S(x) = \alpha x + (1-\alpha)Tx$ with T nonexpansive.

- $x - \gamma \nabla f(x)$ is α -averaged with $\alpha = (1 - \frac{\gamma L}{2})$
- $\text{Prox}_{\lambda g}$ is $\frac{1}{2}$ -averaged

Hence, (FB) is again a (KM) iteration since:

Lemma: If S_i are α_i -averaged for $i = 1, 2$ then $S_1 \circ S_2$ is $(\alpha_1 \alpha_2)$ -averaged.

Example: Right-shift in $C = \{x \in \ell_+^1(\mathbb{N}) : \sum_{i=0}^{\infty} x_i = 1\}$

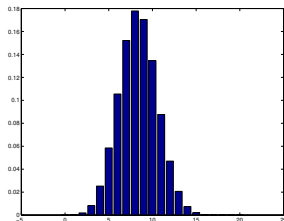
$T(x_0, x_1, x_2, \dots) = (0, x_0, x_1, x_2, \dots)$ is an ℓ^1 -isometry

$$x^0 = (1, 0, 0, 0, \dots)$$

$$x^1 = (1 - \alpha_1, \alpha_1, 0, 0, \dots)$$

$$x^2 = ((1 - \alpha_2)(1 - \alpha_1), (1 - \alpha_2)\alpha_1 + \alpha_2(1 - \alpha_1), \alpha_2\alpha_1, 0, \dots)$$

$$x^3 = \dots$$



$$x_k^n = \mathbb{P}(X_1 + \dots + X_n = k)$$

$$X_i \sim \text{Bernoulli}(\alpha_i)$$

$$\|x^n - Tx^n\|_1 = 2 \max_k x_k^n$$

Example: “Lazy” random walks

A **random walk** on a metric space (X, d) is described by $\mu^{n+1} = T\mu^n$, with the evolution operator T induced by a Markov transition kernel $(m_x)_{x \in X}$

$$T\mu(A) \triangleq \int_X m_x(A) d\mu(x) \quad \forall A \in \mathcal{B}(X), \forall \mu \in \mathcal{P}_1(X).$$

- ▷ $\text{Fix}(T)$ is the set of invariant measures
- ▷ T is nonexpansive in total variation $\|\cdot\|_{\text{tv}}$
- ▷ residuals $\|\mu^n - T\mu^n\|_{\text{tv}}$

For *lazy random walks* with kernel

$$m_x^\alpha = (1 - \alpha)\delta_x + \alpha m_x$$

the evolution is a (KM) iteration.

From PEP (back) to optimal transport

- PEP techniques, introduced by Drori & Teboulle around 2012, yield convergence rates for convex optimization, either in terms of the function values $f(x^n) - f(x^*)$ or the gradient norms $|\nabla f(x^n)|$. These techniques seem inherently restricted to Hilbert spaces.
- For fixed point iterations the natural metric is the residual $\|x^n - Tx^n\|$. An approach to get convergence rates was proposed by Baillon & Bruck in 1992-1996, and completed by C-Soto-Vaisman in 2014. The principle is similar to PEP except that it uses optimal transport instead of semidefinite programming. It works on general normed spaces.

Conjecture (Baillon-Bruck 1992)

There exists a universal constant κ such that

$$\|x^n - Tx^n\| \leq \kappa \frac{\text{diam}(C)}{\sqrt{\sum_{i=1}^n \alpha_i(1-\alpha_i)}}. \quad (\text{BB})$$

Theorem (Baillon-Bruck 1996)

For constant $\alpha_n \equiv \alpha$, (BB) holds with $\kappa = 1/\sqrt{\pi}$.

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For constant $\alpha_n \equiv \alpha$, (BB) holds with $\kappa = 1/\sqrt{\pi}$.

Our contribution (C-Soto-Vaisman 2014, Bravo-C 2016, Bravo-C-Pavez 2017)

- 1 (BB) holds for general α_n with $\kappa = 1/\sqrt{\pi} \sim 0.5642$
- 2 Nonlinear maps: the constant $\kappa = 1/\sqrt{\pi}$ is tight
- 3 Affine maps: tight bound with $\kappa = \max_z \sqrt{z} e^{-z} I_0(z) \sim 0.4688$
- 4 Extension to inexact KM: $x^{n+1} = (1-\alpha_{n+1})x^n + \alpha_{n+1}(Tx^n + \varepsilon^{n+1})$
- 5 Rates of convergence for nonlinear semigroups in continuous time

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A recursive bound

(KM)

$$x^{n+1} = (1 - \alpha_{n+1}) x^n + \alpha_{n+1} T x^n$$

- We look for sharp bounds for $\|x^n - T x^n\| = \|x^{n+1} - x^n\| / \alpha_{n+1}$
- This is achieved by bounding $\|x^m - x^n\|$ for all $m \leq n$

A recursive bound

(KM)

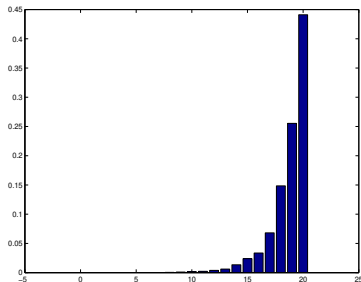
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- This is achieved by bounding $\|x^m - x^n\|$ for all $m \leq n$

Set $\alpha_0 = 1$ and $T x^{-1} = x^0$

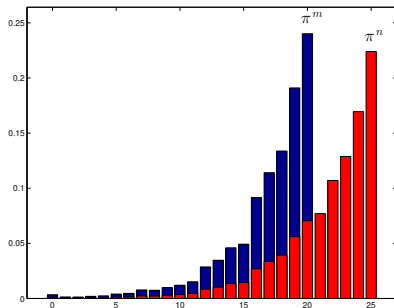
$$x^n = \sum_{i=0}^n \pi_i^n T x^{i-1}$$

$$\pi_i^n = \alpha_i \prod_{k=i+1}^n (1 - \alpha_k)$$



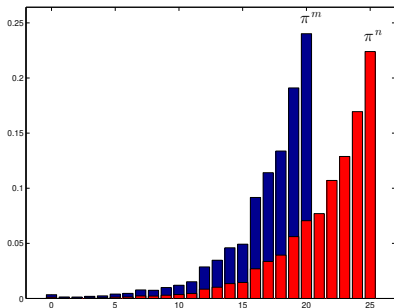
A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$x^m - x^n = \sum_{i=0}^m \pi_i^m T x^{i-1} - \sum_{j=0}^n \pi_j^n T x^{j-1}$$



A recursive bound $\|x^m - x^n\| \leq d_{mn}$

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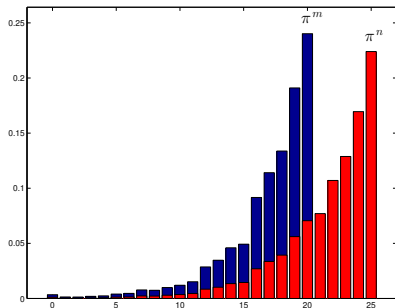
Let Z^{mn} be the set of transport plans $z \geq 0$ taking π^m to π^n

$$\pi_i^m = \sum_{j=0}^n z_{ij}$$

$$\pi_j^n = \sum_{i=0}^m z_{ij}$$

A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$x^m - x^n = \sum_{i=0}^m \sum_{j=0}^n z_{ij} T x^{i-1} - \sum_{j=0}^n \sum_{i=0}^m z_{ij} T x^{j-1}$$



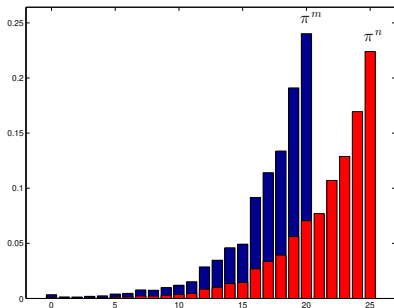
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A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$x^m - x^n = \sum_{i=0}^m \sum_{j=0}^n z_{ij} [Tx^{i-1} - Tx^{j-1}]$$



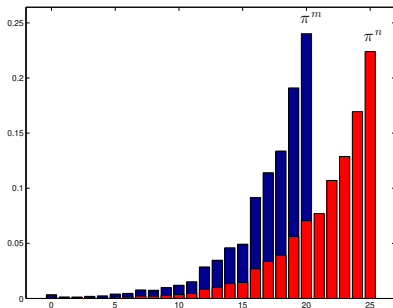
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A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$\|x^m - x^n\| \leq \sum_{i=0}^m \sum_{j=0}^n z_{ij} \|x^{i-1} - x^{j-1}\|$$



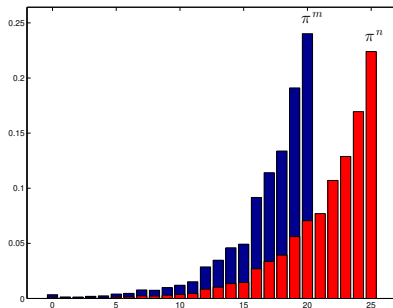
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A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$\|x^m - x^n\| \leq \sum_{i=0}^m \sum_{j=0}^n z_{ij} d_{i-1,j-1}$$



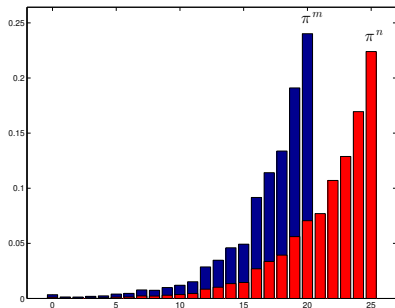
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A recursive bound $\|x^m - x^n\| \leq d_{mn}$

$$\|x^m - x^n\| \leq \sum_{i=0}^m \sum_{j=0}^n z_{ij} d_{i-1,j-1} \longrightarrow \min_z$$



Let Z^{mn} be the set of transport plans $z \geq 0$ taking π^m to π^n

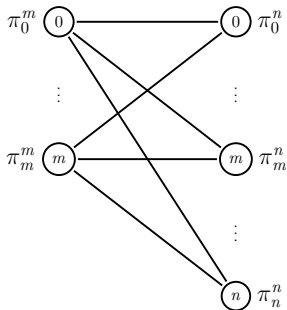
$$\pi_i^m = \sum_{j=0}^n z_{ij}$$

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Recursive optimal transports

Suppose w.l.o.g. $\text{diam}(C)=1$. Set $d_{-1,n} = 1$ and define d_{mn} inductively as

$$(R) \quad d_{mn} := \min_{z \in Z^{mn}} \sum_{i=0}^m \sum_{j=0}^n z_{ij} d_{i-1,j-1}$$



Property

Let $T : C \rightarrow C$ be a nonexpansive map on a convex set C with $\text{diam}(C) = 1$. Then the KM iterates satisfy $\|x^m - x^n\| \leq d_{mn}$ for all $m, n \in \mathbb{N}$.

The bounds d_{mn} are:

- Independent of the space X
- Independent of the operator $T : C \rightarrow C$

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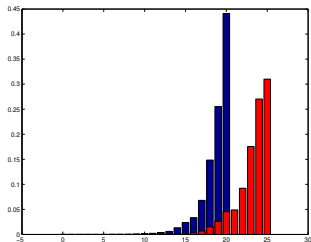
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Theorem (Bravo-C 2016)

These bounds are uniformly tight: There exists a nonexpansive $T : C \rightarrow C$ on the unit cube $C = [0, 1]^{\mathbb{N}} \subseteq \ell^\infty(\mathbb{N})$ and a corresponding KM sequence such that $\|x^m - x^n\|_\infty = d_{mn}$ for all $m, n \in \mathbb{N}$.

\Rightarrow The d_{mn} 's are the right object to get sharp convergence rates !

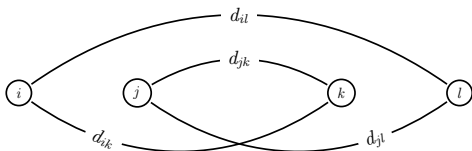
Metric properties of optimal transport bounds



$$d_{mn} \triangleq \min_{z \in P_{mn}} \sum_{i=0}^m \sum_{j=0}^n z_{ij} d_{i-1, j-1}$$

Theorem (Aygen-Satik'1994, Bravo-C.'2016, Bravo-Champion-C.'2018)

The d_{mn} 's define a metric in \mathbb{N} and $d_{il} + d_{jk} \leq d_{ik} + d_{jl}$ for all $i < j < k < l$.

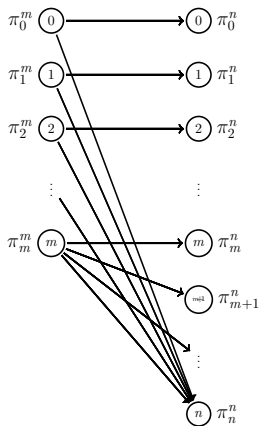


No flow-crossing in
optimal transport



Greedy algorithm

Example: $\alpha_n \geq \frac{1}{2}$



Optimal transport

$$z_{ii} = \pi_i^n$$

$$z_{mj} = \pi_j^n$$

$$z_{in} = \pi_i^m - \pi_i^n$$

$$z_{mn} = \pi_m^m - \sum_{j=m}^{n-1} \pi_j^n$$

for $i = 0, \dots, m,$

for $j = m + 1, \dots, n - 1,$

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

This yields the “*simpler*” explicit recursion

$$d_{mn} = \sum_{j=m+1}^{n-1} \pi_j^n d_{m-1, j-1} + \sum_{i=0}^{m-1} (\pi_i^m - \pi_i^n) d_{i-1, n-1} + (\pi_m^m - \sum_{j=m}^{n-1} \pi_j^n) d_{m-1, n-1}$$

Example: $\alpha_n \equiv \alpha \geq \frac{1}{2}$

$$\begin{aligned}
 d_{6,10}(\alpha) = & \alpha(4 - 36\alpha + 328\alpha^2 - 2671\alpha^3 + 19853\alpha^4 - 132880\alpha^5 + 785003\alpha^6 \\
 & - 4016624\alpha^7 + 17541102\alpha^8 - 64796454\alpha^9 + 201809157\alpha^{10} \\
 & - 530670200\alpha^{11} + 1183318617\alpha^{12} - 2250818306\alpha^{13} + 3675506816\alpha^{14} \\
 & - 5184593492\alpha^{15} + 6352439437\alpha^{16} - 6792441644\alpha^{17} + 6361687020\alpha^{18} \\
 & - 5232669869\alpha^{19} + 3785701567\alpha^{20} - 2409974375\alpha^{21} + 1348858198\alpha^{22} \\
 & - 662337623\alpha^{23} + 284299971\alpha^{24} - 106102624\alpha^{25} + 34171973\alpha^{26} \\
 & - 9400913\alpha^{27} + 2178730\alpha^{28} - 417352\alpha^{29} + 64328\alpha^{30} \\
 & - 7667\alpha^{31} + 663\alpha^{32} - 37\alpha^{33} + \alpha^{34})
 \end{aligned}$$

...??????????

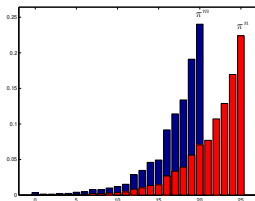
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Upper estimate: $d_{mn} \leq c_{mn}$

Consider the sub-optimal transport plan

$$\hat{z}_{ij} = \begin{cases} \pi_j^n & \text{for } i = j \leq m \\ \pi_i^m \pi_j^n & \text{for } j = m + 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$



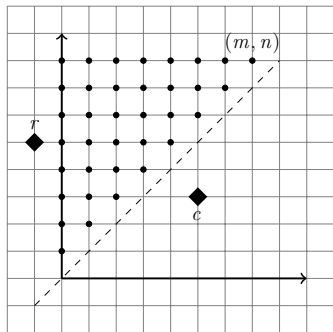
Setting $c_{-1,n} = 1$ for all $n \in \mathbb{N}$ we get inductively

$$\|x^m - x^n\| \leq d_{mn} \leq c_{mn} \triangleq \sum_{i=0}^m \sum_{j=m+1}^n \pi_i^m \pi_j^n c_{i-1,j-1}$$

Two Markov chains

Both c_{mn} and d_{mn} can be interpreted as the absorption probability of two Markov chains with state space $\mathcal{S} = \{(m, n) : 0 \leq m < n\} \cup \{r, c\}$.

$$\text{transition probabilities} \quad \left\{ \begin{array}{l} Q_{ij}^{mn} = \hat{z}_{ij}^{mn} \quad (\text{sub-optimal transports for } c_{mn}) \\ P_{ij}^{mn} = z_{ij}^{mn} \quad (\text{optimal transports for } d_{mn}) \end{array} \right.$$



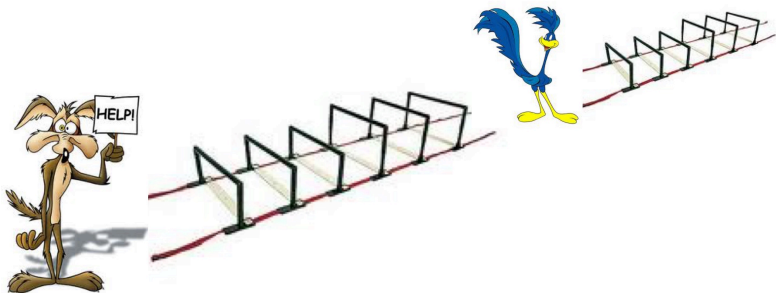
$$c_{mn} = \mathbb{P}_Q(\text{absorbed at } r | mn)$$

$$d_{mn} = \mathbb{P}_P(\text{absorbed at } r | mn)$$

Probabilistic interpretation of c_{mn}

$$\mathbb{P}[C_i = 1] = \mathbb{P}[R_i = 1] = \alpha_i$$

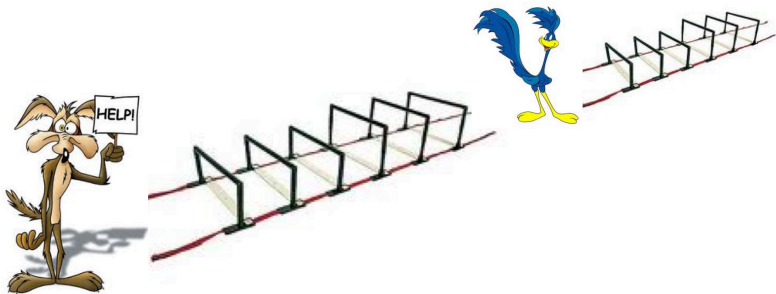
$$\pi_j^n = \alpha_j \prod_{k=j+1}^n (1 - \alpha_k)$$



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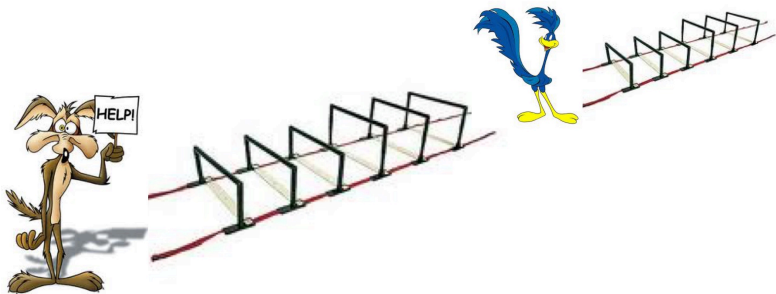


$$\tilde{c}_{mn} = \mathbb{P}[\text{roadrunner escapes}]$$

Probabilistic interpretation of c_{mn}

$$\mathbb{P}[C_i = 1] = \mathbb{P}[R_i = 1] = \alpha_i$$

$$\pi_j^n = \alpha_j \prod_{k=j+1}^n (1 - \alpha_k)$$

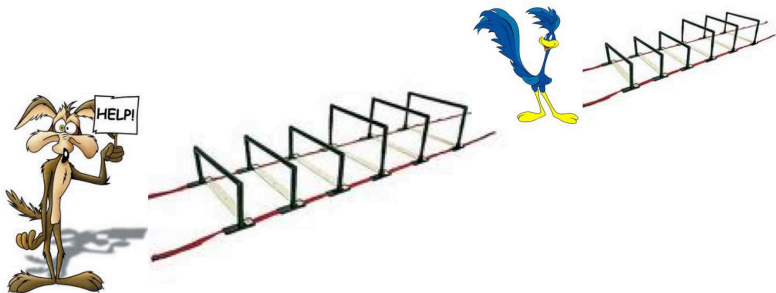


$$\tilde{c}_{mn} = \sum_{i=0}^m \sum_{j=m+1}^n \pi_i^m \pi_j^n \tilde{c}_{i-1, j-1}$$

Probabilistic interpretation of c_{mn}

$$\mathbb{P}[C_i = 1] = \mathbb{P}[R_i = 1] = \alpha_i$$

$$\pi_j^n = \alpha_j \prod_{k=j+1}^n (1 - \alpha_k)$$



$$c_{mn} = \mathbb{P}[\sum_k^n C_i > \sum_k^m R_i, \forall k = m + 1, \dots, 1]$$

Coyote must fall more often than Roadrunner

The random walk and the gambler's ruin appear...

Probabilistic arguments yield an explicit formula for the bound

$$\|x^n - Tx^n\| \leq \frac{c_{n,n+1}}{\alpha_{n+1}} = \mathbb{E}[F(M)]$$

where M is a sum of independent nonhomogeneous Bernoulli trials

$$M = M_1 + \dots + M_n \quad ; \quad \mathbb{P}(M_i = 1) = p_i \triangleq 2\alpha_i(1 - \alpha_i)$$

and $F(m)$ is the probability that the standard random walk in \mathbb{Z} remains non-negative for the first m stages

$$F(m) = \binom{m}{\lfloor m/2 \rfloor} 2^{-m}.$$

Upper estimate

Thus (BB) has been reduced to show that

$$\mathbb{E}[F(M)] \leq \frac{1}{\sqrt{\pi \sum_{i=1}^n \alpha_i(1-\alpha_i)}}$$

Since $p_i = 2\alpha_i(1-\alpha_i)$ this is equivalent to

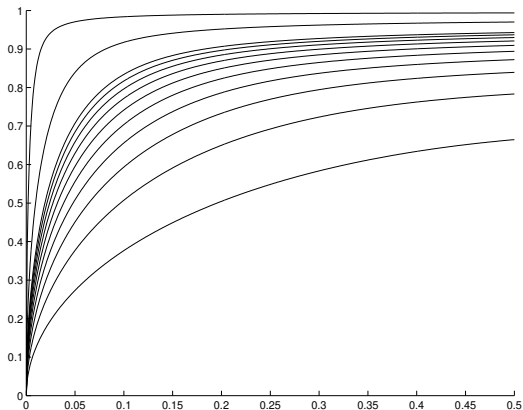
$$\underbrace{\sqrt{\frac{\pi}{2}(p_1 + \dots + p_n)} \mathbb{E}[F(M_1 + \dots + M_n)]}_{R_n(p)} \leq 1$$

Lemma

$R_n(p)$ is maximal when $p_i \in \{u, \frac{1}{2}\}$ for some $u \in]0, \frac{1}{2}[$

Upper estimate – Case 1: all $p_i = u$

$$R_n(p) = \sqrt{\frac{\pi}{2}nu} \mathbb{E}[F(B(n, u))] = \sqrt{\frac{\pi}{2}nu} {}_2F_1\left(-n, \frac{1}{2}; 2; 2u\right) \leq 1$$



Upper estimate – Case 2: some $p_i = \frac{1}{2}$

Suppose $p_1 = \frac{1}{2}$ and let $S = M_2 + \dots + M_n$. Conditioning on M_1

$$\mathbb{E}[F(M)] = \mathbb{E}[G(S)]$$

where $G(k) = \frac{1}{2}[F(k) + F(k+1)]$ is convex so we may use the following Hoeffding-type inequality

Theorem (C.-Soto-Vaisman'2014, *Israel J. Math.*)

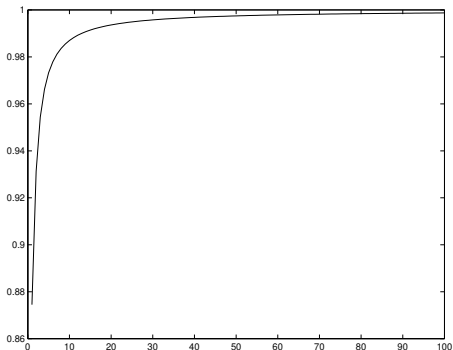
$$\mathbb{E}[G(S)] \leq \mathbb{E}[G(Z)] \text{ where } Z \sim \text{Poisson}(z) \text{ with } z = \mathbb{E}(S).$$

$$\Rightarrow \mathbb{E}[F(M)] \leq \mathbb{E}[G(Z)] = I_0(z) + (1 - \frac{1}{2z})I_1(z)$$

with $I_0(z), I_1(z)$ modified Bessel functions

Upper estimate – Case 2: some $p_i = \frac{1}{2}$

$$R(p) \leq \sqrt{\frac{\pi}{2} \left(\frac{1}{2} + z\right) [I_0(z) + \left(1 - \frac{1}{2z}\right) I_1(z)]} \leq 1$$



Conclusion: (BB) holds with $\kappa = 1/\sqrt{\pi} \sim 0.5642$

Both cases combined yield

Theorem (C.-Soto-Vaisman'2014, *Israel J. Math.*)

$$\|x^n - Tx^n\| \leq \frac{\text{diam}(C)}{\sqrt{\pi \sum_{k=1}^n \alpha_k (1 - \alpha_k)}}$$

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(BB) with constant $\alpha_n \equiv \alpha \geq \frac{1}{2}$

For the operator T on the cube $[0, 1]^{\mathbb{N}}$ that attains the bounds d_{mn} we have

$$\sqrt{n\alpha(1-\alpha)} \|x^n - Tx^n\| = \kappa_n(\alpha) \leq \tilde{\kappa}_n(\alpha)$$

where

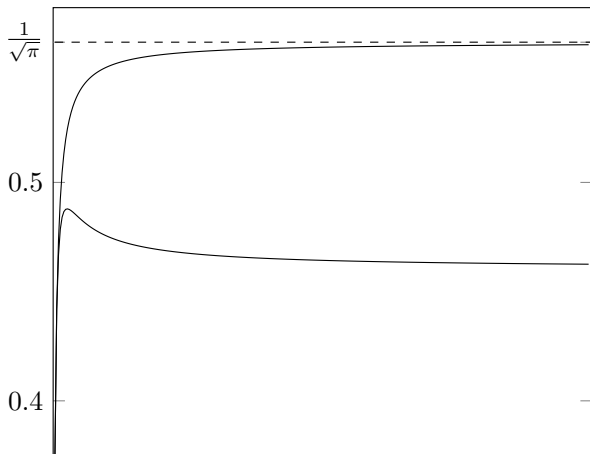
$$\kappa_n(\alpha) = \sqrt{n\alpha(1-\alpha)} d_{n,n+1}(\alpha)/\alpha,$$

$$\tilde{\kappa}_n(\alpha) = \sqrt{n\alpha(1-\alpha)} c_{n,n+1}(\alpha)/\alpha.$$

Explicit formula (C-Soto-Vaisman 2014)

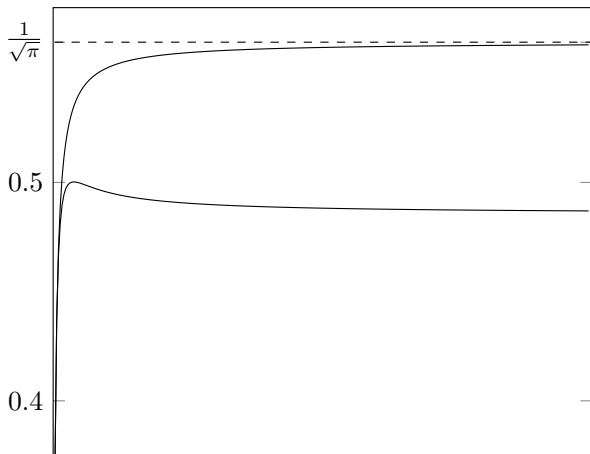
$$\tilde{\kappa}_n(\alpha) = \frac{1}{\pi} \int_0^{4n\alpha(1-\alpha)} \sqrt{\frac{1}{s} - \frac{1}{4n\alpha(1-\alpha)}} \left(1 - \frac{s}{n}\right)^n ds \nearrow \frac{1}{\pi} \Gamma\left(\frac{1}{2}\right) = \frac{1}{\sqrt{\pi}}.$$

Difference between $\kappa_n(\alpha)$ and $\tilde{\kappa}_n(\alpha)$ for $n = 1, \dots, 300$



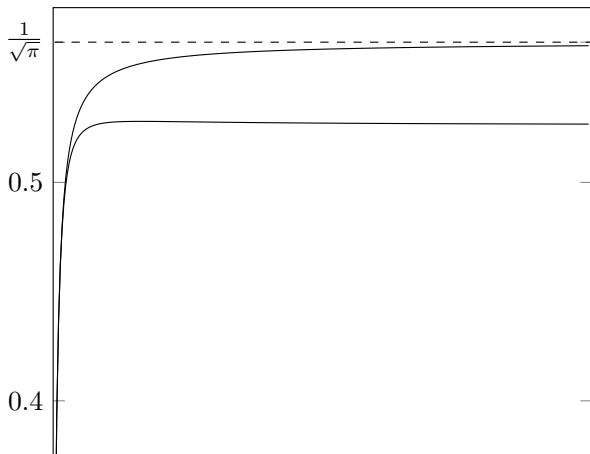
$\alpha = 0.5.$

Difference between $\kappa_n(\alpha)$ and $\tilde{\kappa}_n(\alpha)$ for $n = 1, \dots, 300$



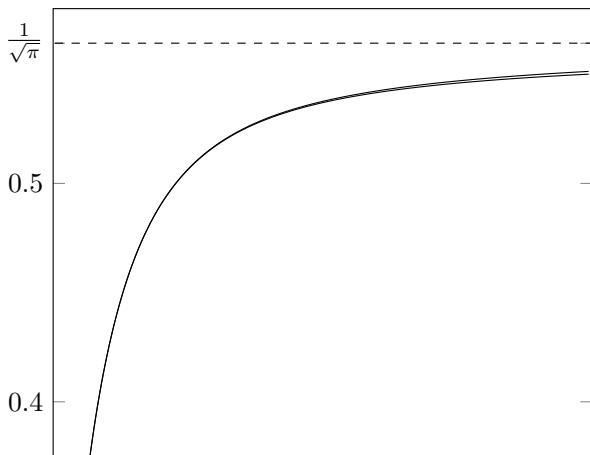
$\alpha = 0.65$.

Difference between $\kappa_n(\alpha)$ and $\tilde{\kappa}_n(\alpha)$ for $n = 1, \dots, 300$



$\alpha = 0.85.$

Difference between $\kappa_n(\alpha)$ and $\tilde{\kappa}_n(\alpha)$ for $n = 1, \dots, 300$



$\alpha = 0.99$.

Conclusion

Theorem (Bravo-C.'2016)

The constant $\kappa = \frac{1}{\sqrt{\pi}}$ is the best possible in (BB).

Proof. For constant $\alpha \geq \frac{1}{2}$ we have

$$0 \leq c_{n,n+1}(\alpha) - d_{n,n+1}(\alpha) \leq 4n(1-\alpha)^2$$

Taking $\alpha_n = 1 - \ln(n)/n$ we get $\kappa_n(\alpha_n) \sim \tilde{\kappa}_n(\alpha_n) \rightarrow \frac{1}{\sqrt{\pi}}$. □

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Inexact KM

$$x^{n+1} = (1 - \alpha_{n+1}) x^n + \alpha_{n+1} (Tx^n + \varepsilon^{n+1})$$

Suppose $x_n \in C$ and $\|Tx_n - x_0\| \leq \kappa$ for some $\kappa \geq 0$ and all $\forall n \in \mathbb{N}$.
 Let $\sigma(y) = \min\{1, 1/\sqrt{\pi y}\}$ and $\tau_n = \sum_{k=1}^n \alpha_k (1 - \alpha_k)$. Then

$$\|x_n - Tx_n\| \leq \kappa \sigma(\tau_n) + \sum_{i=1}^n 2 \alpha_i \|\varepsilon^i\| \sigma(\tau_n - \tau_i) + 2 \|\varepsilon^{n+1}\|.$$

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Corollary

Suppose $\|\varepsilon^n\| = O(1/n^a)$ with $a \geq \frac{1}{2}$, and α_n bounded away from 0 and 1.

- a) If $\frac{1}{2} \leq a < 1$ then $\|x_n - Tx_n\| = O(1/n^{a-1/2})$.
- b) If $a = 1$ then $\|x_n - Tx_n\| = O(\log n / \sqrt{n})$.
- c) If $a > 1$ then $\|x_n - Tx_n\| = O(1/\sqrt{n})$.

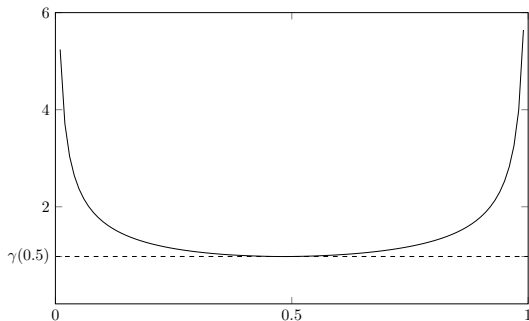
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Best constant stepsize $\alpha_n \equiv \alpha$?

$$\|Tx^n - x^n\| \leq \gamma(\alpha)/\sqrt{n}$$

$$\gamma(\alpha) = \sup_{n \in \mathbb{N}} \sqrt{n} d_{n,n+1}(\alpha)/\alpha$$



The minimum of $\gamma(\alpha)$ is attained near $\alpha = 0.4623$

Krasnoselskii's original iteration $\alpha_n \equiv \frac{1}{2}$

$$\gamma(\alpha) = \sup_{n \in \mathbb{N}} \sqrt{n} d_{n,n+1}(\alpha) / \alpha$$

For $\alpha = \frac{1}{2}$ the sup [seems](#) to be attained at $n = 8$

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For $\alpha = \frac{1}{2}$ the sup [seems](#) to be attained at $n = 8$

$$\begin{aligned} d_{8,9}(\alpha) / \alpha = & 1 - 8\alpha + 64\alpha^2 - 448\alpha^3 + 2835\alpha^4 - 16008\alpha^5 + 79034\alpha^6 \\ & - 334908\alpha^7 + 1201873\alpha^8 - 3622324\alpha^9 + 9129380\alpha^{10} \\ & - 19214722\alpha^{11} + 33796129\alpha^{12} - 49776610\alpha^{13} + 61566687\alpha^{14} \\ & - 64152608\alpha^{15} + 56488500\alpha^{16} - 42133404\alpha^{17} + 26651679\alpha^{18} \\ & - 14288252\alpha^{19} + 6472429\alpha^{20} - 2462126\alpha^{21} + 778478\alpha^{22} \\ & - 201354\alpha^{23} + 41584\alpha^{24} - 6604\alpha^{25} + 758\alpha^{26} - 56\alpha^{27} + 2\alpha^{28} \end{aligned}$$

\Rightarrow the sharp rate in Krasnoselskii's iteration [would be](#)

$$\gamma\left(\frac{1}{2}\right) = \frac{46302245}{67108864} \sqrt{2} \sim 0.9757 \quad \left(\text{smaller than } \frac{2}{\sqrt{\pi}} \sim 1.1284\right)$$

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Which is the best α if n is fixed, say $n = 150$?

Sharp rates in Hilbert spaces?

- For $\alpha_n \equiv \alpha$, Browder and Petryshin'66 proved that

$$\sum \|x^{n+1} - x^n\|^2 < \infty$$

- Since $\|x^{n+1} - x^n\|$ is decreasing, this readily gives a faster rate (already observed in Baillon-Bruck'92, if not earlier)

$$\|x^n - Tx^n\| = o(1/\sqrt{n})$$

- Which is the exact rate? $O(1/\sqrt{n \log n})$?



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