



# Transporting iterative algorithms from Euclidean space to manifolds

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# overview

- **the Newton iteration**



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- **parametrisations**



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- **the new algorithm**



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joint work with J. Manton





# the Newton iteration



## Newton's method

$$x_{k+1} = x_k - \{\text{Hess } f(x_k)\}^{-1} \text{grad } f(x_k), \quad x_0 \in \mathbb{R}^n$$

is an iteration

$$x_{k+1} = N(f)(x_k), \quad x_0 \in \mathbb{R}^n$$

which is defined for any twice differentiable function  $f : \mathbb{R}^n \longrightarrow \mathbb{R}$ .



# the Newton iteration

## The sequence

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**it generates converges locally quadratic to non-degenerate critical points of  $f$ .**



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**it generates converges locally quadratic to non-degenerate critical points of  $f$ .**

**In particular, it converges locally to any (isolated) strict local maximum of  $f$ .**



# parametrisations



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**One description of manifolds is that they look locally like an  $\mathbb{R}^n$ . This means that the manifold can be covered by a collection of subsets for each of which there is a homeomorphism (coordinate chart) onto an open set in  $\mathbb{R}^n$ .**



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**The whole atlas has to fit nicely together, i.e. via diffeomorphisms in overlapping regions.**





# parametrisations



**This implies that for each point  $p$  of the manifold  $M$  there exists a *local parametrisation*, i.e. a smooth injective map**

$$\mu_p : \mathbb{R}^n \longrightarrow M, \quad \mu_p(0) = p$$



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**We consider the special case where  $\mu_p$  varies locally smoothly with the base point, which might only be possible in a small neighborhood of a given point  $p^*$  (hedgehog theorem).**





# parametrisations



**Take e.g. the sphere and the operation of the special orthogonal group on it**

$$\begin{aligned}\phi : SO(n + 1) \times S^n &\longrightarrow S^n, \\ (Q, p) &\longmapsto Qp\end{aligned}$$

**and consider the exponential map**

$$\begin{aligned}\exp : so(n + 1) &\longrightarrow SO(n + 1), \\ \Omega &\longmapsto \exp \Omega .\end{aligned}$$





# parametrisations



**It can be shown that**

$$\phi(\exp(\cdot), p^*) : so(n + 1) \longrightarrow S^n$$

**is locally injective around 0 when restricted to the subspace**

$$\left\{ \begin{pmatrix} 0 & Z \\ -Z^\top & 0 \end{pmatrix} \mid Z \in \mathbb{R}^{k \times (n-k)} \right\} .$$

**This defines a local parametrisation  $\mu_{p^*}$  which can be “moved around”  $S^n$  by applying  $\phi$ .**





# the new algorithm



**Let  $\mu_p$  and  $\nu_p$  be two families of local parametrisations and consider the iteration**

$$p_{k+1} = \nu_{p_k}(\mathbf{N}(f \circ \mu_{p_k})(0)), \quad p_0 \in M$$

**which is defined for every twice differentiable function  $f : M \longrightarrow \mathbb{R}$ .**



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**Note that for  $M = \mathbb{R}^n$  and  $\nu_p = \mu_p$  the obvious parametrisation  $x \mapsto p + x$  this is the standard Newton method.**



# convergence properties



**Theorem: If  $\mu_p$  and  $\nu_p$  are smooth around a non-degenerate critical point  $p^*$  of  $f$  and if moreover  $\mu'_{p^*}(0) = \nu'_{p^*}(0)$  then our algorithm converges locally quadratic to  $p^*$ .**



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**In general, nothing is said (and known) about global convergence.**



# an example



**Consider a real symmetric  $n \times n$  matrix  $N$  with eigenvalues  $\lambda_1 \geq \dots \geq \lambda_k > \lambda_{k+1} \geq \dots \geq \lambda_n$ . Its  $k$ -dimensional *principal eigenspace* is the subspace spanned by the eigenvectors to  $\lambda_1, \dots, \lambda_k$ .**



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**Consider the function (generalised Rayleigh quotient)**

$$f : \text{Grass}(k, n) \longrightarrow \mathbb{R}, [X] \mapsto \text{tr } X^\top N X$$







# an example

$\mu_p$  is given by

$$p = \begin{bmatrix} Q \begin{pmatrix} I \\ 0 \end{pmatrix} \end{bmatrix}$$
$$\mu_p(Z) = \begin{bmatrix} Q \exp \begin{pmatrix} 0 & Z \\ -Z^\top & 0 \end{pmatrix} \begin{pmatrix} I \\ 0 \end{pmatrix} \end{bmatrix}$$

where  $Q \in O(n)$  and  $Z$  is  $k \times (n - k)$ .



# an example



Then

$$\text{grad}(f \circ \mu_p)(0) = \left[ Q^\top N Q, \begin{pmatrix} I & 0 \\ 0 & 0 \end{pmatrix} \right] = \begin{pmatrix} 0 & -N_{12} \\ N_{12}^\top & 0 \end{pmatrix}$$



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**Then**

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**and**

$$\text{Hess}(f \circ \mu_p)(0)Z = \begin{pmatrix} 0 & Z N_{22} - N_{11} Z \\ Z^\top N_{11} - N_{12} Z^\top & 0 \end{pmatrix}$$





# an example



So computing  $N(f \circ \mu_p)(0)$  amounts to solving the Sylvester equation

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This  $Z$  could then be plugged into

$$\nu_p(Z) = \left[ Q \exp \begin{pmatrix} 0 & Z \\ -Z^\top & 0 \end{pmatrix} \begin{pmatrix} I \\ 0 \end{pmatrix} \right]$$

to get a new  $Q$ .



## an example



It's much better though to use an orthogonal projection onto  $O(n)$  instead by computing a  $QR$ -decomposition of

$$\begin{pmatrix} I \\ -Z^\top \end{pmatrix} = Q_Z R$$

and to use  $Q Q_Z$  as the new  $Q$ .



# general iterates



**Replacing the Newton iteration  $N(f) : \mathbb{R}^n \longrightarrow \mathbb{R}^n$  by any other iteration  $G(f) : \mathbb{R}^n \longrightarrow \mathbb{R}^n$  that is locally order  $q$  converging to non-degenerate critical points of  $f$ , we can derive sufficient conditions on a family  $\mu_p$  of local parametrisations that guarantee local order  $q$  convergence of the “transported algorithm”**

$$p_{k+1} = \mu_{p_k}(G(f \circ \mu_{p_k})(0)), \quad p_0 \in M$$



# general iterates



**Let  $G(f) : \mathbb{R}^n \longrightarrow \mathbb{R}^n$  be defined by**

$$G(f)(x) := g(x, f(x), \text{grad } f(x), \text{Hess } f(x))$$

**where**

$$g : \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^n \times \mathbb{R}^{n \times n} \longrightarrow \mathbb{R}^n$$

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**For  $N(f)$  it would be  $g(x, \alpha, y, Z) = x - Z^{-1}y$ .**



# general iterates



**Theorem: If  $G(\cdot)$  is order  $q$  locally convergent to non-degenerate critical points and  $\mu_p$  is a locally smooth family of local parametrisations which are local diffeomorphisms then the transported algorithm is locally order  $q$  convergent to non-degenerate critical points.**



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**This result can be further generalised (see forthcoming paper).**



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Thank you.

