# **Incremental Minimization in Spaces of Nonpositive Curvature**

Existing algorithms converge at unknown rate and rely on proximal steps (difficult) **Example:** The Weber problem (optimal facility location) is

<sup>3</sup>Babeş-Bolyai University

 $f(0) = x_0, r(\infty) = \xi$ 

uclidean case shows Busemann ns generalize affine functions

) where  $v^{k,i} \in \partial f_{i+1}(x^{k,i})$ 

#### **The Problem: Minimizing a Sum of Functions**

$$
\min \left\{ f(x) = \sum_{i=1}^{m} f_i(x) \mid x \in C \right\} \tag{S}
$$

 $f_i\colon C\subseteq X\to\mathbb{R}$  are functions,  $(X,d)$  is a complete geodesic metric space

$$
\min_{x \in X} \sum_{i=1}^m w_i d(x, a_i)^{p_i}
$$

The special case  $p_i = p \geq 1$  for  $1 \leq i \leq m$  is the *p*-mean problem

#### **Hadamard Spaces**

Geodesics are paths  $\gamma$  in X with  $d(\gamma(t), \gamma(t')) = |t - t'|$ *X* has curvature  $\leq 0$  (CAT(0)) if  $t \mapsto d(\gamma(t), y)^2 - t^2$  is convex  $\forall y \in X, \gamma$  geodesic **Hadamard Space:** Complete geodesic space of curvature  $\leq 0$ Includes Euclidean and Hilbert space (classical optimization), but also:

For *n*-manifolds the space of directions *X*<sup>∞</sup> is S *n*−1 , but for the tripod it is discrete To a direction  $\xi \in X^\infty$  we associate the **Busemann function**  $b_\xi \colon X \to \mathbb{R}$ :



Hyperbolic Space H*<sup>n</sup>*



Positive Definite Cone  $S^n_+$  $E_{\rm eff}$  is a cubical complex of three points in a cubical complex of thr

Metric Trees



 $++$ 



CAT(0) Cubical Complexes

Applications modeled in such spaces include hierarchical classification, matrix means, phylogenetics, facility location, and robotic motion

Any two points in a Hadamard space are joined by a unique geodesic

#### Poster available at [arielgoodwin.github.io/talks](https://arielgoodwin.github.io/talks) Center for Applied Mathematics, [awg77@cornell.edu](mailto:awg77@cornell.edu)

<sup>1</sup>Cornell University

<sup>2</sup>University of Seville

## $UM)$

### **Busemann Convexity**

- A median of  $A = \{a_1, \ldots, a_m\} \subseteq X$  is a solution to (SUM) with  $f_i = w_i d(\cdot, a_i)$
- *f*<sub>*i*</sub> has Busemann subgradient  $(r_i(\infty), w_i)$  at  $x \neq a_i$  where  $r_i(d(x, a_i)) = a_i$
- The resulting incremental subgradient step is  $x^{k,i+1} = \mathrm{proj}_C(r_i(t_k w_i))$
- At step *i* in each internal loop, the iterate moves towards *a<sup>i</sup>* proportionally to *w<sup>i</sup>*



- Several candidate phylogenetic trees may be generated to model an evolutionary history; means and medians condense this data into one representative tree
- The **BHV tree space**  $\mathcal{T}_n$  models the set of all binary trees on *n* labelled leaves, each with *n*−2 nonnegative internal edge lengths (viewed as a point in [0*,* ∞) *n*−2 )
- Geodesics in  $\mathcal{T}_n$  are computable in polynomial time (Owen and Provan, 2011)
- In both experiments below we compute the median of three trees in  $\mathcal{T}_4$

*<sup>n</sup> along supporting rays* Examples: Busemann functions, distances to points/balls/horoballs (sublevel *n .* sets of Busemann functions)

$$
b_{\xi}(y) := \lim_{t \to \infty} (d(y, r(t)) - t) \qquad (r(t))
$$



Definition:  $f: C \to \mathbb{R}$  has a Busemann subgradient  $(\xi, s) \in X^\infty \times \mathbb{R}_+$  at  $x$  if  $f(y) - sb_{\xi}(y) \ge f(x) - sb_{\xi}(x) \quad \forall y \in C$ Then *f* is **Busemann convex** if it has a Busemann subgradient at each  $x \in C$ 

- Stronger than geod • Stronger than geodesic convexity in general (equivalent in  $\mathbb{R}^n$ )
- Simple calculus: max rule, chain rule, but no sum rule... (splitting is key)

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- [2] M.R. Bridson and A. Haefliger. *Metric Spaces of Non-Positive Curvature.* Springer-Verlag Berlin, 1999.
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### **An Incremental Subgradient Algorithm**

Simple algorithm for solving (SUM) in  $X = \mathbb{R}^n$  due to Bertsekas and Nedić (2001):

For 
$$
k = 0, 1, 2, ...
$$
 do  
\nFor  $i = 0, 1, ..., m - 1$  do  
\n
$$
x^{k,i+1} = \text{proj}_C(x^{k,i} - t_k v^{k,i}) \text{ where}
$$
\n
$$
x^{k+1} = x^{k,m}
$$

, 168 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / 169 / Generalizing, use Busemann subgradient  $(\xi^{k,i}, s_{k,i})$  for  $f_{i+1}$  at  $x^{k,i}$  to update iterate:  $x^{k,i+1} = \text{proj}_C(r(t_k s_{k,i}))$  where  $r(0) = x^{k,i}, r(\infty) = \xi^{k,i}$ 

### Ariel Goodwin<sup>1</sup> Adrian S. Lewis<sup>1</sup> Genaro López-Acedo<sup>2</sup> Adriana Nicolae<sup>3</sup>

#### **Computing Medians**

Theorem (Median Complexity)  
\nIf 
$$
C = B(x^0, f(x^0)/w_1)
$$
,  $t_k = 2/(w_1 m\sqrt{k+1})$  then f has a minimizer in C and  
\n
$$
\min_{i=1,\dots,k} f(x^i) - f_{\text{opt}} = O(1/\sqrt{k})
$$

### **Application: Computing the Median of Phylogenetic Trees**



#### **References and Acknowledgements:**

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