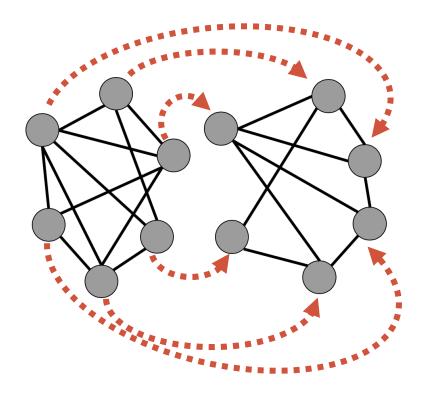
(Probably) Concave Graph Matching

Haggai Maron and Yaron Lipman

Weizmann Institute of Science

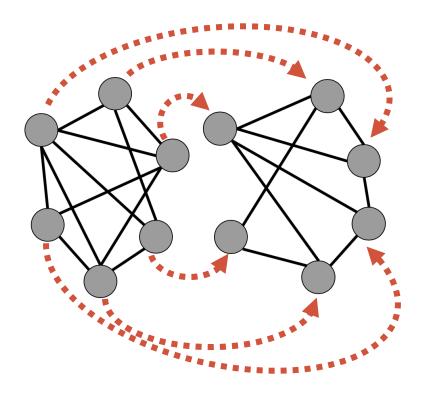


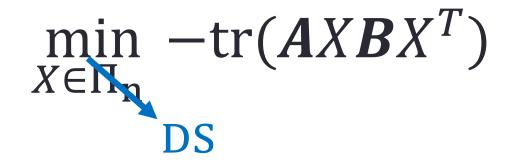
Graph Matching



$\min_{X \in \Pi_n} -tr(AXBX^T)$

Graph Matching





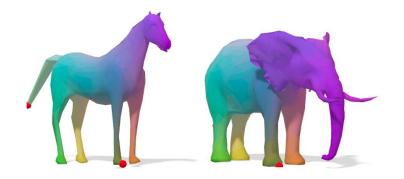
Previous Work

- Superiority of the indefinite relaxation
 - [Lyzinski et al. PAMI 2016]

Graph Matching: Relax at Your Own Risk

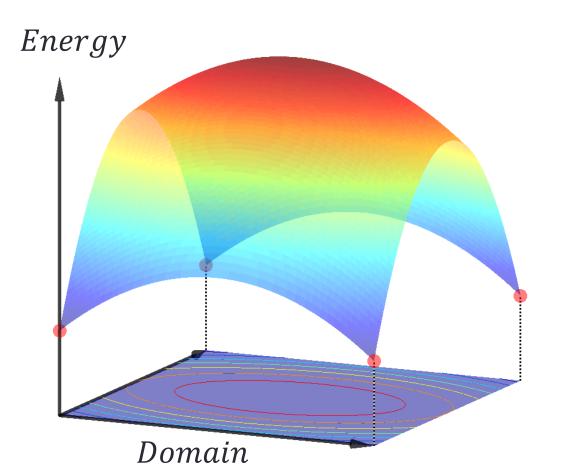
Vince Lyzinski, Donniell E. Fishkind, Marcelo Fiori, Joshua T. Vogelstein, Carey E. Priebe, and Guillermo Sapiro, *Fellow, IEEE*

- Efficient graph matching via concave energies
 - [Vestner et al. CVPR 2017, Boyarski et al. 3DV 2017]

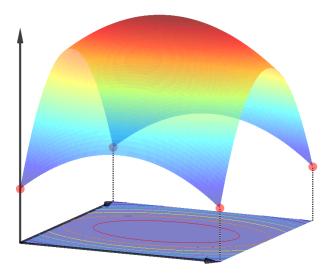


Advantages of Concave Relaxations

• All local minima are permutation matrices



Many important graph matching problems are concave!



Which *A*, *B* give rise to concave relaxations?

Concavity of Indefinite Relaxation

• Theorem: It is sufficient that

$$A = \Phi(x_i - x_j), B = \Psi(y_i - y_j)$$

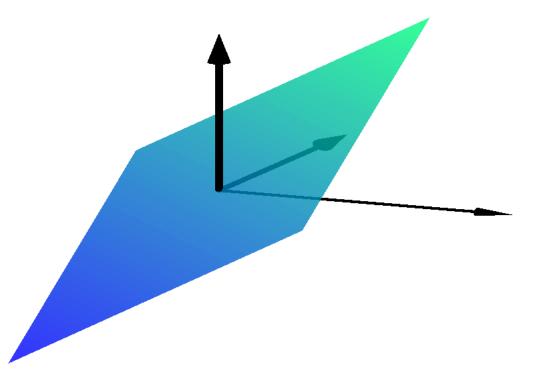
where Φ , Ψ are positive definite functions of order one.

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Concave Energies

Euclidean distance in any dimension

- Mahalanobis distances
- Spectral graph distances
- Matching objects with deep descriptors

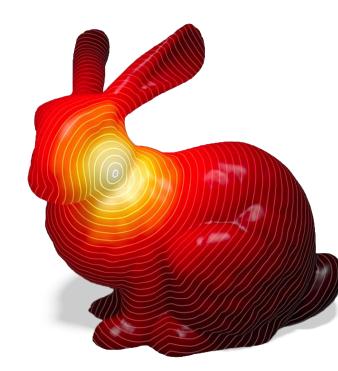
Spherical distance in any dimension [bogomolny, 2007]

$$A_{ij} = ||x_i - x_j||_2$$

$$A_{ij} = d_{S^n} \left(x_i, x_j \right)$$

Do we really need a concave relaxation?

Do we really need a concave relaxation?



Probably Concave Energies

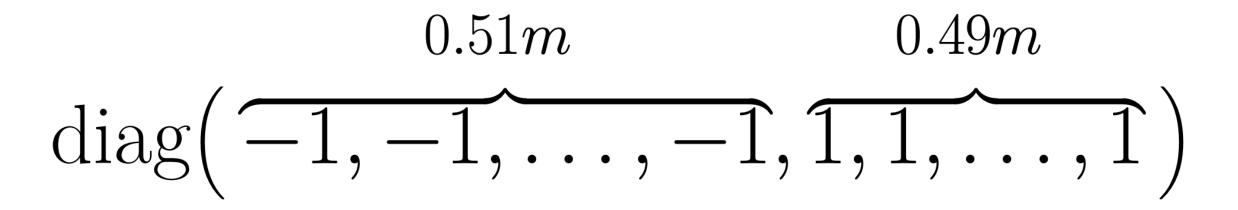
• Theorem (upper bound on the probability of convex restriction)

Let $M \in \mathbb{R}^{m \times m}$ and $D \leq \mathbb{R}^m$ a uniformly sampled *d*-dimensional subspace, then: $Pr\left[M\Big|_D > 0\right] \leq \min_t \prod_{i=1}^n (1 - 2t\lambda_i)^{-d/2}$

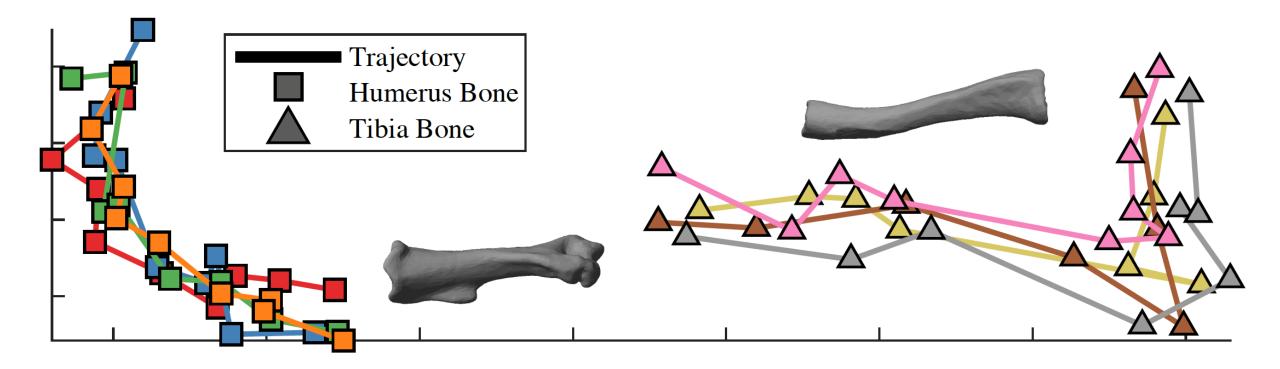
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Applications



Conclusion

- A large family of concave or probably concave relaxations
- Checking probable concavity with eigenvalue bound
- Extension of [Lyzinsky et al. 2016] to practical matching problems

The End

Support

- ERC Grant (LiftMatch)
- Israel Science Foundation
- Thanks for listening!

