Trustworthy Geometric Perception: Certifiable Optimization and Robust Estimation

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1474

1. Motivation: Why Trustworthy Perception?

2. Certifiable Global Optimization
   - GlobustVP: Certifiable VP Estimation [CVPR 2025, Best Paper Award Candidate]
   - NPC: RL-Accelerated Homotopy Solvers [ICLR 2026]
   - Survey of Global Solvers for 3D Vision

3. Open challenges

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3 Open challenges

Motivation: Why Trustworthy Perception

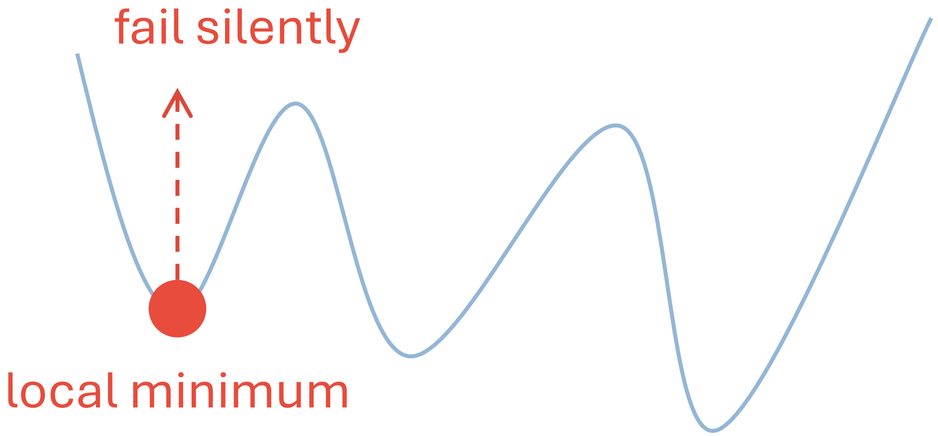
Local Optimization

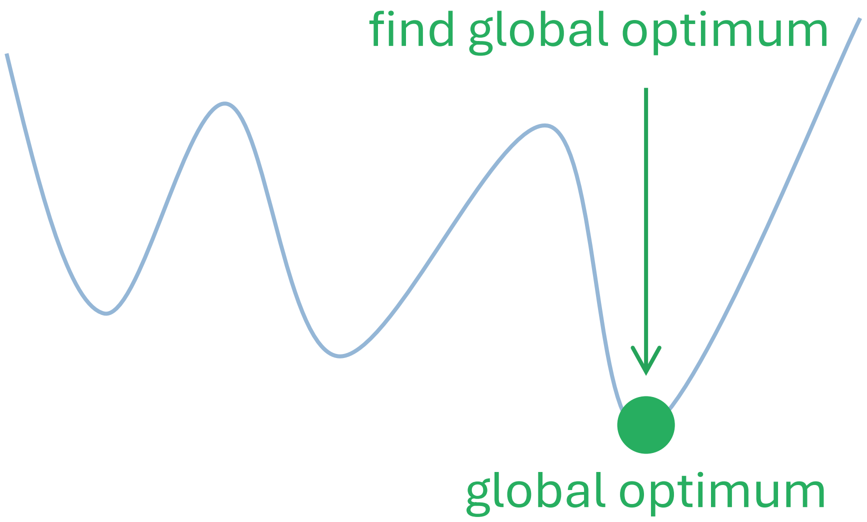
- ❌ Sensitive to initialization
- ❌ Fails silently, no warning when wrong
- ❌ No optimality guarantee

vs.

Certifiable Optimization

- ✓ Globally optimal solution
- ✓ Knows when it is correct
- ✓ Optimality certificate provided





Research Vision: Trustworthy Geometric Perception

Direction 1

Certifiable Global Optimization

Convex relaxation (SDP/QCQP) and polynomial methods providing formal optimality guarantees

This talk!

Direction 2

Robust Estimation

Perception reliability under motion blur, dynamic scenes, and featureless environments

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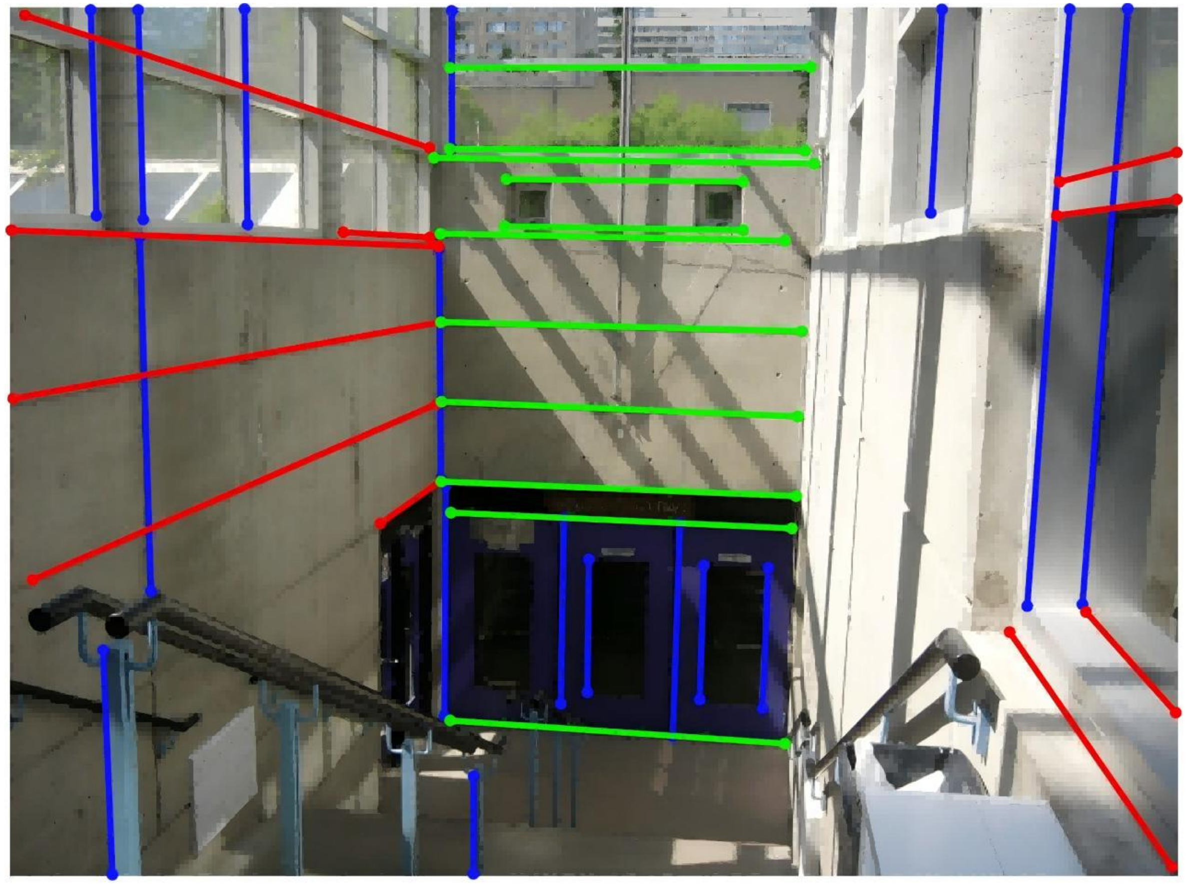
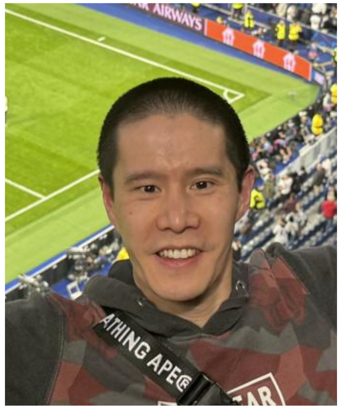
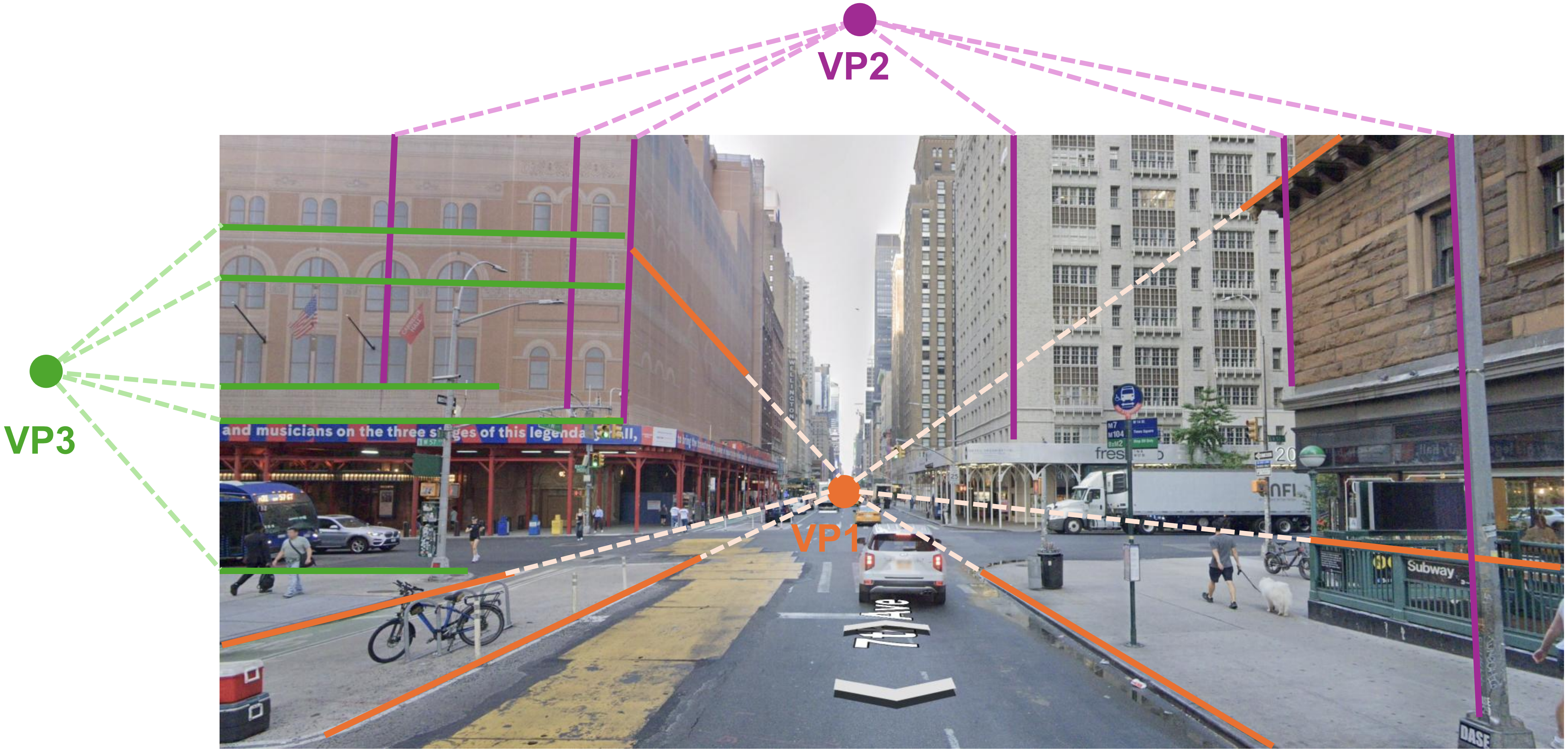
GlobustVP:

Convex Relaxation for Robust Vanishing Point Estimation in Manhattan World





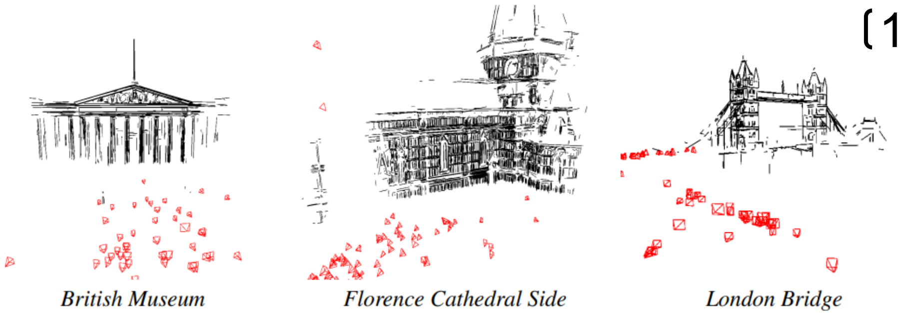
Vanishing Point in Manhattan World



Applications of Vanishing Point

Structure from Motion (SFM)

[1]

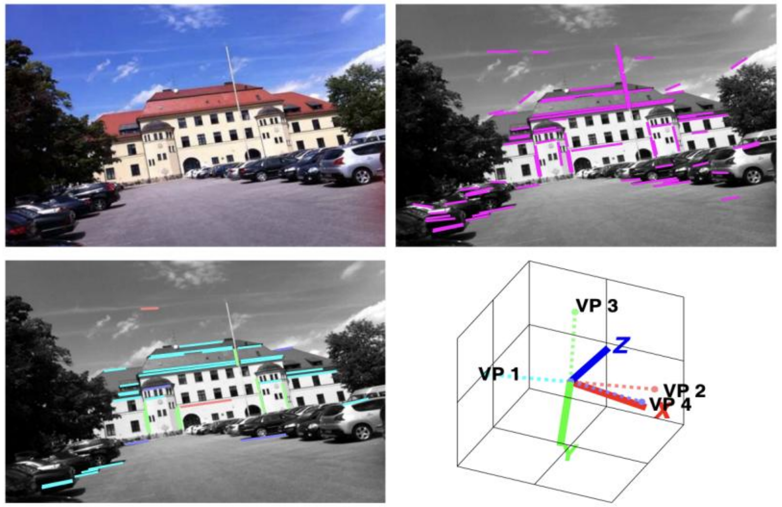


Simultaneous Localization And Mapping (SLAM)

[2]

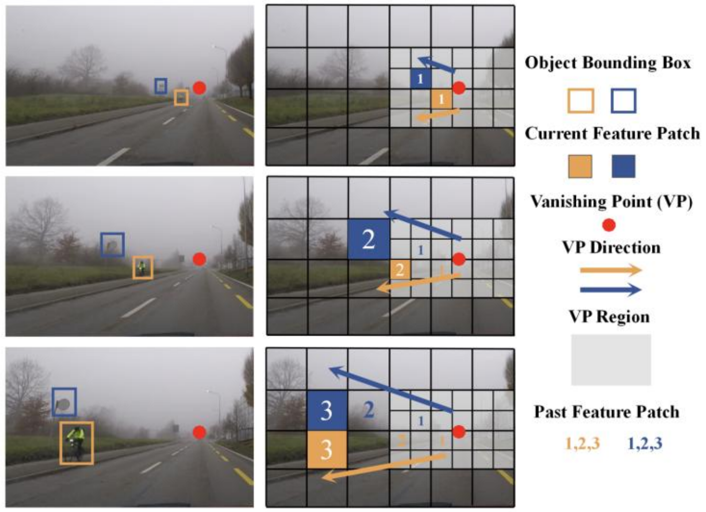
Camera Rotation Estimation

[3]



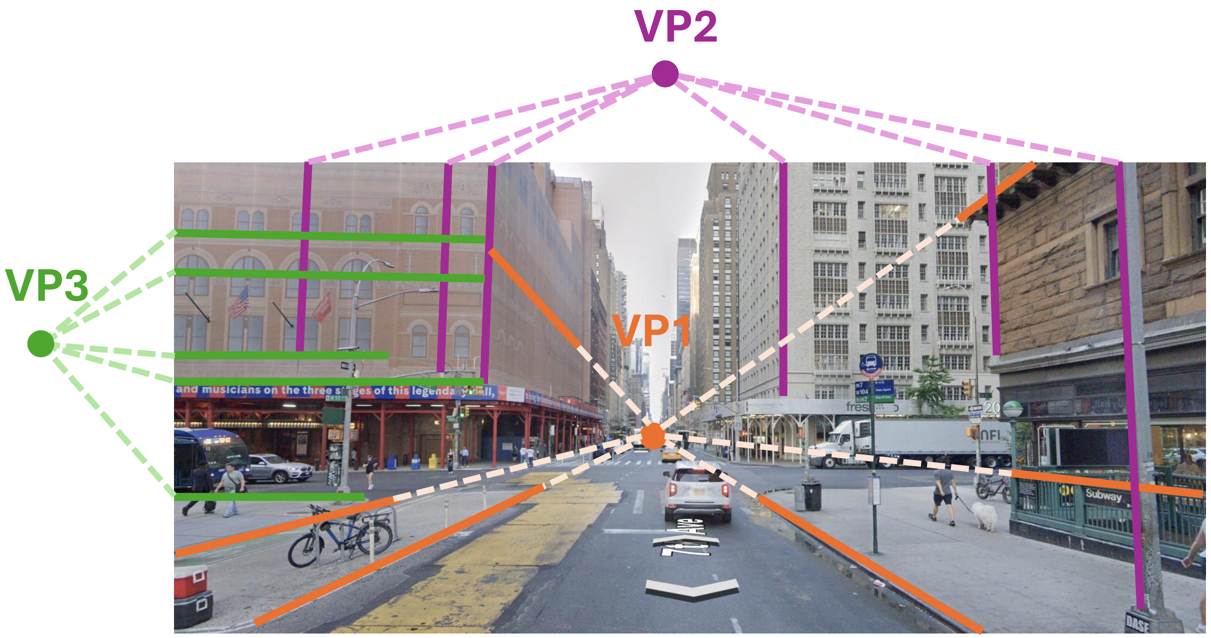
Structural Understanding

[4]



[1] Liu S, Yu Y, Pautrat R, et al. 3d line mapping revisited. CVPR 2023.
[2] Li Y, Yunus R, Brasch N, et al. RGB-D SLAM with structural regularities. ICRA 2021.
[3] Lee J K, Yoon K J. Real-time joint estimation of camera orientation and vanishing points. CVPR 2015.
[4] Guo D, Fan D P, Lu T, et al. Vanishing-point-guided video semantic segmentation of driving scenes. CVPR 2024.

Problem: **VPs Estimation & Line Labeling**



Input: Unlabeled Lines
Intrinsic Parameters

Output: Labeled Lines
Vanishing Points (VP)

Global Optimality ***Efficiency*** ***Outlier Robustness*** ***Generalization***

Prior Methods

RANSAC-based

Global Optimality

Efficiency

Outlier Robustness

Generalization

Branch-and-Bound

Global Optimality

Efficiency

Outlier Robustness

Generalization

Learning-based

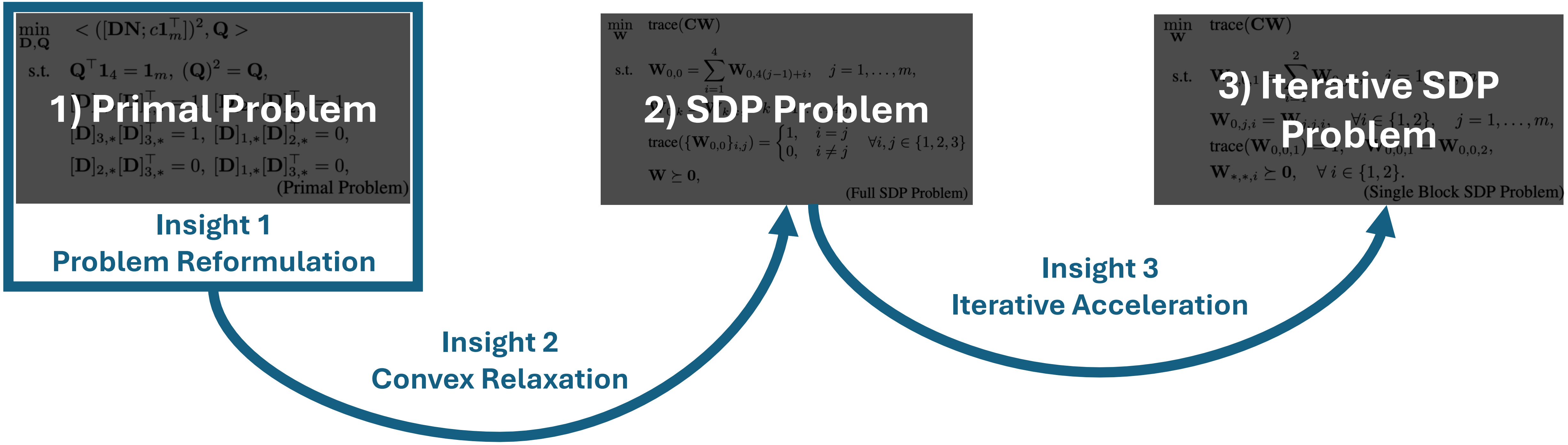
Global Optimality

Efficiency

Outlier Robustness

Generalization

Ours Method: **GlobustVP**



Global Optimality

Efficiency

Outlier Robustness

Generalizable

Insight 1: Primal Problem Reformulation

$$\min_{VP1,\, VP2,\, VP3,\, Permutation} \text{Loss}(\text{Lines}, VP1, VP2, VP3, \text{Permutation})$$

How to represent discrete labels?

-> continuous constraint

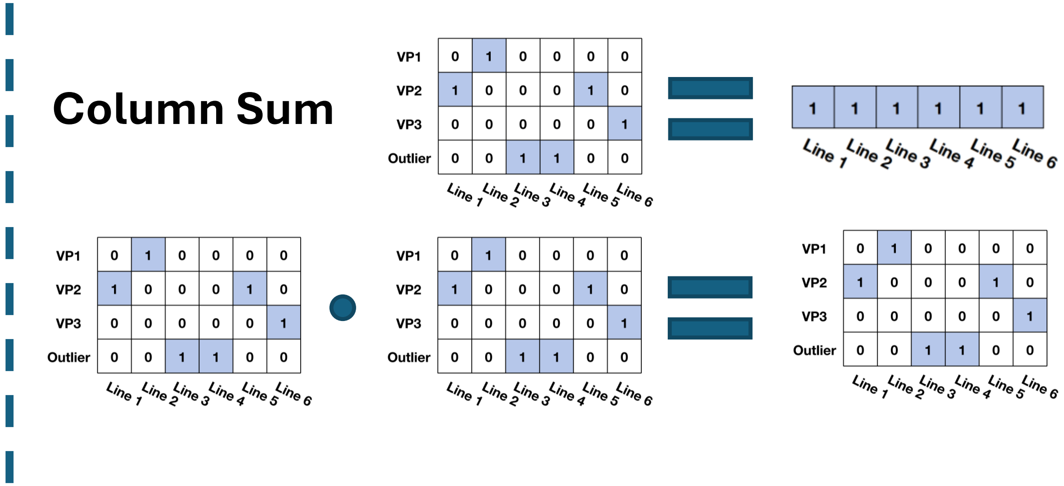
$$q = q^2 \iff q = 1 \text{ or } q = 0$$

$$q_{VP1} + q_{VP2} + q_{VP3} + q_{Outlier} = 1$$

-> scales to all lines

	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP1	0	1	0	0	0	0
VP2	1	0	0	0	1	0
VP3	0	0	0	0	0	1
Outlier	0	0	1	1	0	0

Permutation Matrix



Insight 1: Primal Problem Reformulation

Primal Problem

$$\min_{\mathbf{D},\mathbf{Q}} \quad < ([\mathbf{DN}; c\mathbf{1}_m^\top])^2, \mathbf{Q} >$$

$$\text{s.t.} \quad \mathbf{Q}^\top \mathbf{1}_4 = \mathbf{1}_m, \ (\mathbf{Q})^2 = \mathbf{Q},$$

$$[\mathbf{D}]_{1,*}[\mathbf{D}]_{1,*}^\top = 1, \ [\mathbf{D}]_{2,*}[\mathbf{D}]_{2,*}^\top = 1,$$

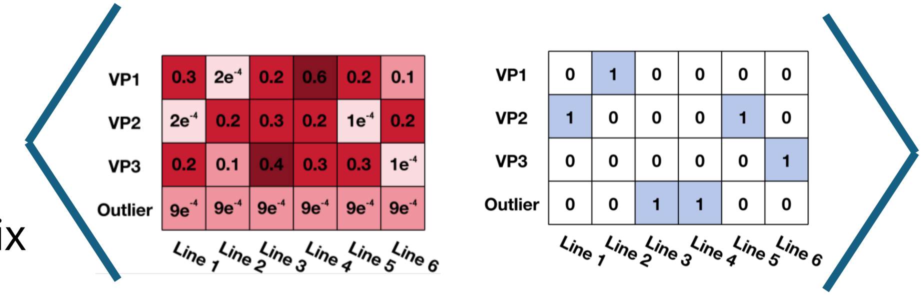
$$[\mathbf{D}]_{3,*}[\mathbf{D}]_{3,*}^\top = 1, \ [\mathbf{D}]_{1,*}[\mathbf{D}]_{2,*}^\top = 0,$$

$$[\mathbf{D}]_{2,*}[\mathbf{D}]_{3,*}^\top = 0, \ [\mathbf{D}]_{1,*}[\mathbf{D}]_{3,*}^\top = 0,$$

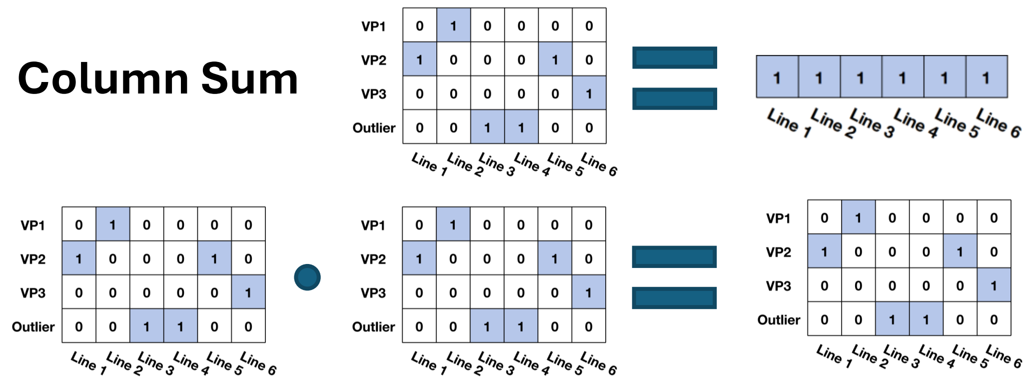
min

VP1,VP2,VP3

Permutation Matrix



Column Sum



Manhattan Constraint

Ours Method: **GlobustVP**

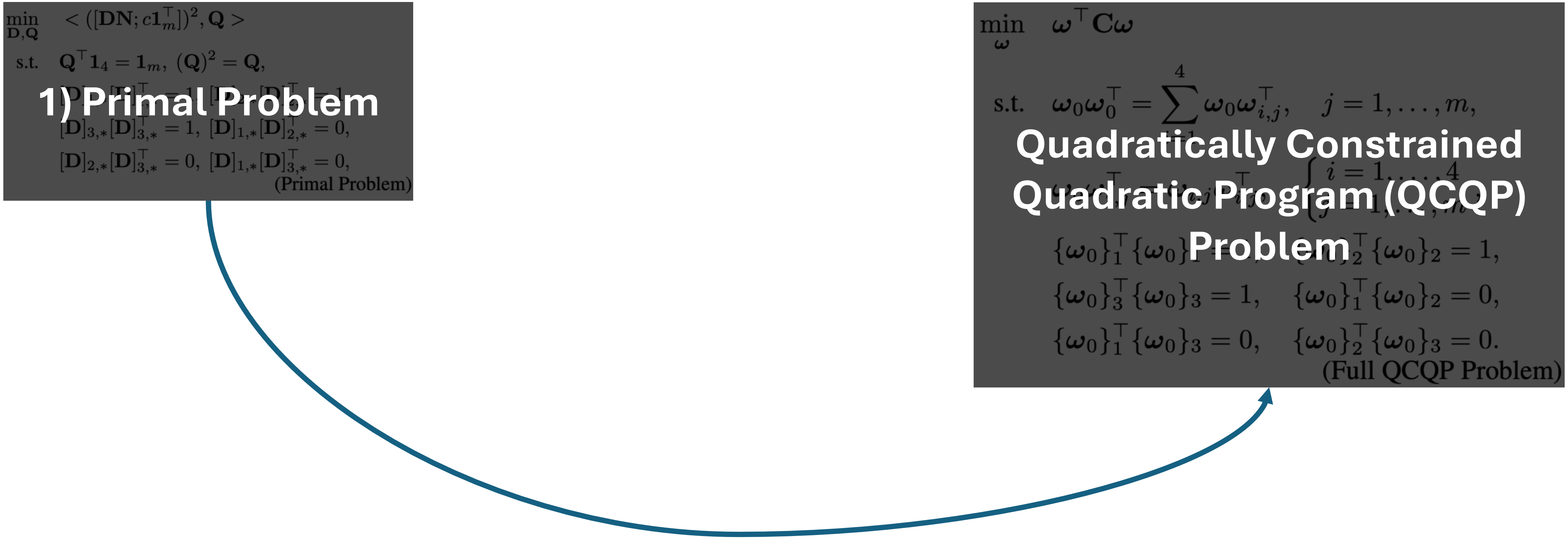
$$
\begin{aligned}
\min_{\mathbf{D},\mathbf{Q}} \quad & < ([\mathbf{DN}; c\mathbf{1}_m^\top])^2, \mathbf{Q} > \\
\text{s.t.} \quad & \mathbf{Q}^\top \mathbf{1}_4 = \mathbf{1}_m,\ (\mathbf{Q})^2 = \mathbf{Q}, \\
& [\mathbf{D}]_{3,*}[\mathbf{D}]_{3,*}^\top = 1,\ [\mathbf{D}]_{1,*}[\mathbf{D}]_{2,*}^\top = 0, \\
& [\mathbf{D}]_{2,*}[\mathbf{D}]_{3,*}^\top = 0,\ [\mathbf{D}]_{1,*}[\mathbf{D}]_{3,*}^\top = 0,
\end{aligned}
\qquad \text{(Primal Problem)}
$$

1) Primal Problem

Insight 1
Problem Reformulation

Generalizable

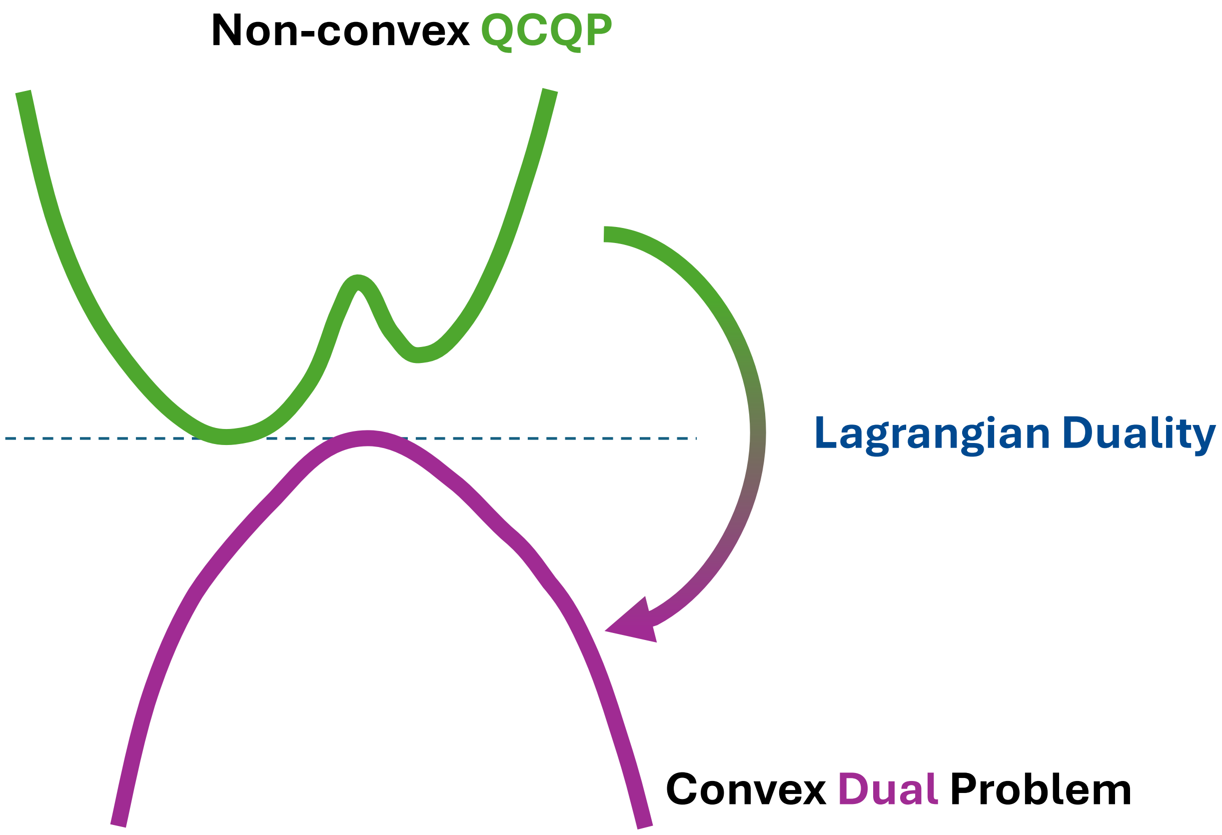
Insight 2: QCQP -> Convex Relaxation -> SDP



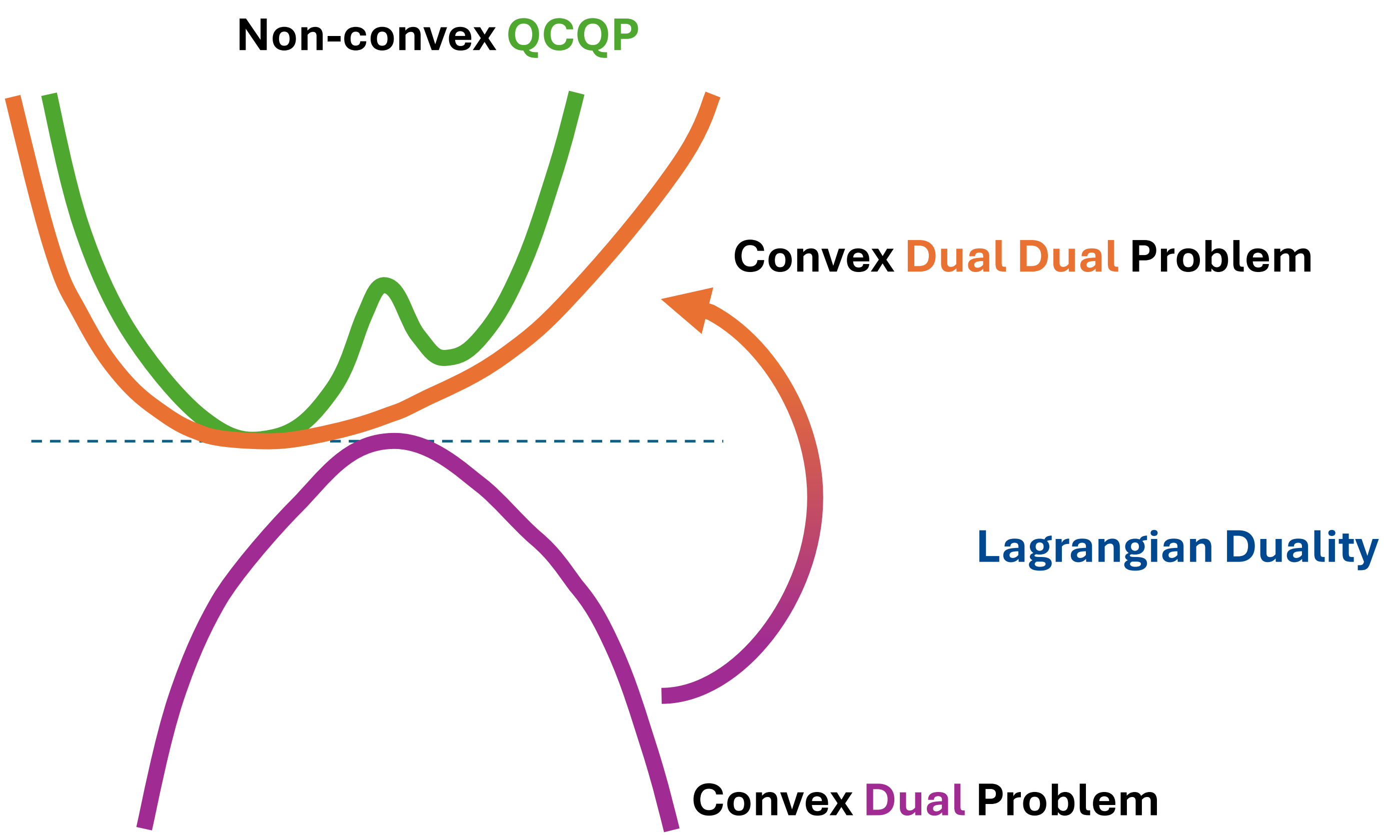
Equivalent to Higher Dimension QCQP

Insight 2: QCQP -> Convex Relaxation -> SDP

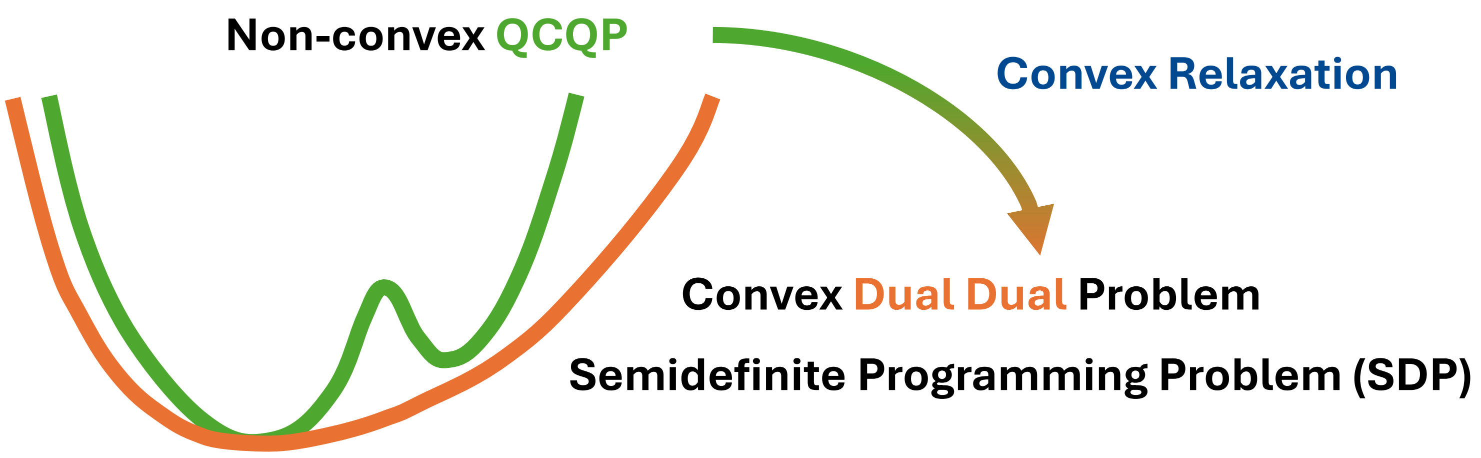
Insight 2: QCQP -> Convex Relaxation -> SDP

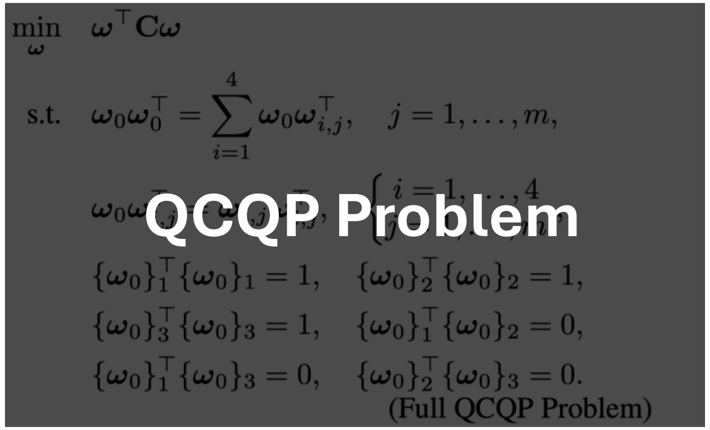


Insight 2: QCQP -> Convex Relaxation -> SDP



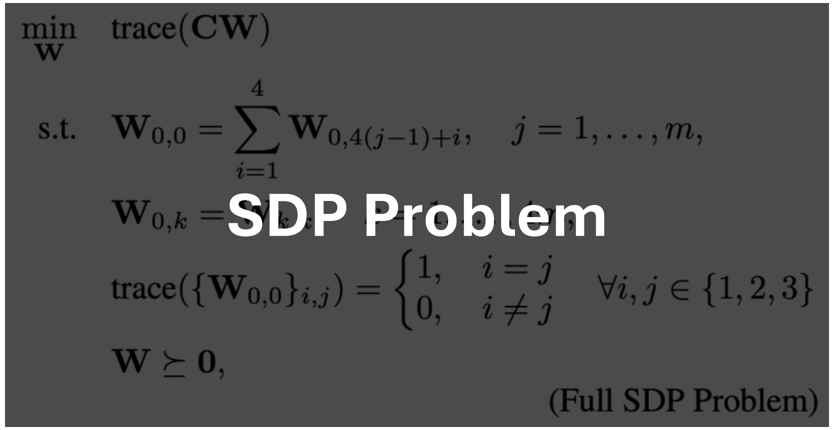
Insight 2: QCQP -> Convex Relaxation -> SDP



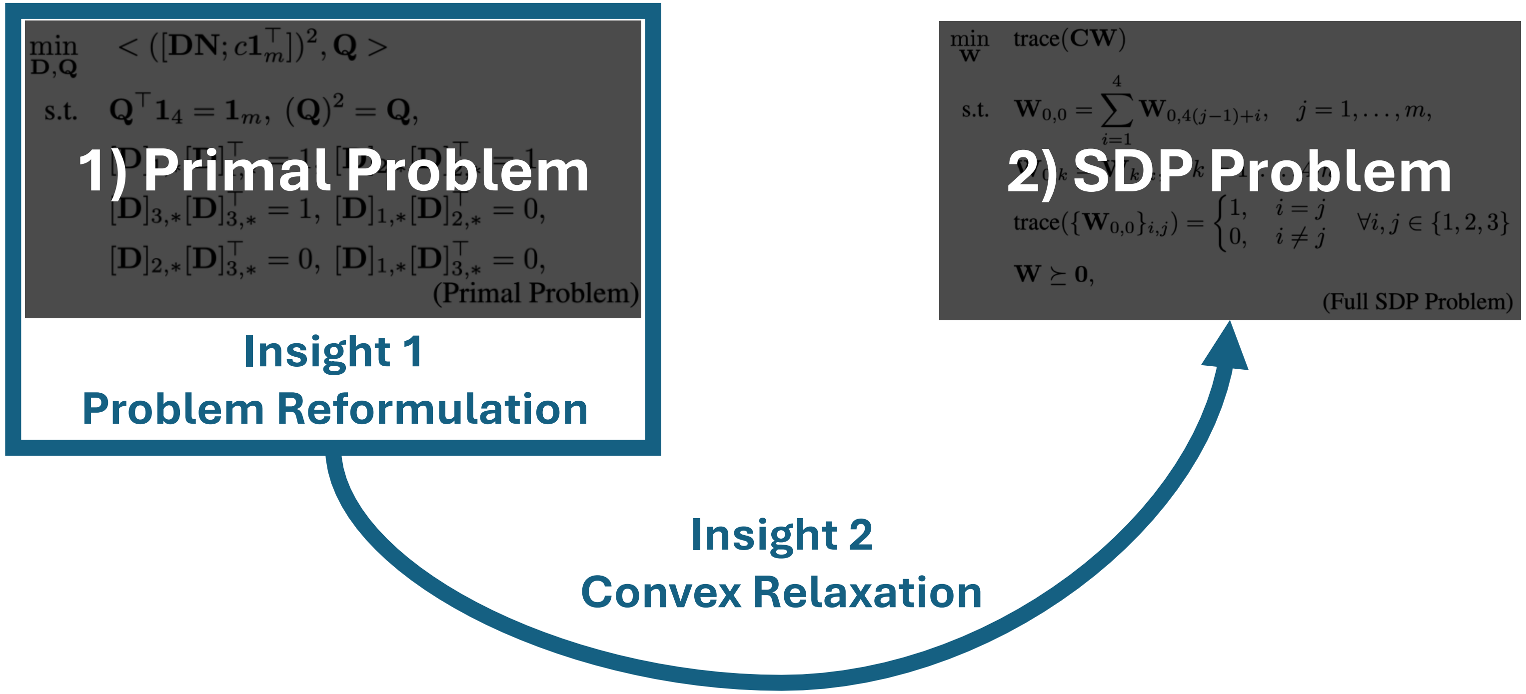


equivalent under

tight relaxation



Ours Method: **GlobustVP**



Global Optimality

Outlier Robustness

Generalizable

Insight 3: Iterative SDP

2) SDP Problem

$$\min_{\mathbf{W}} \quad \mathrm{trace}(\mathbf{C}\mathbf{W})$$

$$\text{s.t.} \quad \mathbf{W}_{0,0} = \sum_{i=1}^{4} \mathbf{W}_{0,4(j-1)+i}, \quad j = 1, \ldots, m,$$

$$\mathrm{trace}(\{\mathbf{W}_{0,0}\}_{i,j}) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \quad \forall i, j \in \{1,2,3\}$$

$$\mathbf{W} \succeq \mathbf{0},$$

(Full SDP Problem)

Large SDP problem is not efficient enough

	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP1	0.3	2e-4	0.2	0.6	0.2	0.1
VP2	2e-4	0.2	0.3	0.2	1e-4	0.2
VP3	0.2	0.1	0.4	0.3	0.3	1e-4
Outlier	9e-4	9e-4	9e-4	9e-4	9e-4	9e-4

	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP1	0	1	0	0	0	0
VP2	1	0	0	0	1	0
VP3	0	0	0	0	0	1
Outlier	0	0	1	1	0	0

3) Iterative SDP Problem

$$\min_{\mathbf{W}} \quad \mathrm{trace}(\mathbf{C}\mathbf{W})$$

$$\text{s.t.} \quad \mathbf{W}_{0,0,1} = \sum_{i=1}^{2} \mathbf{W}_{0,j,i}, \quad j = 1, \ldots, m,$$

$$\mathrm{trace}(\mathbf{W}_{0,0,1}) = 1, \quad \mathbf{W}_{0,0,1} = \mathbf{W}_{0,0,2},$$

$$\mathbf{W}_{*,*,i} \succeq \mathbf{0}, \quad \forall\, i \in \{1,2\}.$$

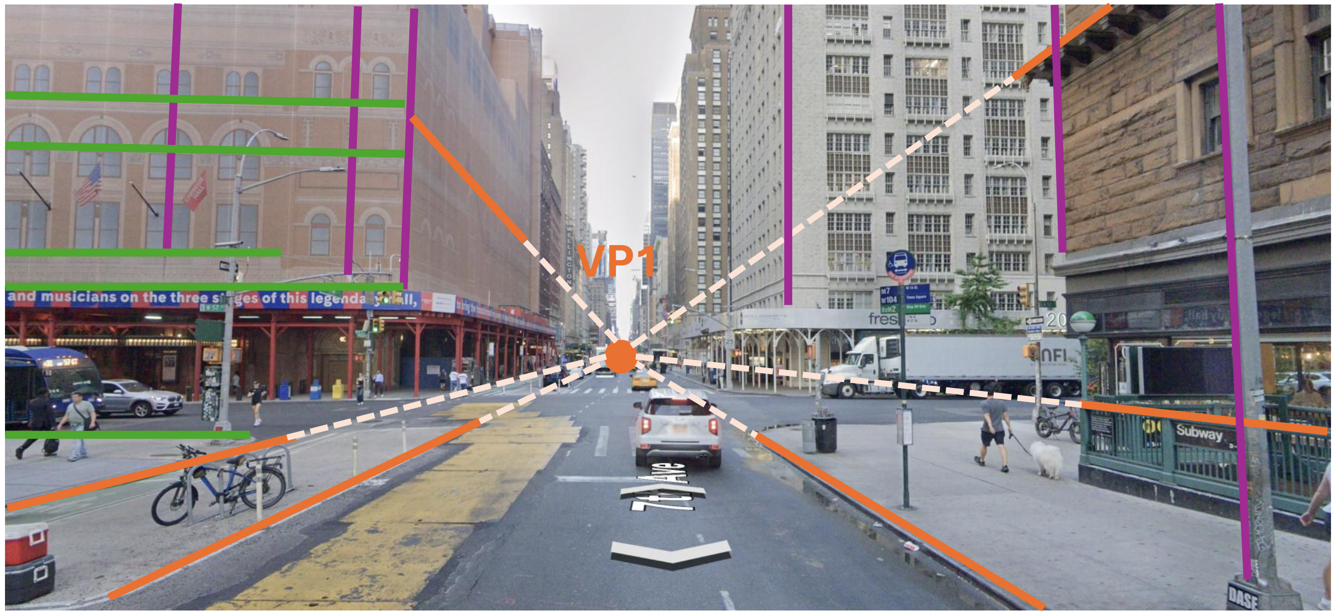
(Single Block SDP Problem)

Find VPs one by one!

	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP	0.2	2e-4	0.4	1e-4	0.3	1e-4
Outlier	9e-4	9e-4	9e-4	9e-4	9e-4	9e-4

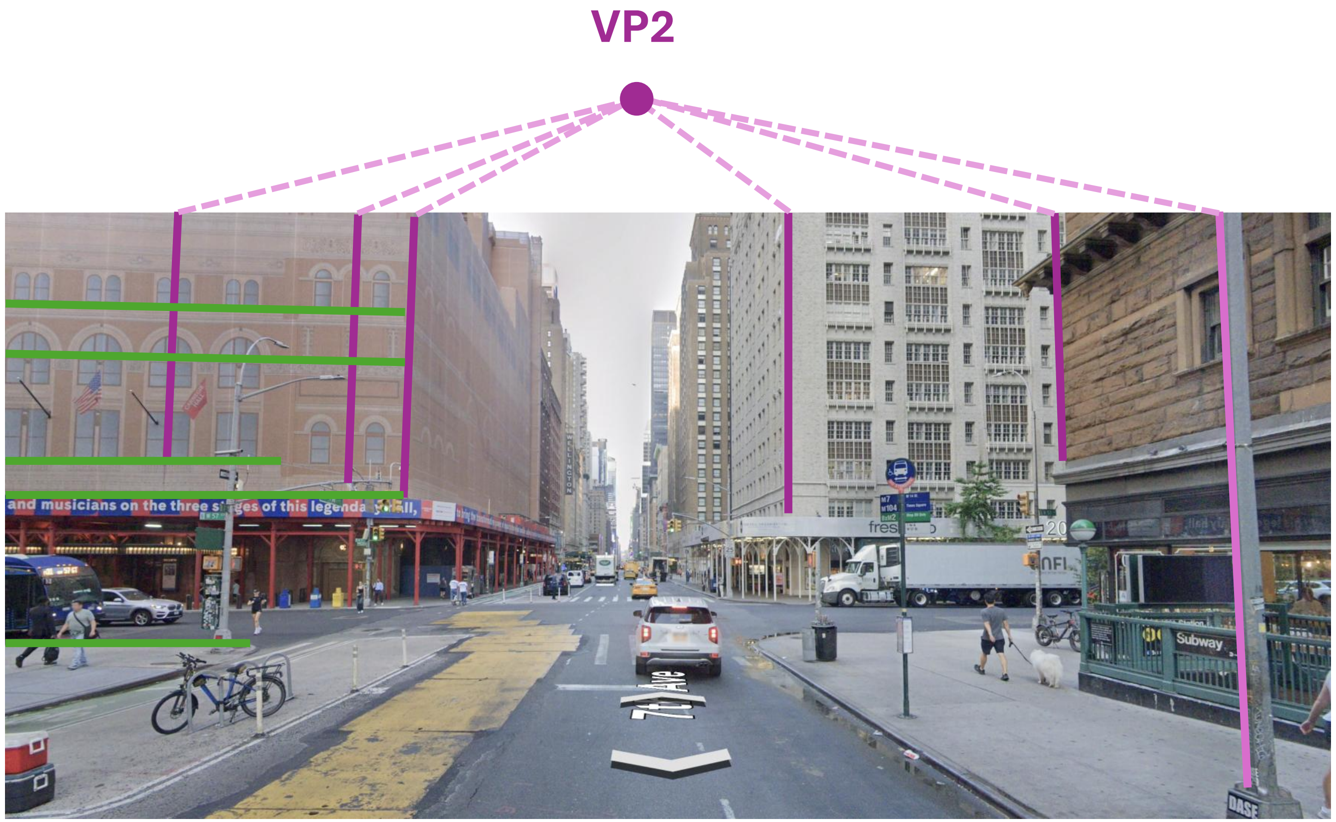
	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP	0	1	0	1	0	1
Outlier	1	0	1	0	1	0

Insight 3: Iterative SDP



Treat Line and Line as Outliers, find VP1

Insight 3: Iterative SDP

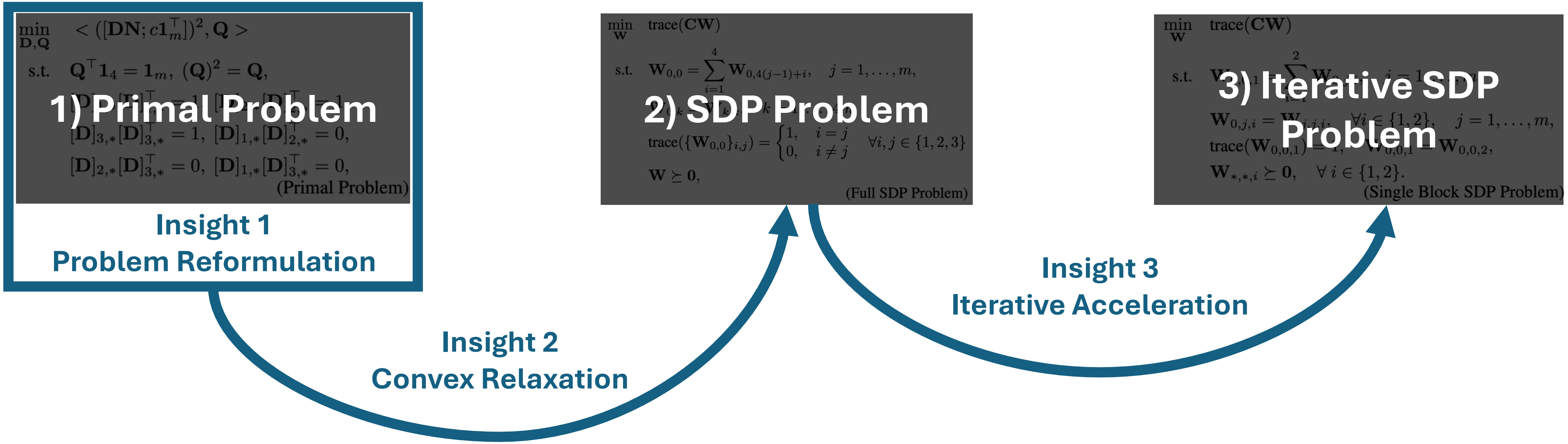


Treat **Line** as Outliers, find **VP2**

Insight 3: Iterative SDP

Find **VP3**

Ours Method: **GlobustVP**



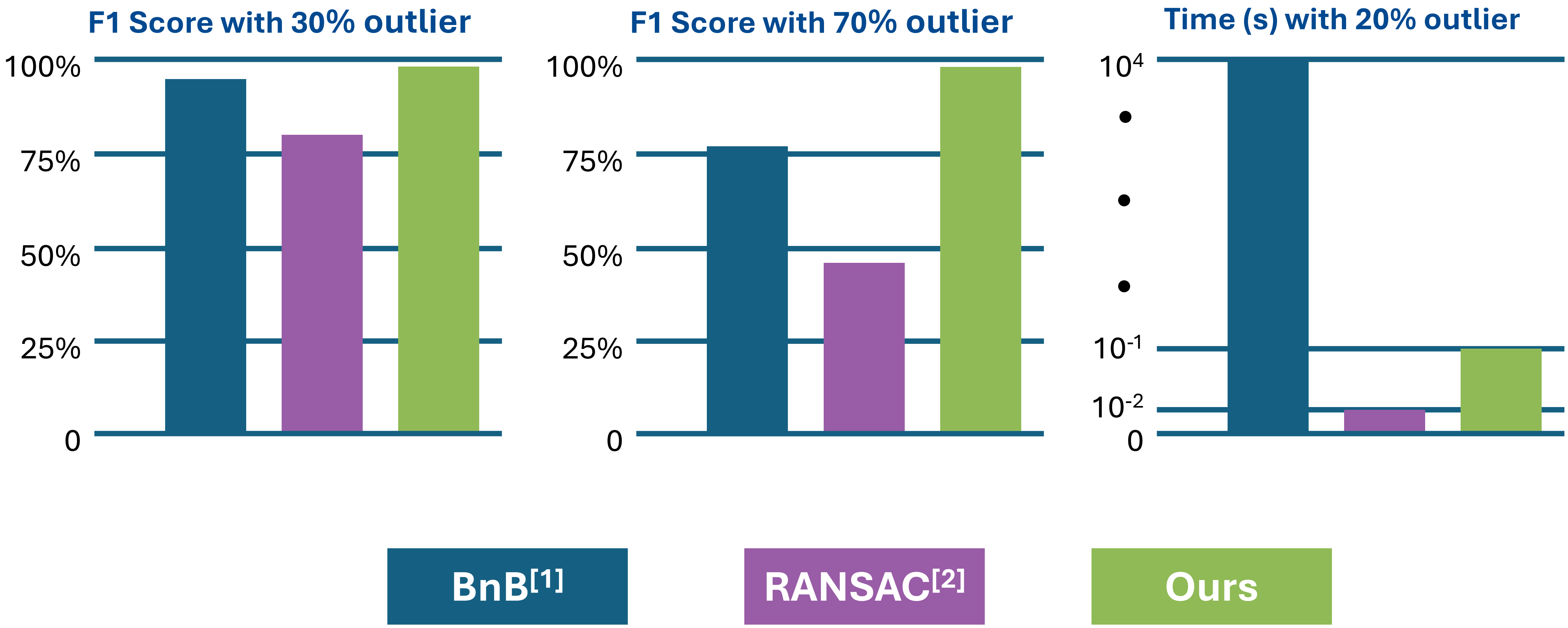
Global Optimality

Efficiency

Outlier Robustness

Generalizable

Synthetic Comparison



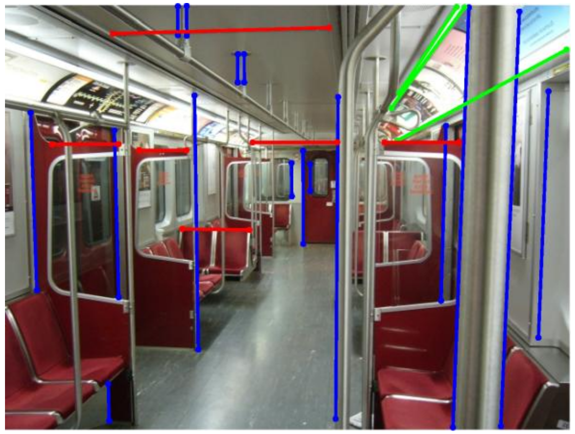
[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
[2] Zhang L, Lu H, Hu X, et al. Vanishing point estimation and line classification in a manhattan world with a unifying camera model. IJCV 2016.

Real-World Comparison

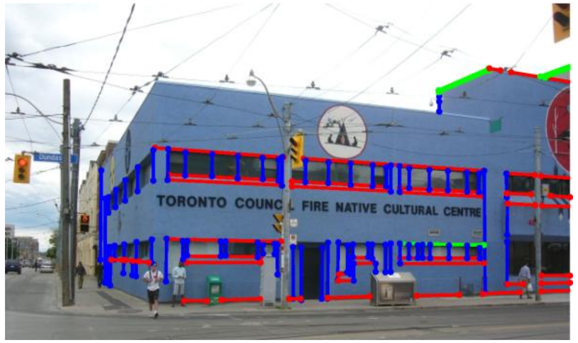
F1-score↑
Consistency error↓

64.29%, 2.19 pix. | 85.71%, 1.01 pix. | 100%, 0.41 pix.






Ground Truth | **BnB[1]** | **RANSAC[2]** | **Ours**



F1-score↑
Consistency error↓

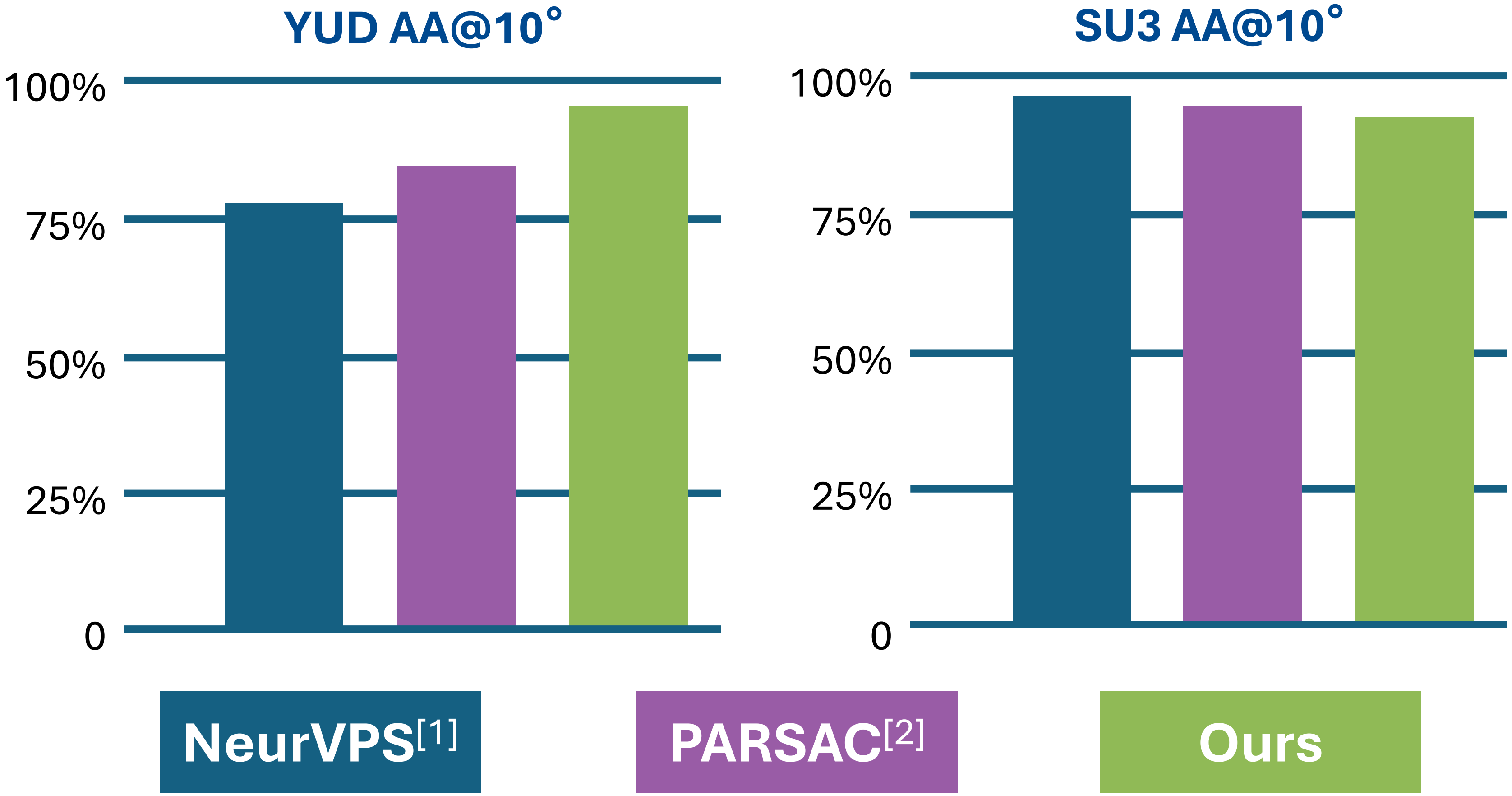
87.60%, 0.52 pix. | 90.08%, 0.45 pix. | 100%, 0.01 pix.

[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
[2] Zhang L, Lu H, Hu X, et al. Vanishing point estimation and line classification in a manhattan world with a unifying camera model. IJCV 2016.

Comparison against Learning-based Method

YUD Dataset

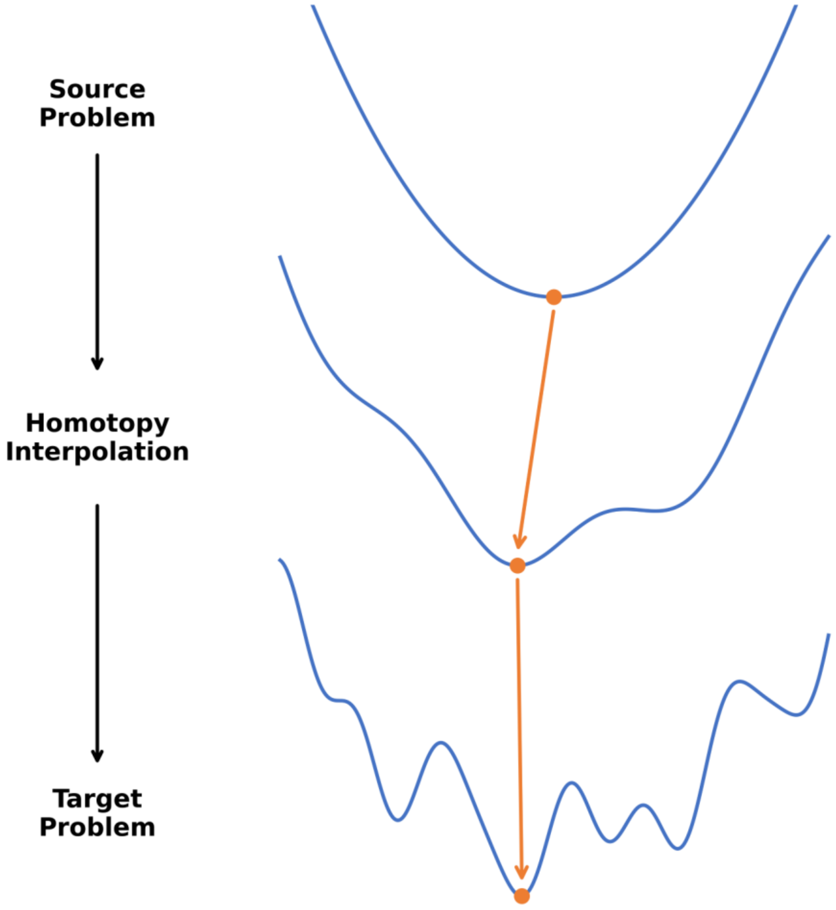
SU3 Dataset

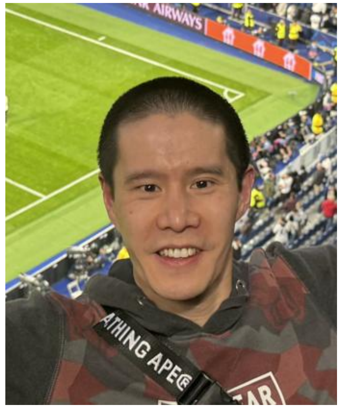


[1] Zhou Y, Qi H, Huang J, et al. Neurvps: Neural vanishing point scanning via conic convolution. NeurIPS 2019.
[2] Kluger F, Rosenhahn B. PARSAC: Accelerating robust multi-model fitting with parallel sample consensus. AAAI 2024.

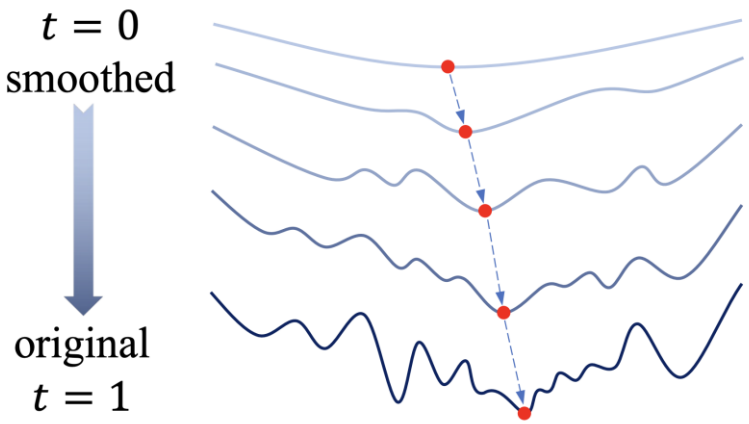
NPC:

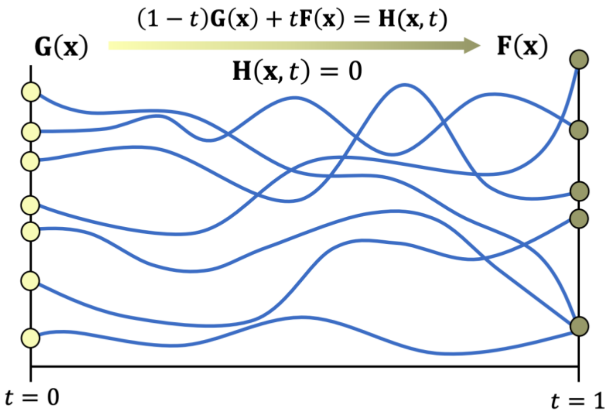
Neural Predictor-Corrector: Solving Homotopy Problems with Reinforcement Learning

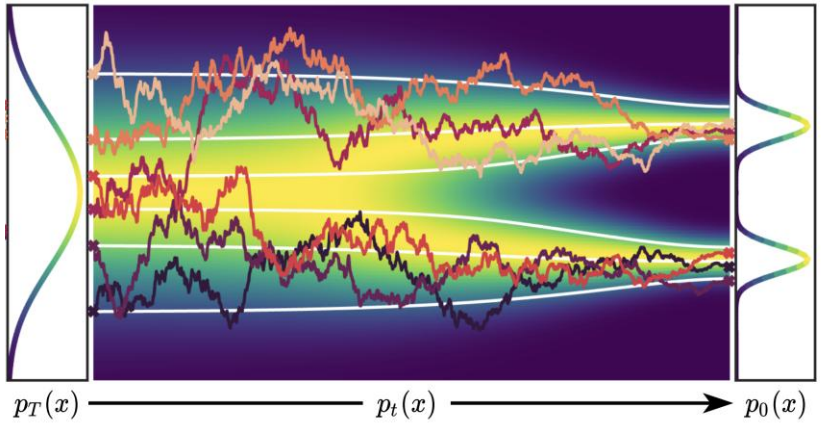




Background: **Homotopy Paradigm**







Optimization[1] **Polynimial Root Finding[2]** **Sampling[3]**

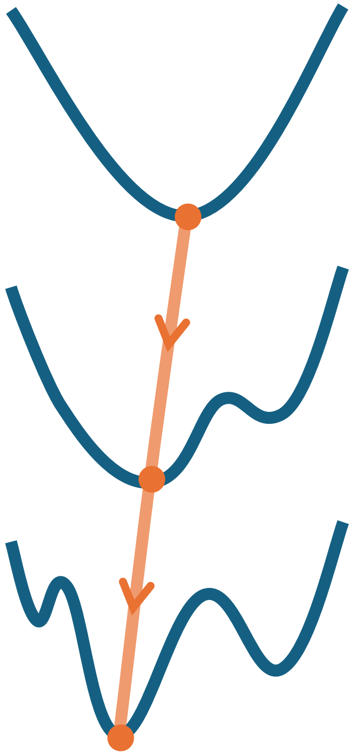
A general principle for solving challenging problems

[1] Lin X, Yang Z, Zhang X, et al. Continuation path learning for homotopy optimization[C]//International Conference on Machine Learning. PMLR, 2023: 21288-21311.
[2] Zhang, Xinyue, et al. "Simulator HC: Regression-based Online Simulation of Starting Problem-Solution Pairs for Homotopy Continuation in Geometric Vision." *2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2025.
[3] Song Y, Sohl-Dickstein J, Kingma D P, et al. Score-based generative modeling through stochastic differential equations[J]. arXiv preprint arXiv:2011.13456, 2020.

Background: **Homotopy Paradigm**

Easy Problem
Known Solutions

Hard Problem
Unknown Solutions



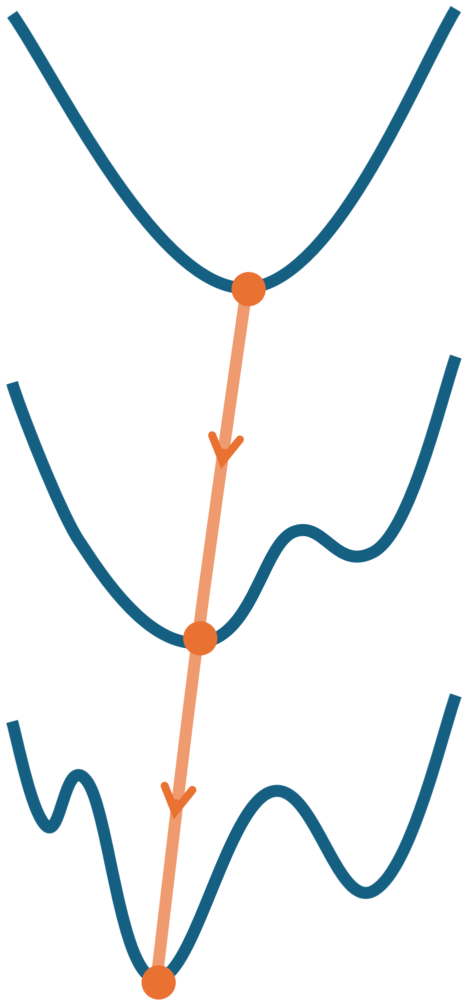
Explicit Homotopy
Interpolation Construction

Implicit Solution
Trajectory Tracing

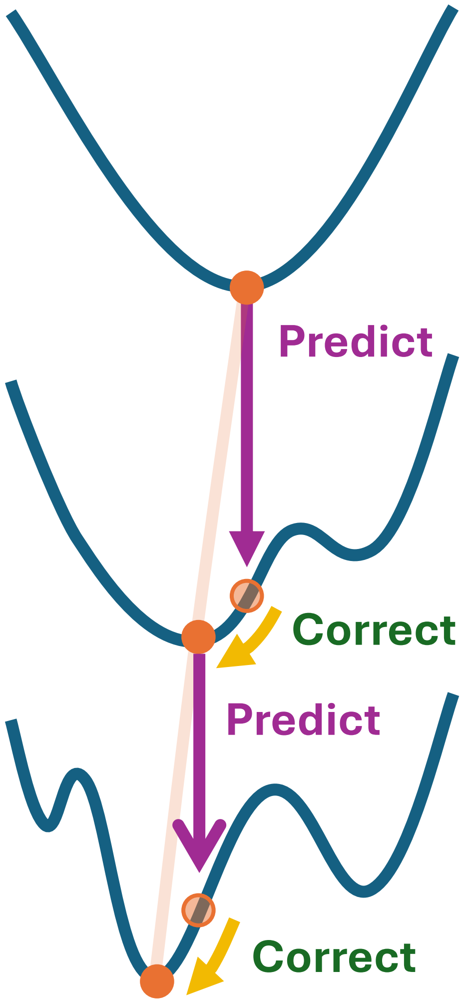
Our Scope

Motivation: **Classical Predictor-Corrector**

Implicit Solution Trajectory



Classical Predictor-Corrector



Algorithm

while $t_n < T$ **do**
  Predictor: Predict next level t_n
  Predictor: Predict $\mathbf{x}_{t_n}$
  while $H(\mathbf{x}_{t_n}, t_n) \leq \epsilon$ **do**
    Corrector: Correct $\mathbf{x}_{t_n}$
  end
end

Classical PC relies on hand-crafted heuristics

Our Method: **Neural Predictor-Corrector (NPC)**

Classical Predictor-Corrector
$\boldsymbol{\Delta t}, \boldsymbol{\epsilon}$

Algorithm 1

while $t_n < T$ **do**
  Predictor: Predict next level $t_n = t_{n-1} + \boldsymbol{\Delta t}$
  Predictor: Predict $\mathbf{x}_{t_n}$
  while $H(\mathbf{x}_{t_n}, t_n) \leq \boldsymbol{\epsilon}$ **do**
    Corrector: Correct $\mathbf{x}_{t_n}$
  end
end

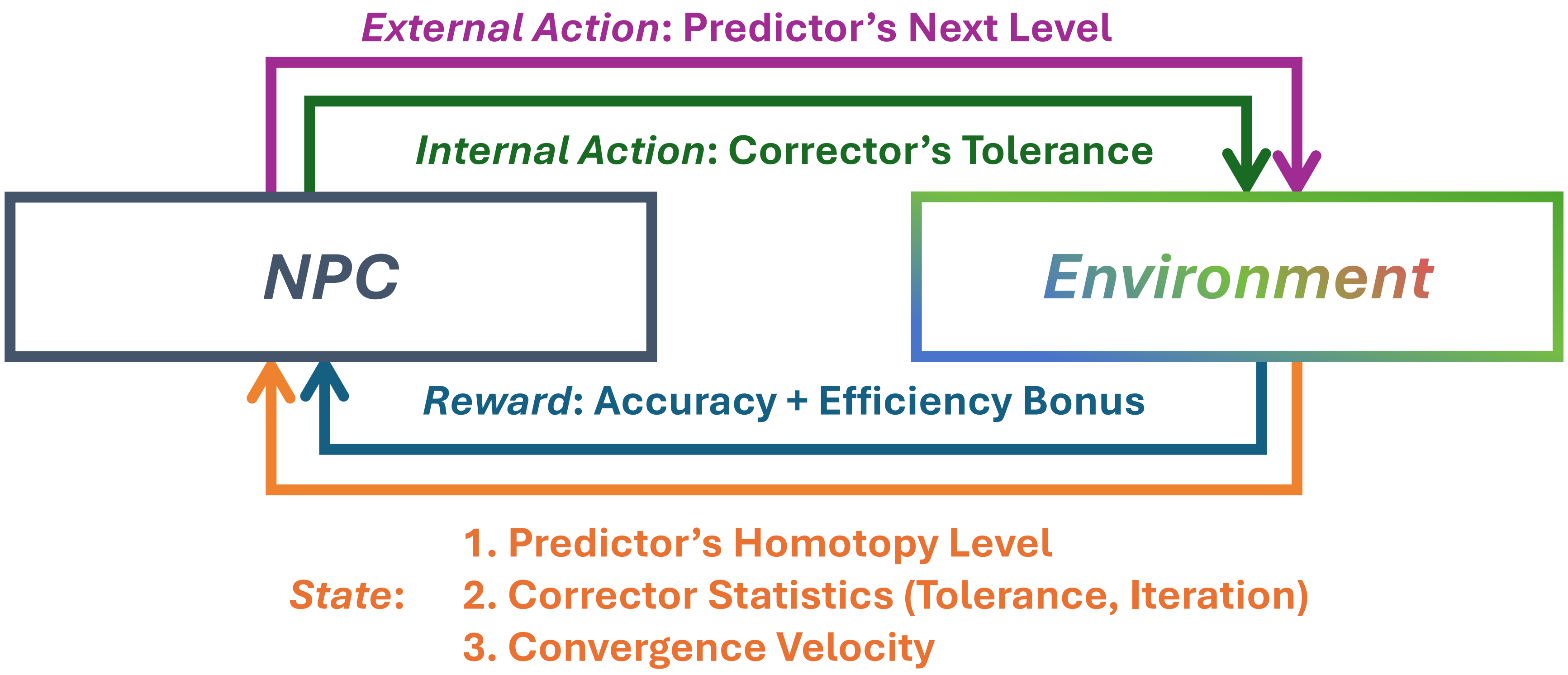
Neural Predictor-Corrector
$\boldsymbol{\Delta t_n}, \boldsymbol{\epsilon_n}$

Algorithm 2

while $t_n < T$ **do**
  NPC: $\{\boldsymbol{\Delta t_n}, \boldsymbol{\epsilon_n}\} = \mathbf{NN}(t_{n-1}, \epsilon_{n-1}, \tau_{n-1})$
  Predictor: Predict next level $t_n = t_{n-1} + \boldsymbol{\Delta t_n}$
  Predictor: Predict $\mathbf{x}_{t_n}$
  while $H(\mathbf{x}_{t_n}, t_n) \leq \boldsymbol{\epsilon_n}$ **do**
    Corrector: Correct $\mathbf{x}_{t_n}$
  end
  Collect corrector statistics ϵ_n
  Collect convergence velocity τ_n
end

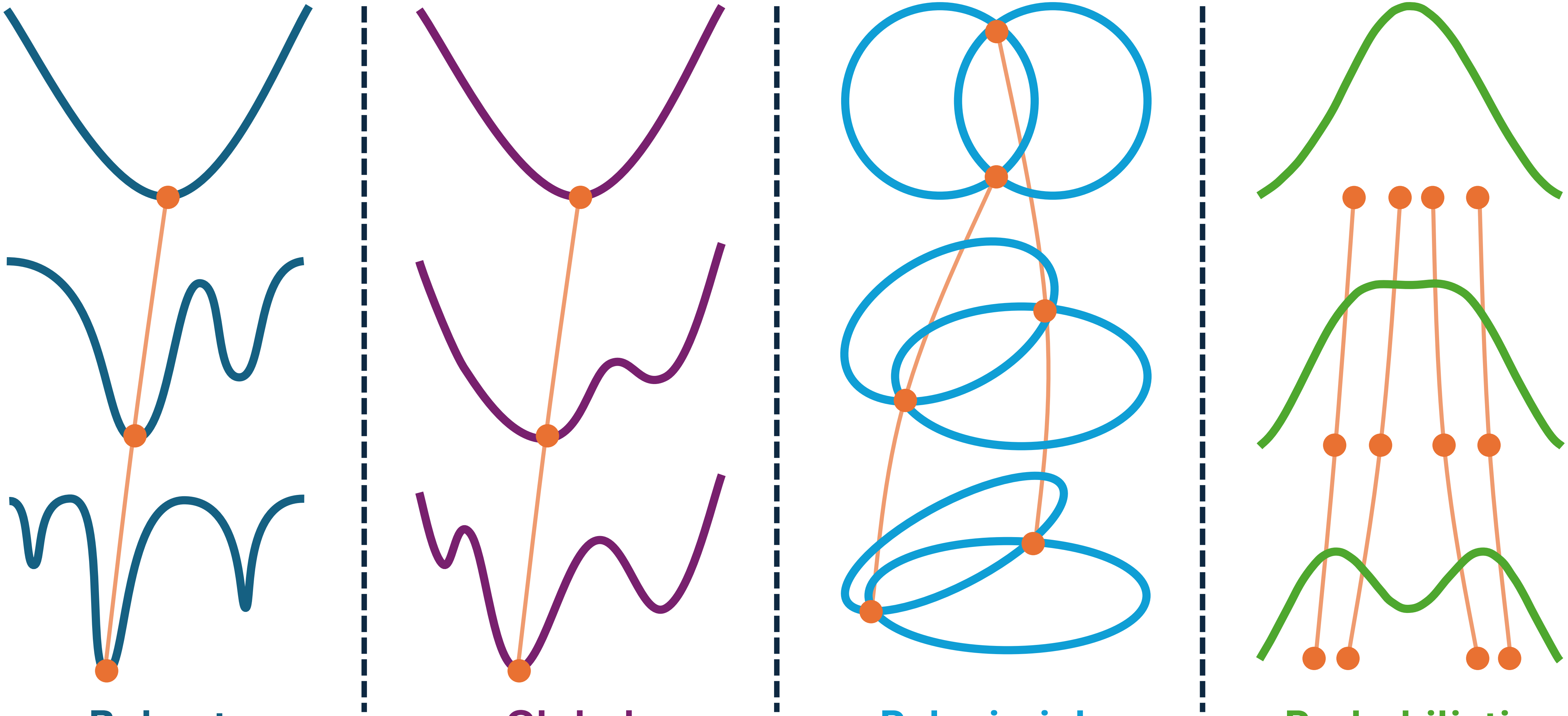
NPC replaces manual heuristics with a neural network

Our Method: **Neural Predictor-Corrector (NPC)**



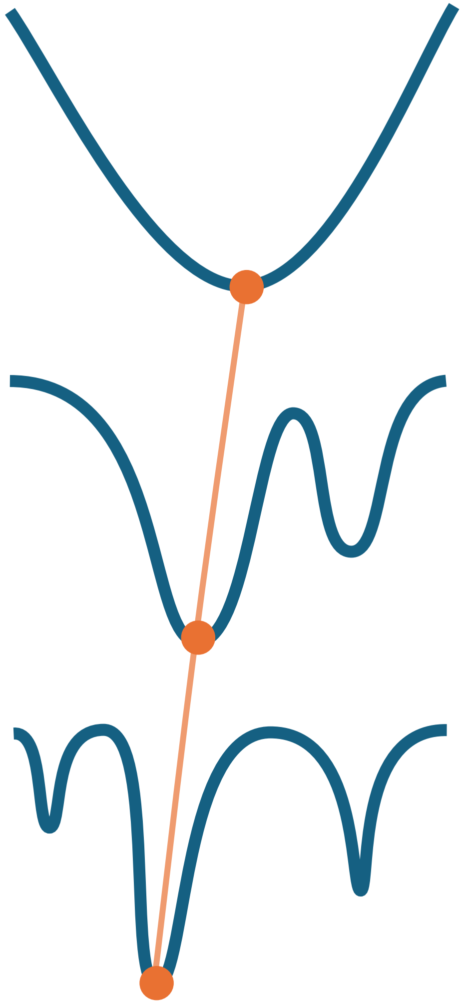
Training NPC via RL to discover optimal policies

Experiments



Robust Optimization | **Global Optimization** | **Polynimial Root Finding** | **Probabilistic Sampling**

Problem 1 : Robust Optimization via GNC

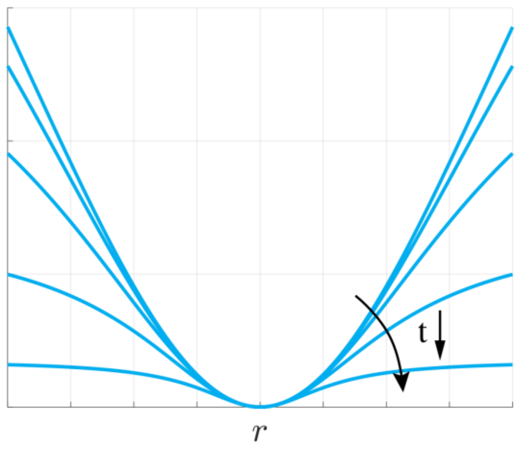


Robust Optimization

Graduated Non-Convexity (GNC)[1]

Outer Interpolation (Geman-McClure)

$$H(\mathbf{x}, t) = \sum_i \frac{\bar{c}^2 r(\mathbf{x}, y_i)^2}{\bar{c}^2 + t r(\mathbf{x}, y_i)^2}$$



Predictor

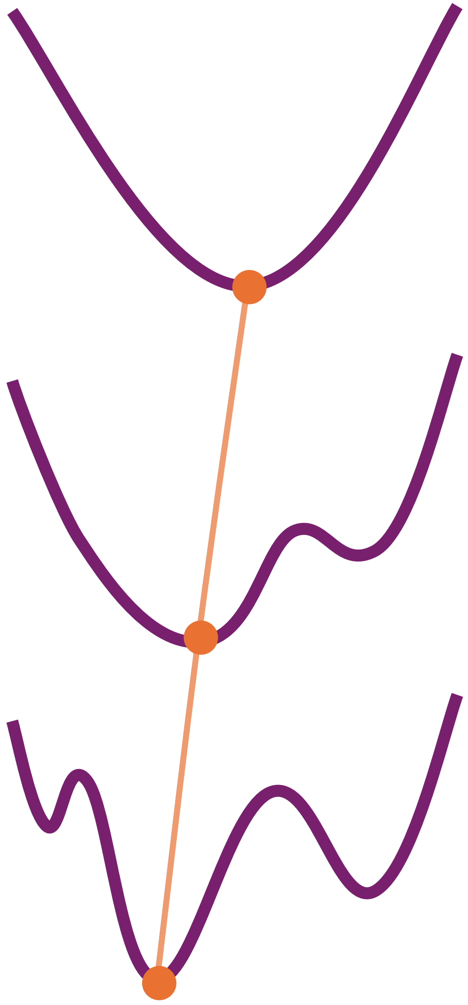
$$t_{i+1} = t_i + \Delta t$$
$$\mathbf{x}_{t_{i+1}} = \mathbf{x}^*_{t_i}$$

Corrector (*Gauss-Newton*)

$$\mathbf{x}^*_t = \arg\min_{\mathbf{x}} H(\mathbf{x}, t)$$

[1] Yang H, Antonante P, Tzoumas V, et al. Graduated non-convexity for robust spatial perception: From non-minimal solvers to global outlier rejection[J]. IEEE Robotics and Automation Letters, 2020, 5(2): 1127-1134.

Problem 2 : Global Optimization via GH

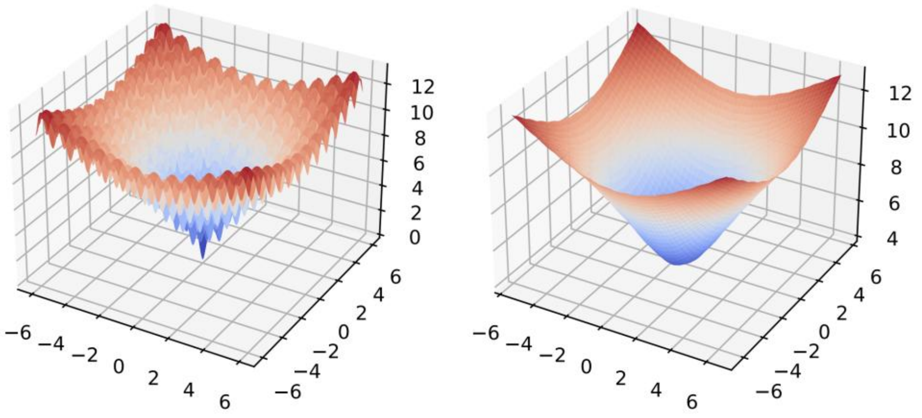


Global Optimization

Gaussian Homotopy (GH)[1]

Outer Interpolation

$$H(\mathbf{x}, t) = g(\mathbf{x}) * \mathcal{N}(0, t\sigma^2)$$



Predictor

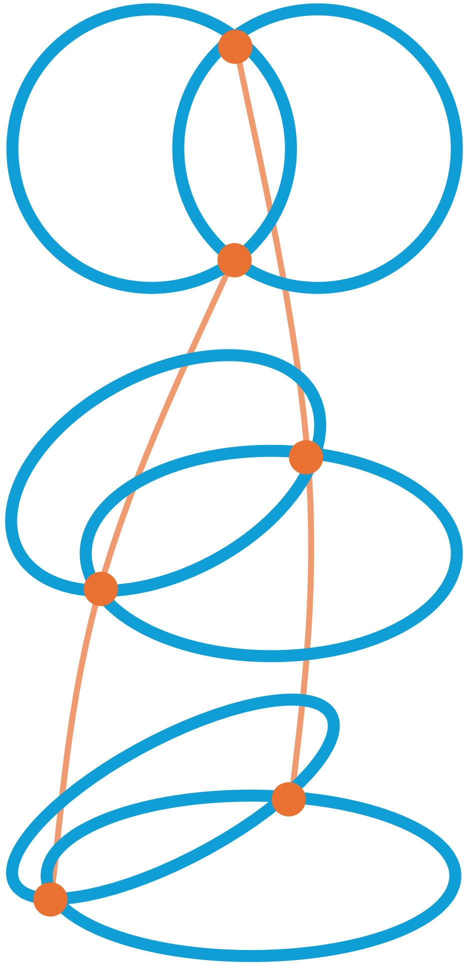
$$t_{i+1} = t_i + \Delta t$$
$$\mathbf{x}_{t_{i+1}} = \mathbf{x}^*_{t_i}$$

Corrector

$$\mathbf{x}^*_t = \arg\min_{\mathbf{x}} H(\mathbf{x}, t)$$

[1] Mobahi H, Fisher III J W. On the link between gaussian homotopy continuation and convex envelopes[C]//International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition. Cham: Springer International Publishing, 2015: 43-56.

Problem 3 : Polynomial Root-Finding via HC

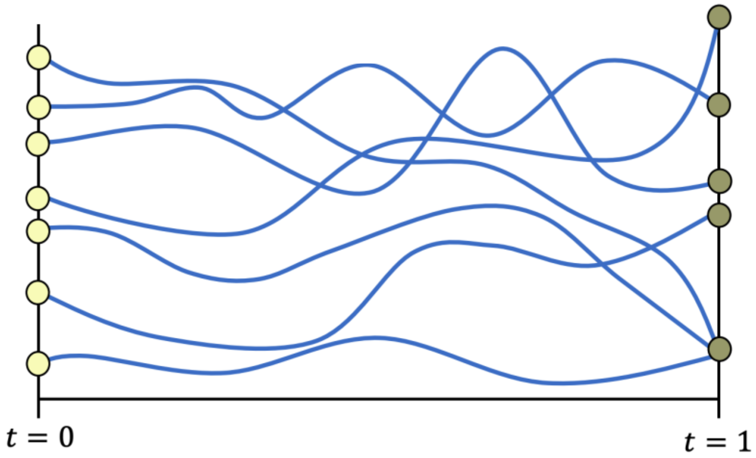


Polynimial Root Finding

Homotopy Continuation (HC)[1]

Outer Interpolation

$$H(\mathbf{x},t) = g(\mathbf{x})(1-t) + f(\mathbf{x})t$$



Predictor

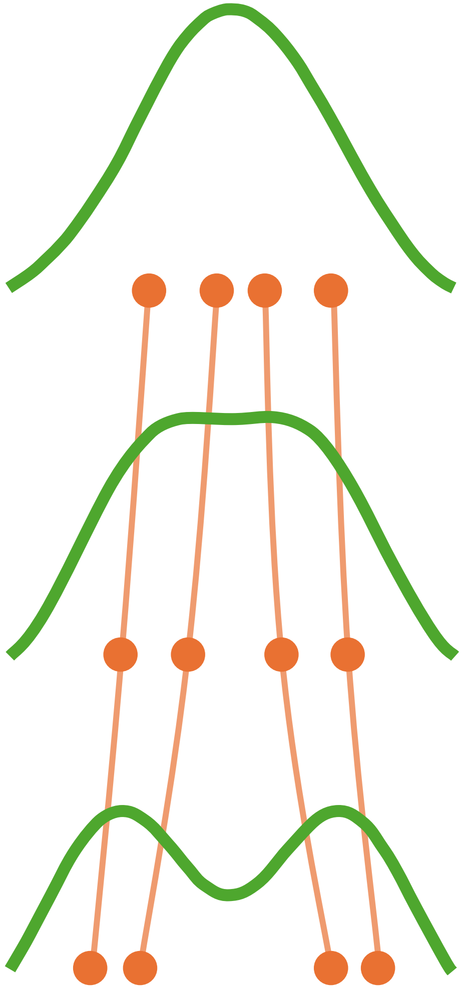
$$t_{i+1} = t_i + \Delta t$$
$$\{\mathbf{x}_{t_{i+1}}\} = \{\mathbf{x}^*_{t_i} + \partial_t H(\mathbf{x}^*_{t_i}, t_i)\Delta t\}$$

Corrector (*Gauss-Newton*)

$$\{\mathbf{x}^*_t\} = \{H(\mathbf{x},t) = 0\}$$

[1] Bates D J, Sommese A J, Hauenstein J D, et al. Numerically solving polynomial systems with Bertini[M]. Society for Industrial and Applied Mathematics, 2013.

Problem 4 : Sampling via ALD

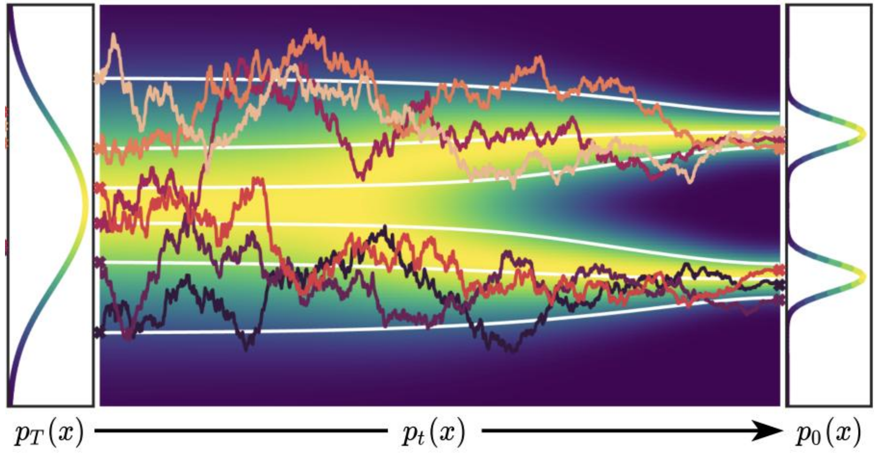


Sampling

Annealed Langevin Dynamics (ALD)[1]

Outer Interpolation

$$H(\mathbf{x}, t) \propto \exp(-g(\mathbf{x})(1-t) - f(\mathbf{x})t)$$



Predictor

$$t_{i+1} = t_i + \Delta t$$
$$\{X_{t_{i+1}}^0\} = \{X_{t_i}^*\}$$

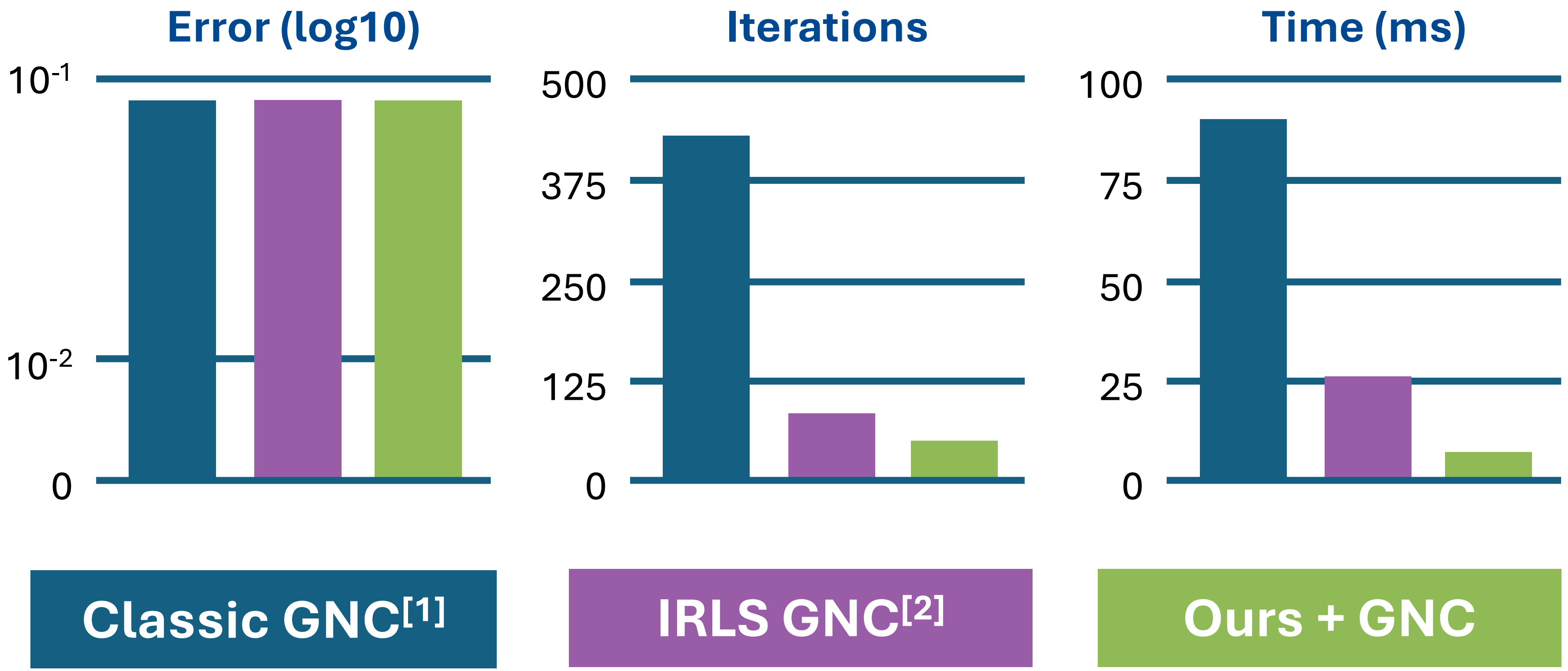
Corrector (*LD*)

$$\mathrm{d}X_t^s = \nabla \log H(\mathbf{x}, t)\,\mathrm{d}s + \mathrm{d}W_s$$

[1] Song Y, Sohl-Dickstein J, Kingma D P, et al. Score-based generative modeling through stochastic differential equations[J]. arXiv preprint arXiv:2011.13456, 2020.

Problem 1 : Robust Optimization via GNC

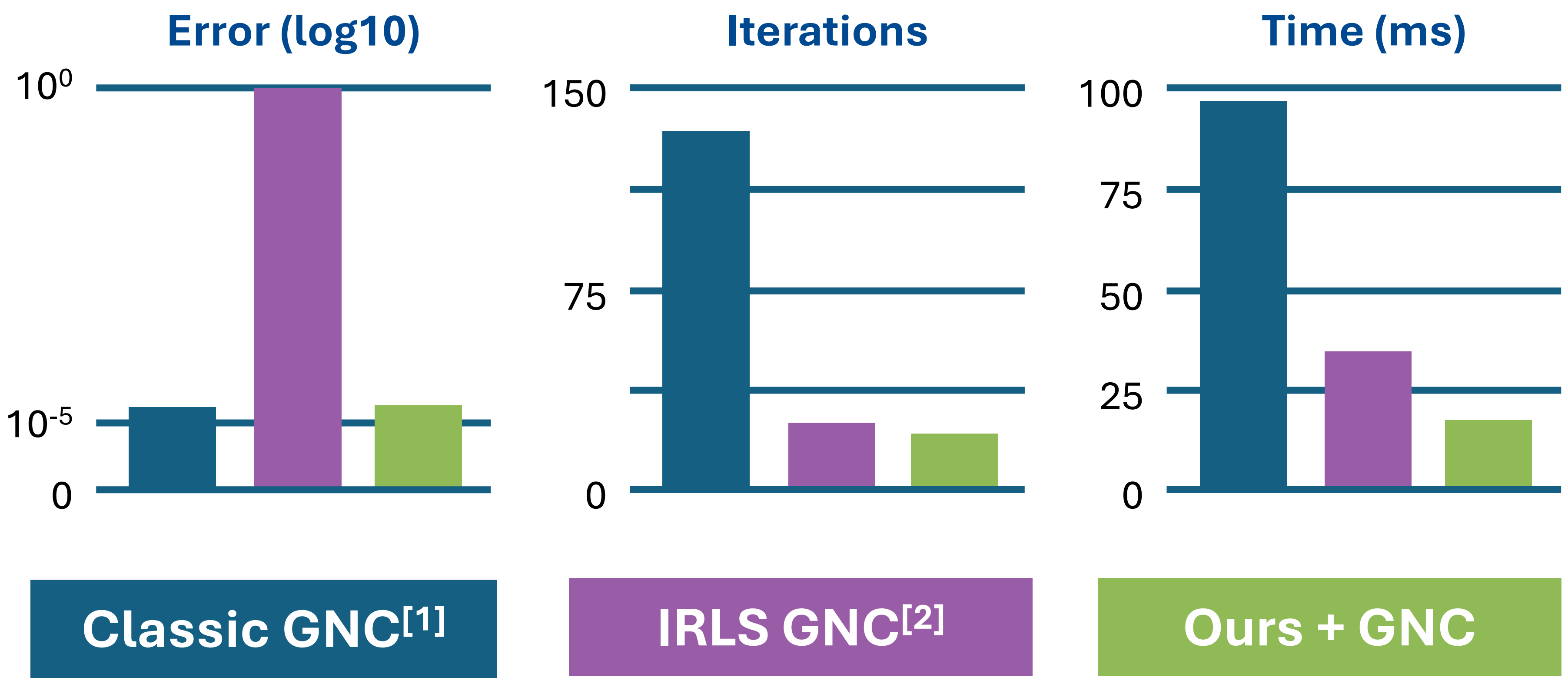
Point Cloud Registration
(Seq cube)



[1] Yang H, Antonante P, Tzoumas V, et al. Graduated non-convexity for robust spatial perception: From non-minimal solvers to global outlier rejection[J]. IEEE Robotics and Automation Letters, 2020, 5(2): 1127-1134.
[2] Peng L, Kümmerle C, Vidal R. On the convergence of IRLS and its variants in outlier-robust estimation[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023: 17808-17818.

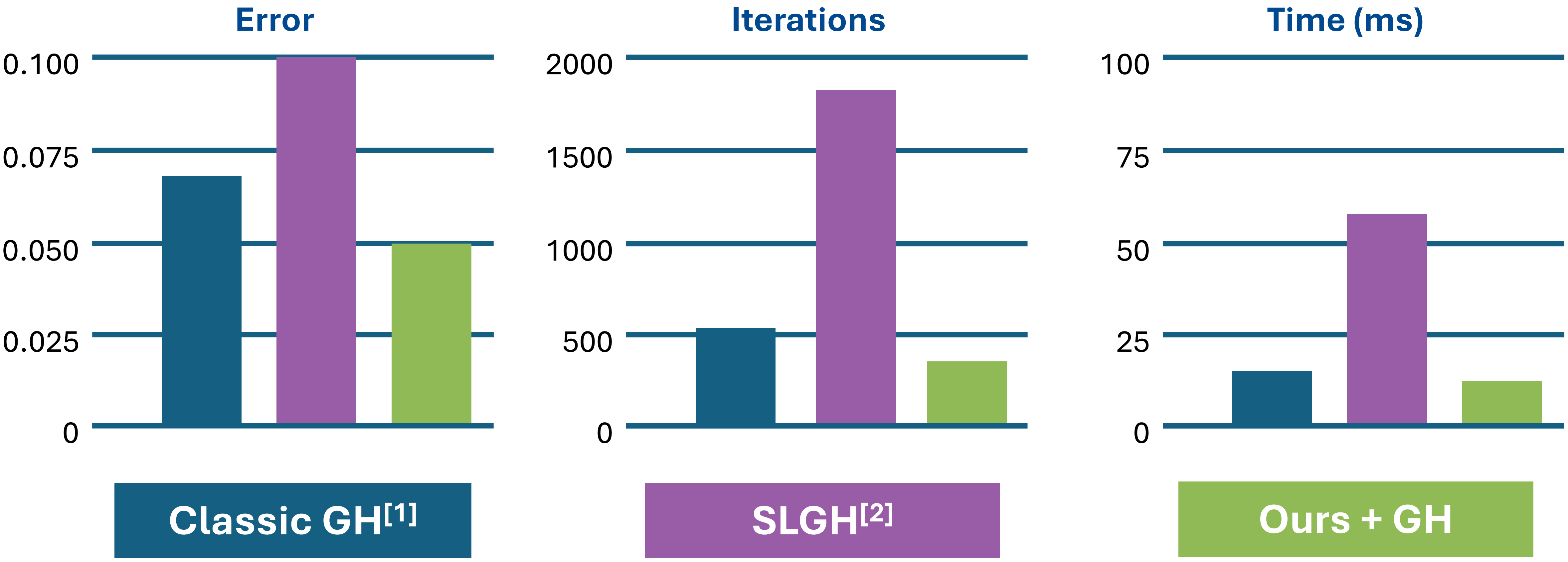
Problem 1 : Robust Optimization via GNC

Multi-view Triangulation
(Seq st_pt_sq)



[1] Yang H, Antonante P, Tzoumas V, et al. Graduated non-convexity for robust spatial perception: From non-minimal solvers to global outlier rejection[J]. IEEE Robotics and Automation Letters, 2020, 5(2): 1127-1134.
[2] Peng L, Kümmerle C, Vidal R. On the convergence of IRLS and its variants in outlier-robust estimation[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023: 17808-17818.

Problem 2 : Global Optimization via GH

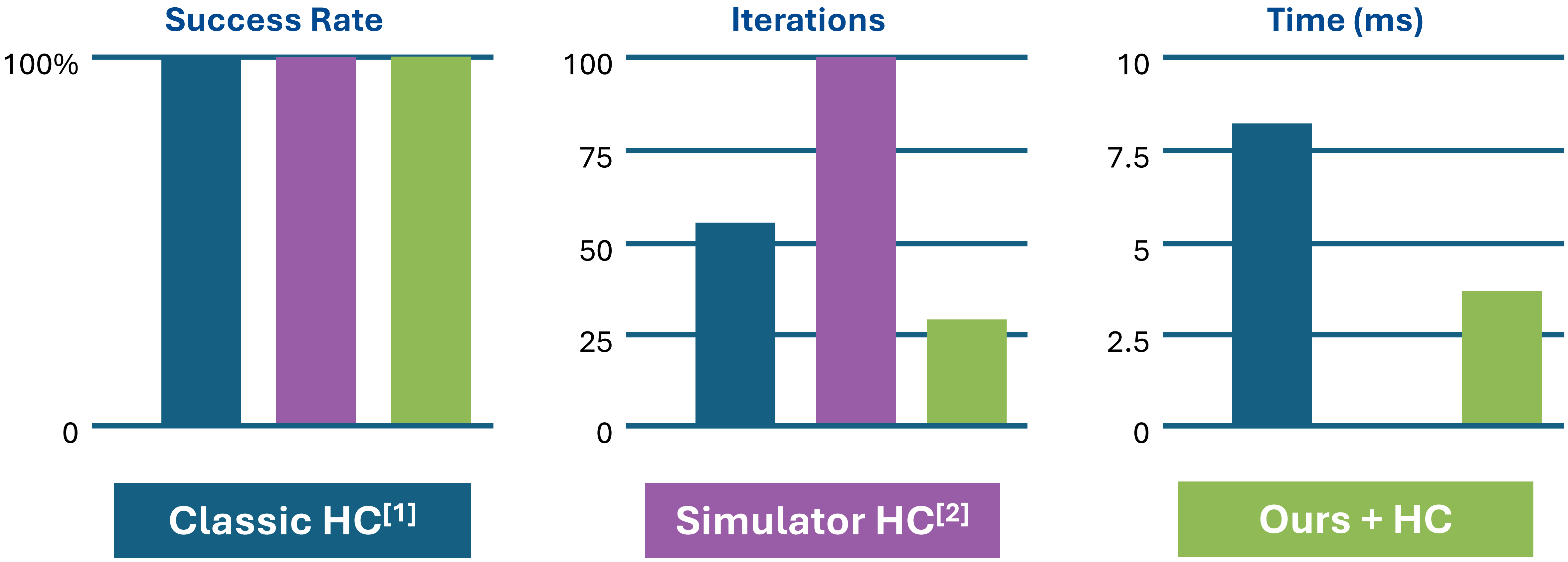


(Seq 2d_Ackley)

[1] Mobahi H, Fisher III J W. On the link between gaussian homotopy continuation and convex envelopes[C]//International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition. Cham: Springer International Publishing, 2015: 43-56.

[2] Iwakiri H, Wang Y, Ito S, et al. Single loop gaussian homotopy method for non-convex optimization[J]. Advances in Neural Information Processing Systems, 2022, 35: 7065-7076.

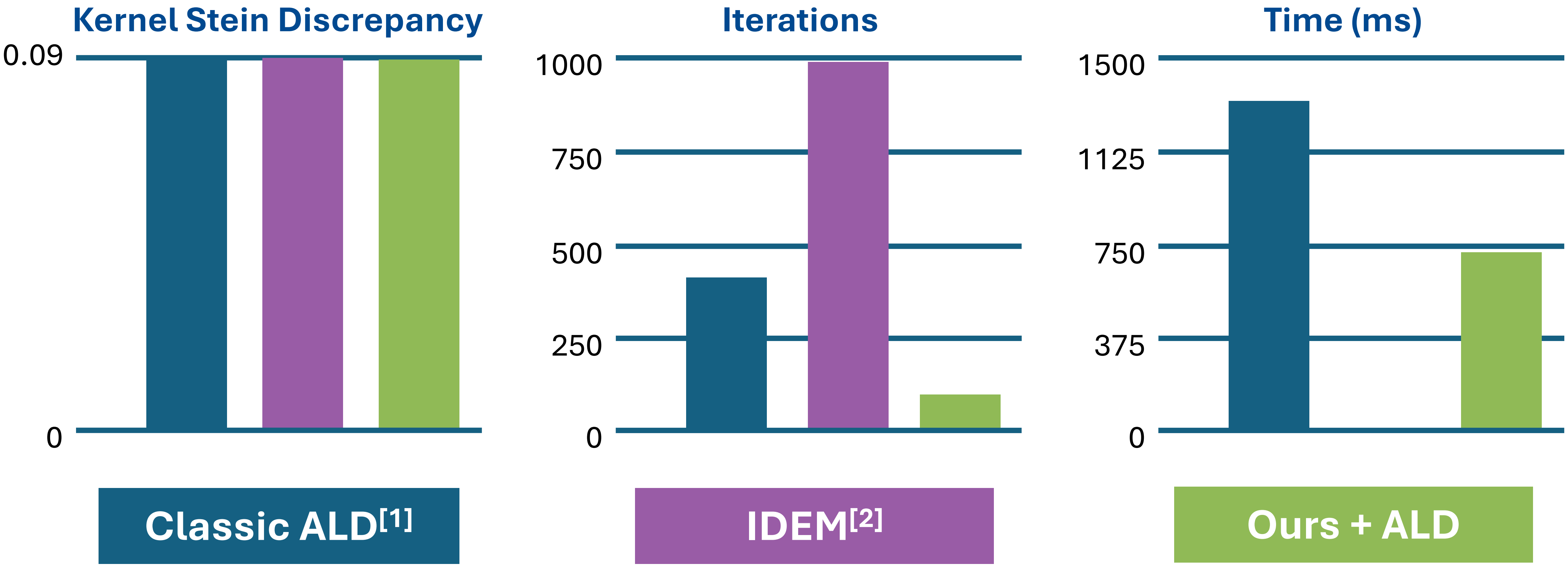
Problem 3 : Polynomial Root-Finding via HC



(Seq UPnP)

[1] Bates D J, Sommese A J, Hauenstein J D, et al. Numerically solving polynomial systems with Bertini[M]. Society for Industrial and Applied Mathematics, 2013.
[2] Zhang X, Dai Z, Xu W, et al. Simulator hc: Regression-based online simulation of starting problem-solution pairs for homotopy continuation in geometric vision[C]//Proceedings of the Computer Vision and Pattern Recognition Conference. 2025: 27103-27112.

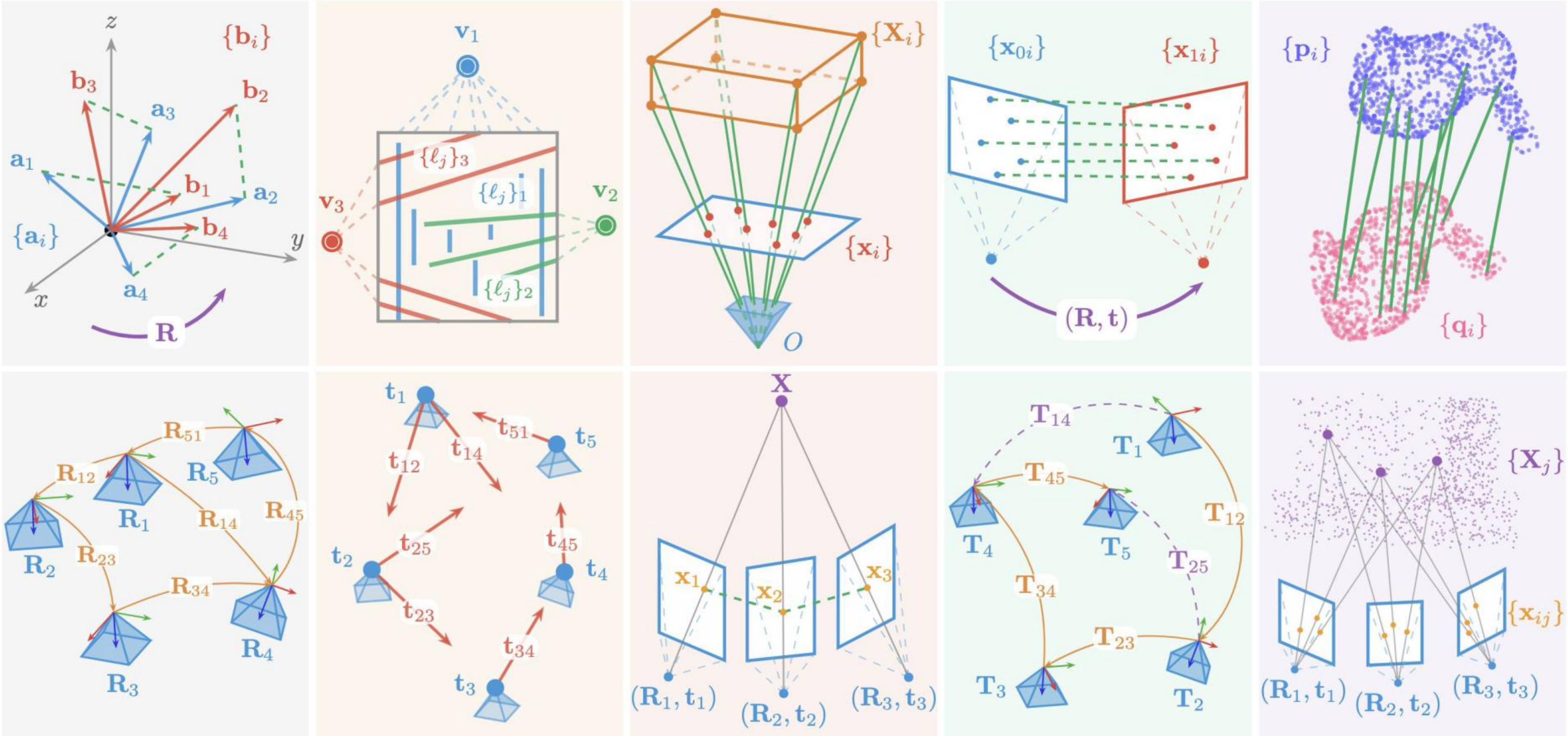
Problem 4 : Sampling via ALD

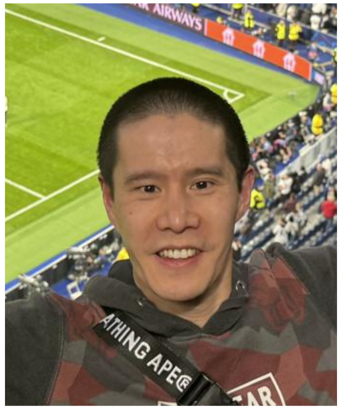


(Seq DW-4)

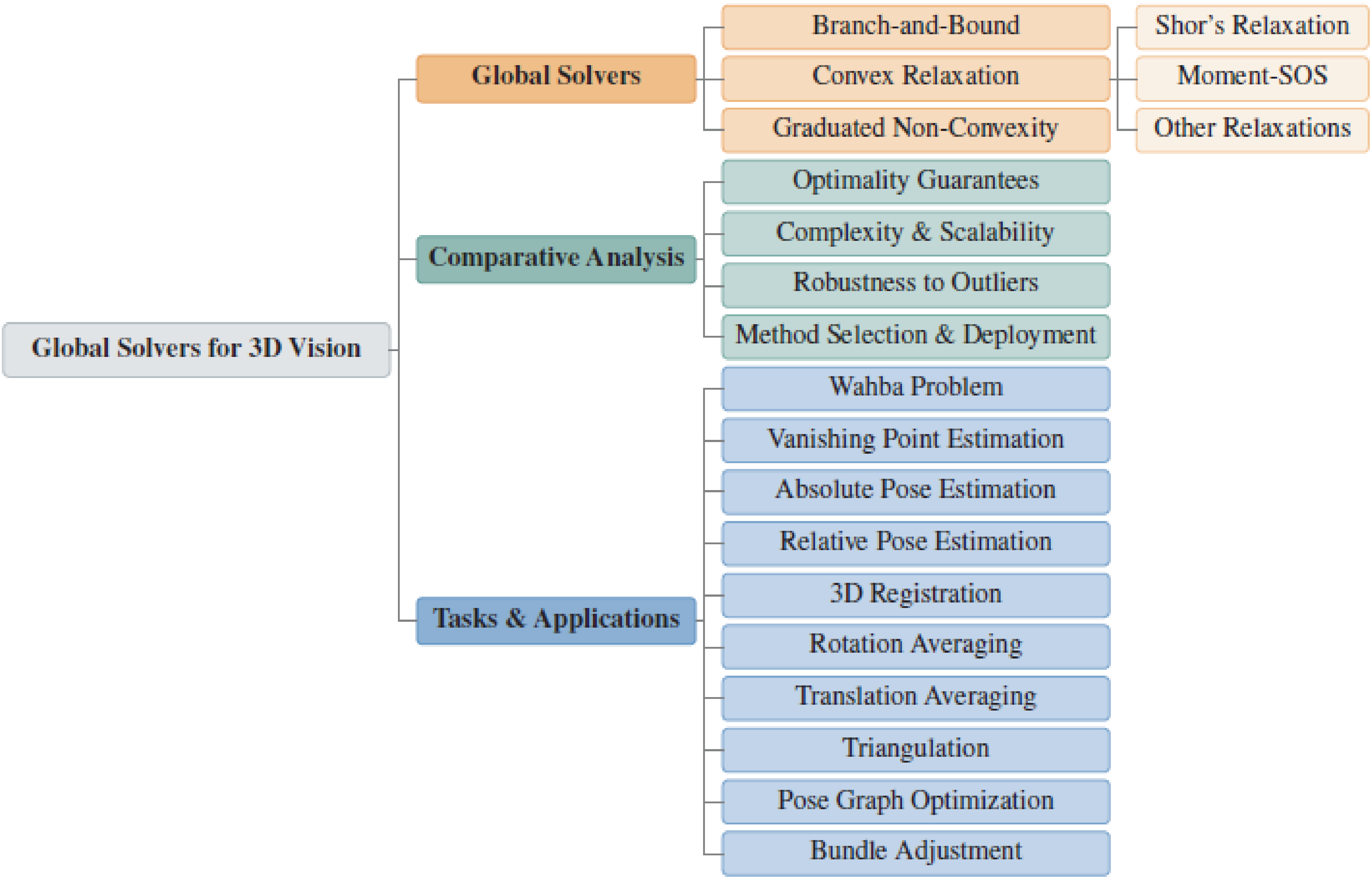
[1] Song Y, Sohl-Dickstein J, Kingma D P, et al. Score-based generative modeling through stochastic differential equations[J]. arXiv preprint arXiv:2011.13456, 2020.
[2] Akhound-Sadegh T, Rector-Brooks J, Bose A J, et al. Iterated denoising energy matching for sampling from boltzmann densities[J]. arXiv preprint arXiv:2402.06121, 2024.

Advances in Global Solvers for 3D Vision

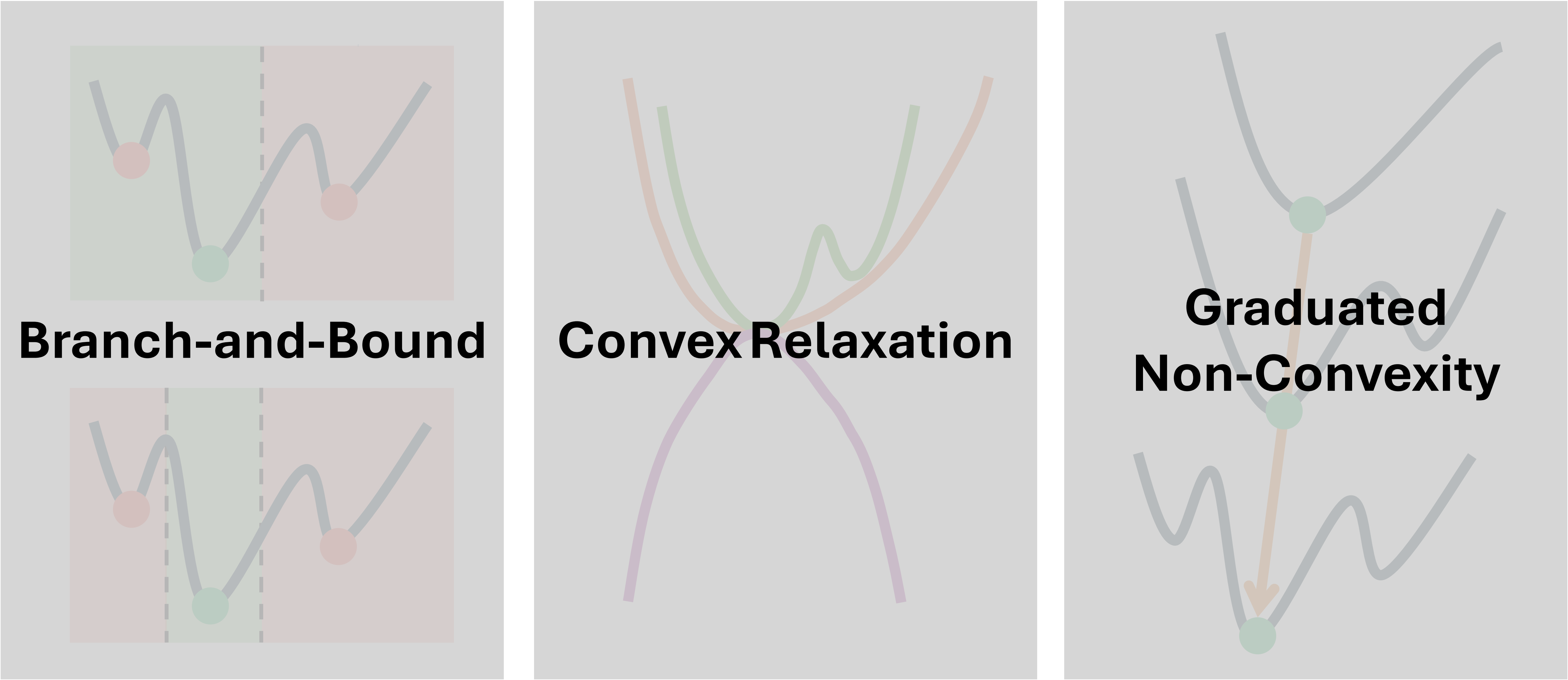




Overview


Global Solvers for 3D Vision
Global Solvers
Comparative Analysis
Tasks & Applications
Branch-and-Bound
Convex Relaxation
Graduated Non-Convexity
Shor's Relaxation
Moment-SOS
Other Relaxations
Optimality Guarantees
Complexity & Scalability
Robustness to Outliers
Method Selection & Deployment
Wahba Problem
Vanishing Point Estimation
Absolute Pose Estimation
Relative Pose Estimation
3D Registration
Rotation Averaging
Translation Averaging
Triangulation
Pose Graph Optimization
Bundle Adjustment

Three Paradigm

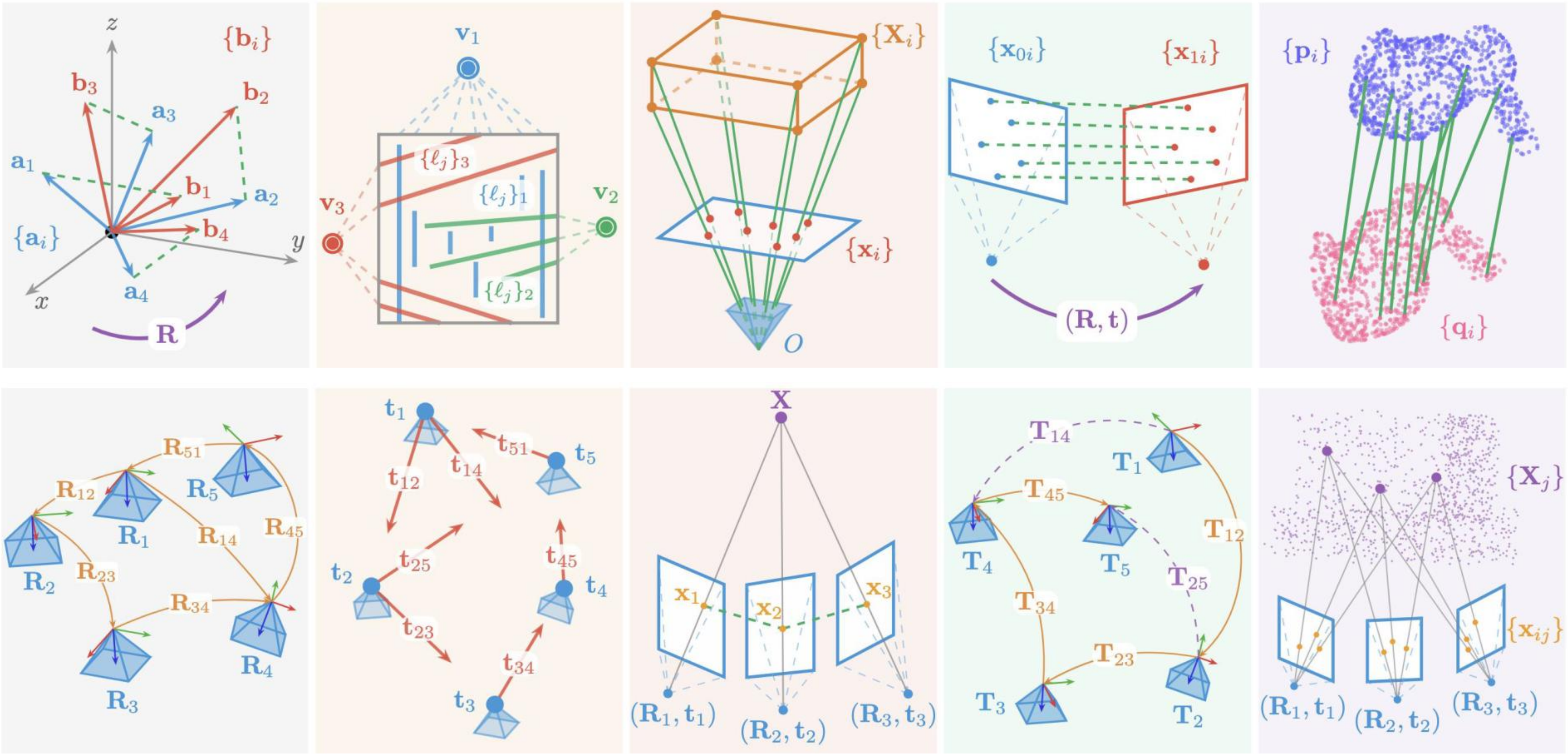


Comparative Analysis

METHOD	OPTIMALITY	SCALABILITY	OUTLIER HANDLING	COMPLEXITY	CERTIFICATES
Branch & Bound BnB	✓ Global	× Poor $N < 20$	↬ Consensus Max (CM)	△ Exponential in dim	✓ Always
Shor's Relaxation Convex Relaxation	♦ Global if tight	• Medium 100–1k	→ M-est robust	▷ $O(n^{3.5})$ SDP	♦ If tight
Moment-SOS Lasserre Hierarchy	♦ Global if tight	× Low $N < 100$	↬ CM + M-est	△ $O(r^{3.5})$ grows fast	♦ If tight
Other Relaxations L_∞ / SOCP / LP / QP	≈ Near-global prob. spec.	⇑ High $N > 1k$	• Problem specific	⇒ $O(n^3)$~$O(n)$ fast	• Prob. specific
GNC Grad. Non-Convexity	∼ Near-global no cert.	★ Excellent $N > 1k$	▲ Built-in 30–50%	⇒ $O(Kn^2)$ linear N	× None

• Strong ♦ Good / Conditional • Moderate • Limited

Ten Geometric Estimation Problems



1 Motivation: Why Trustworthy Perception?

2 Certifiable Global Optimization

- GlobustVP: Certifiable VP Estimation [CVPR 2025, Best Paper Award Candidate]
- NPC: RL-Accelerated Homotopy Solvers [ICLR 2026]
- Survey of Global Solvers for 3D Vision

3 Open challenges

1 Motivation: Why Trustworthy Perception?

2 Certifiable Global Optimization

- GlobustVP: Certifiable VP Estimation [CVPR 2025, Best Paper Award Candidate]
- NPC: RL-Accelerated Homotopy Solvers [ICLR 2026]
- Survey of Global Solvers for 3D Vision

3 Open challenges

Open Challenges and Future Directions

Scalability

BnB and CR costs grow prohibitively with problem size

Open:

Hybrid pipelines pairing fast GNC with lightweight certifiers

Deep Learning Integration

Foundation models produce impressive predictions without certificates.

Open:

CR as differentiable layers and learned priors to warm-start solvers

Standardized Evaluation

The field lacks shared benchmarks enabling fair comparison.

Open:

Certified optimality rate, tightness gaps, runtime-accuracy curves

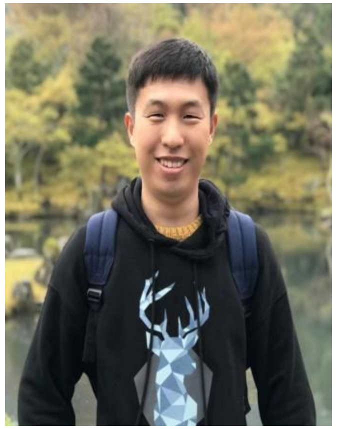
Thank You!

Javier Civera

Haoang Li

Heng Yang

Yi Zhou



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