GlobustVP

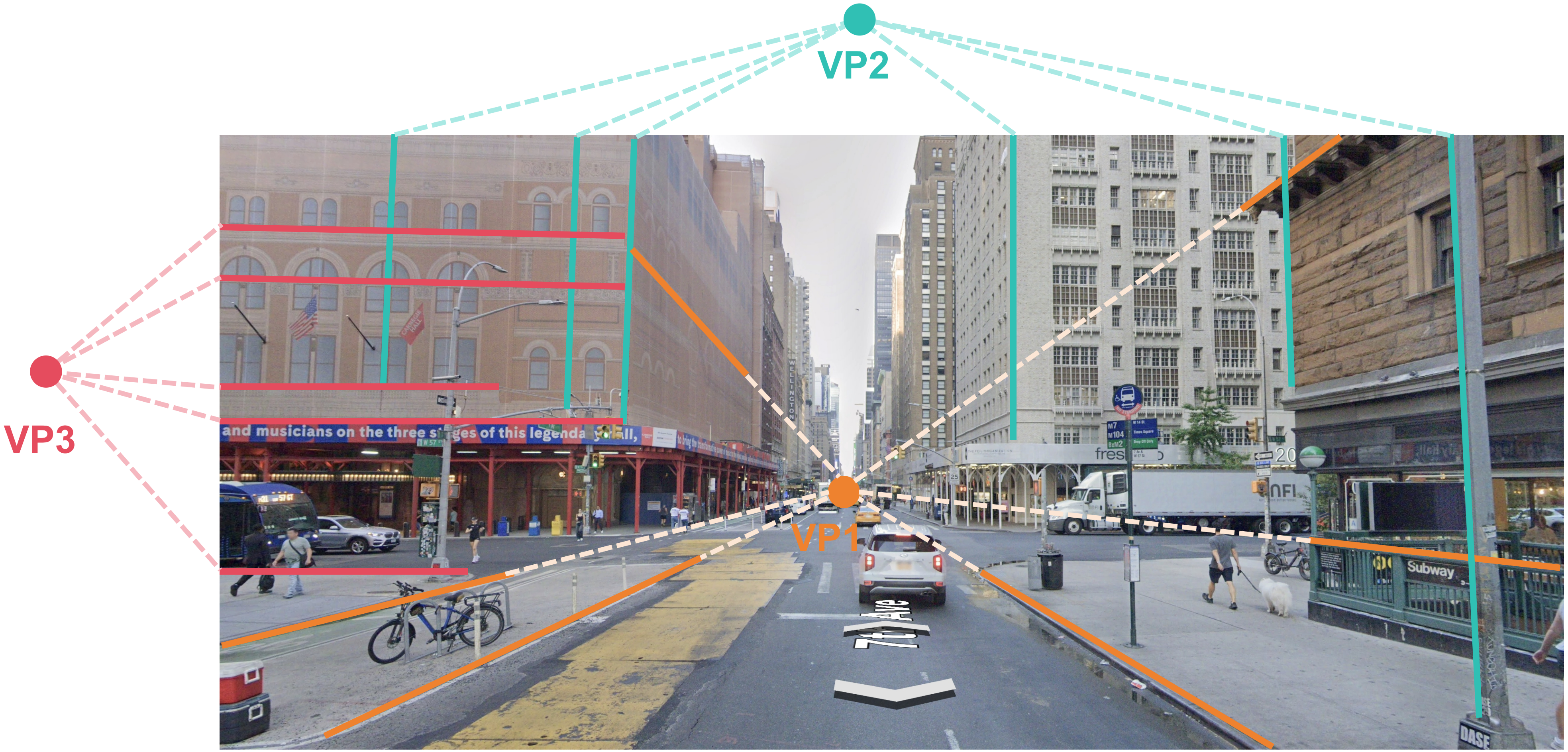
Convex Relaxation for Robust Vanishing Point Estimation in Manhattan World

Bangyan Liao[1,2*], Zhenjun Zhao[3*], Haoang Li[4], Yi Zhou[5], Yingping Zeng[5], Hao Li[1], Peidong Liu[1]

https://github.com/WU-CVGL/GlobustVP/

Vanishing Point in Manhattan World

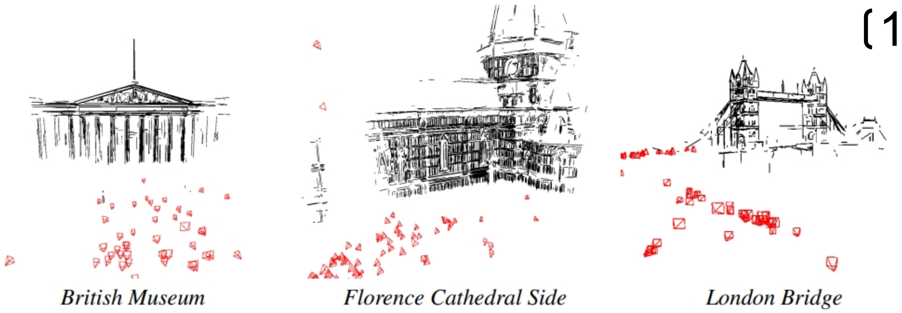
projections of parallel lines intersect at a single point



Applications of Vanishing Point

Structure from Motion (SFM)

(1)

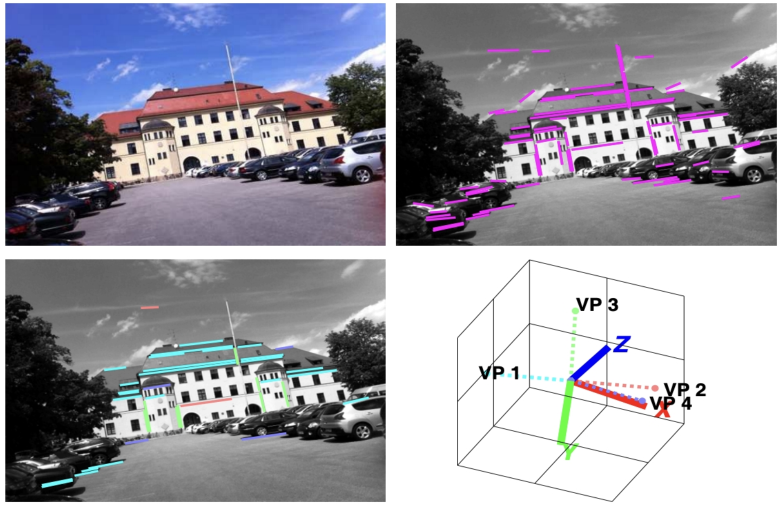


Simultaneous Localization And Mapping (SLAM)

(2)

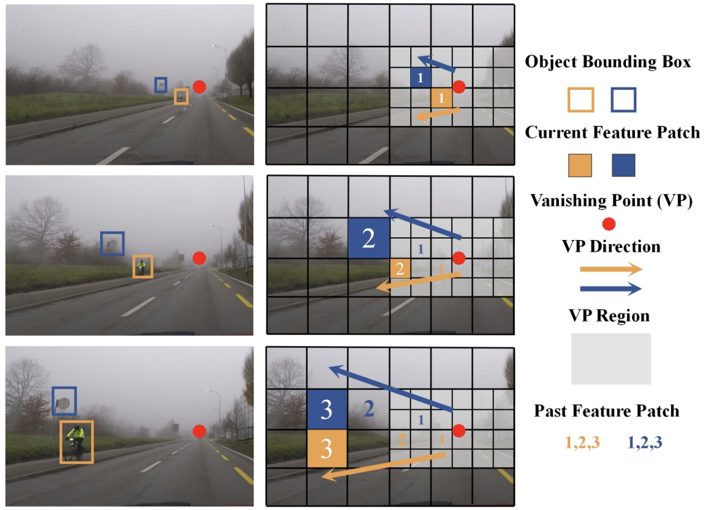
Camera Rotation Estimation

(3)



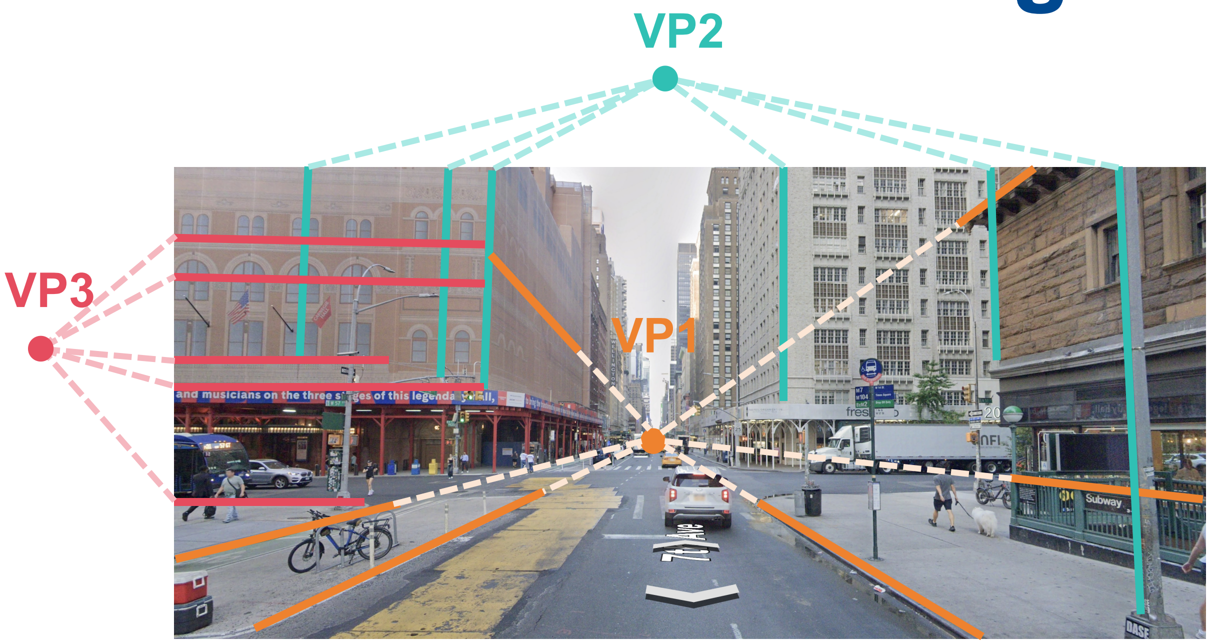
Structural Understanding

(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.

Our Problem: VPs Estimation & Line Labeling



Input: Unlabeled Lines
Intrinsic Parameters

Output: Labeled Lines
Vanishing Points (VP)

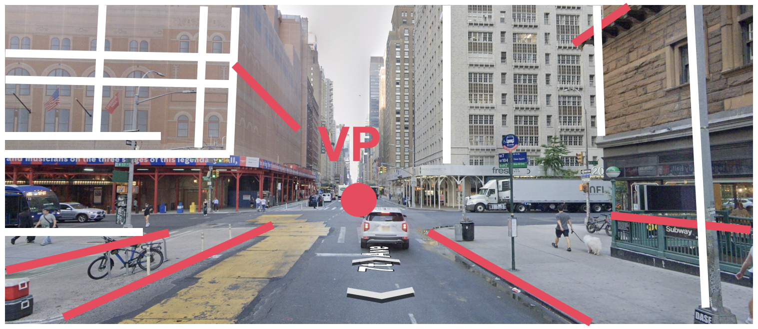
Global Optimality ***Efficiency*** ***Outlier Robustness*** ***Generalization***

Related Works (1/3)

RANdom SAmple Consensus (RANSAC)

Minimal Lines Sampling

VP Hypothesize



Inliers Counting

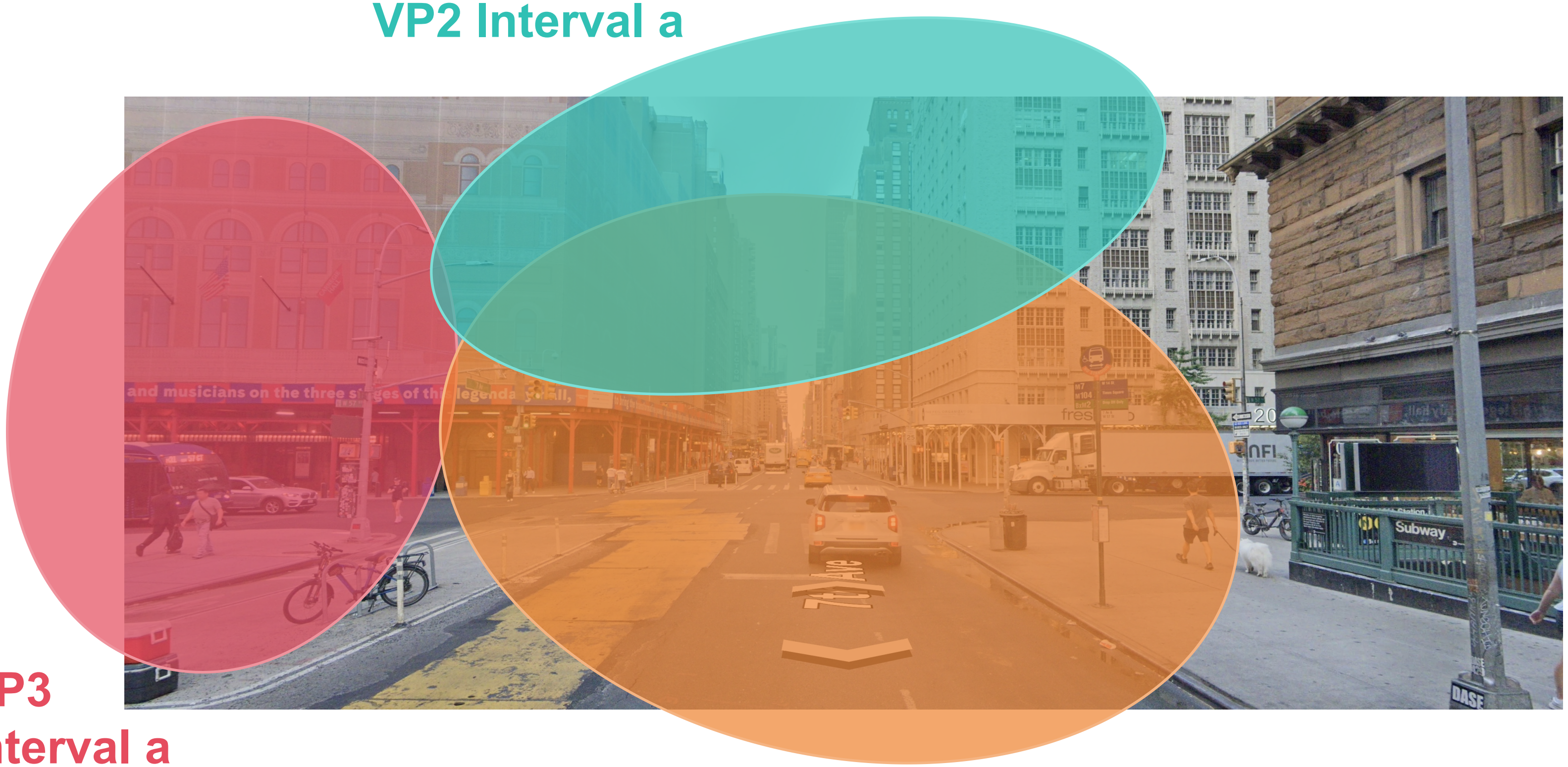
Global Optimality ***Efficiency*** ***Outlier Robustness*** ***Generalization***

[1] Bazin J C, Pollefeys M. 3-line RANSAC for orthogonal vanishing point detection. IROS 2012.
[2] Mirzaei F M, Roumeliotis S I. Optimal estimation of vanishing points in a manhattan world. ICCV 2011.
[3] Sinha S N, Steedly D, Szeliski R, et al. Interactive 3D architectural modeling from unordered photo collections. TOG 2008.
[4] Tardif J P. Non-iterative approach for fast and accurate vanishing point detection. ICCV 2009.
[5] Toldo R, Fusiello A. Robust multiple structures estimation with j-linkage. ECCV 2008.
[6] 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.
[7] Zuliani M, Kenney C S, Manjunath B S. The multiransac algorithm and its application to detect planar homographies. ICIP 2005.

Related Works (2/3)

Branch and Bound (BnB)

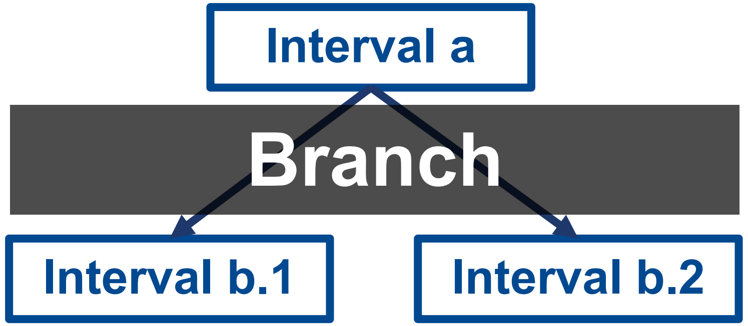
Interval a

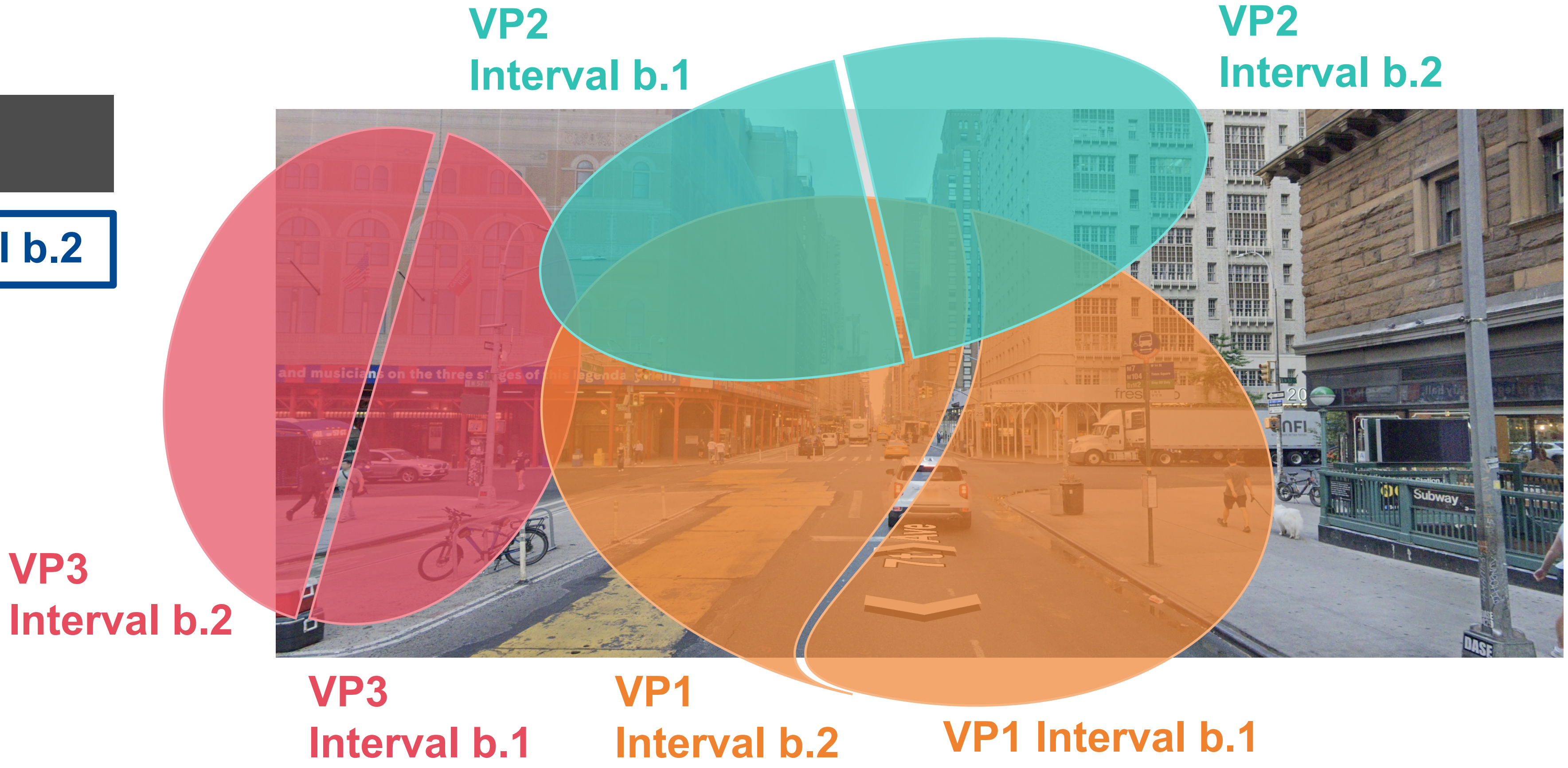


[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
[2] Bazin J C, Seo Y, Pollefeys M. Globally optimal consensus set maximization through rotation search. ACCV 2012.
[3] Li H, Zhao J, Bazin J C, et al. Quasi-globally optimal and efficient vanishing point estimation in Manhattan world. ICCV 2019.
[4] Li H, Zhao J, Bazin J C, et al. Quasi-globally optimal and near/true real-time vanishing point estimation in Manhattan world. T-PAMI 2020.

Related Works (2/3)

Branch and Bound (BnB)





[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
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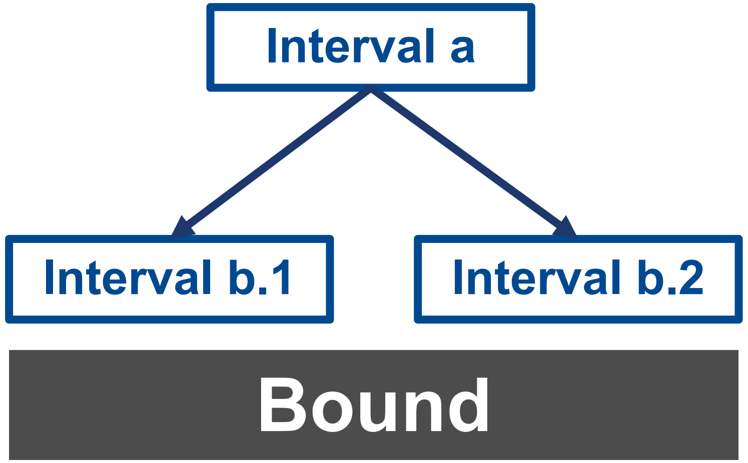
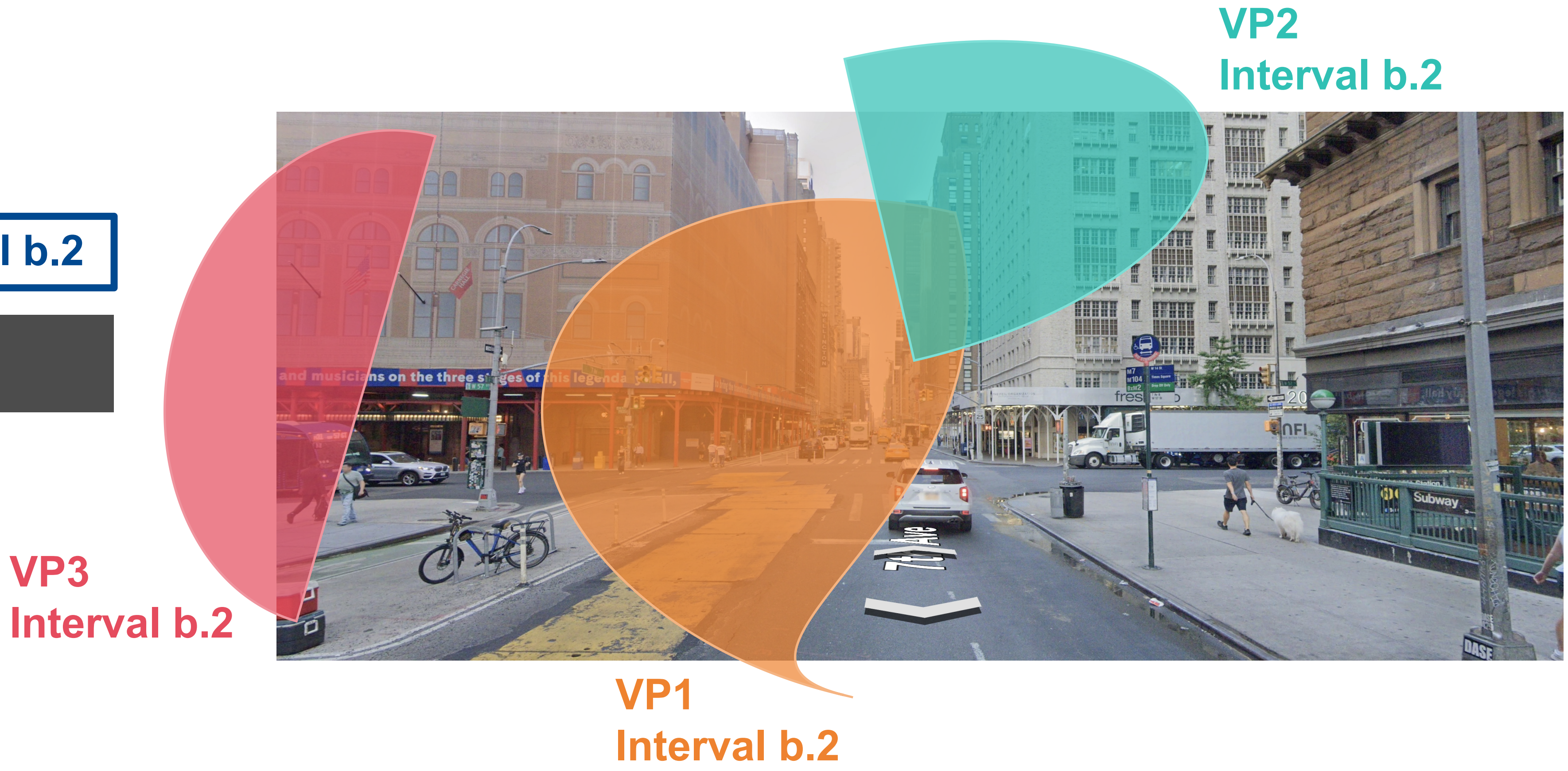
Related Works (2/3)

Branch and Bound (BnB)





[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
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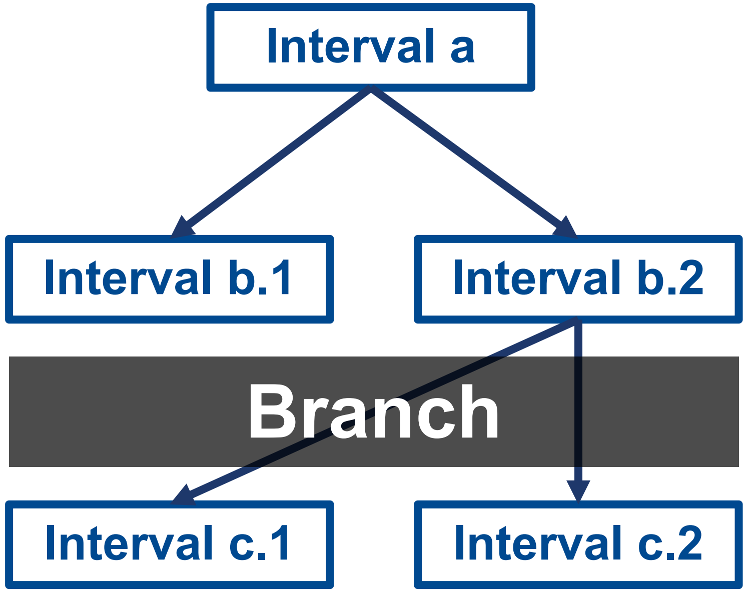
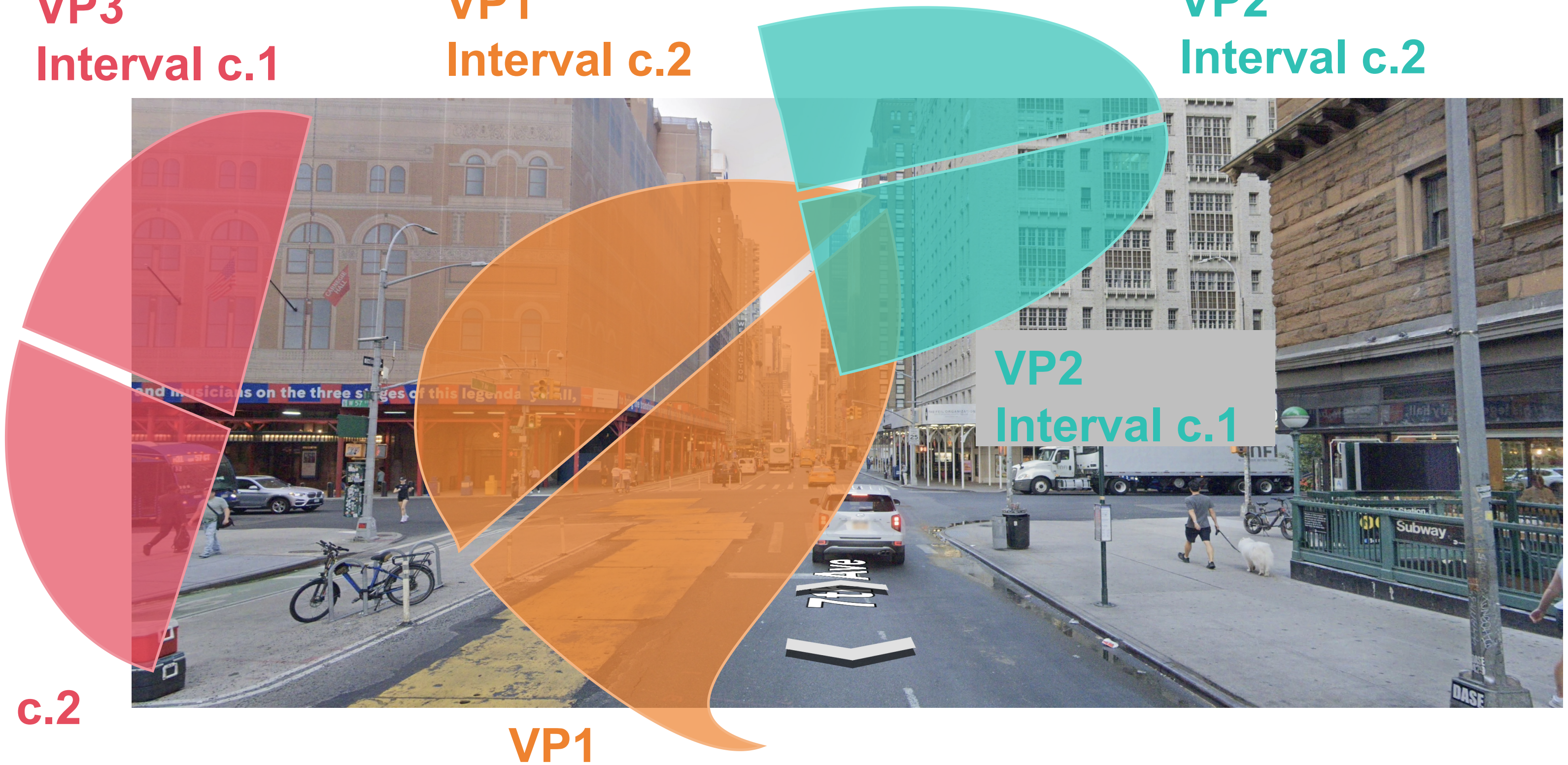
Related Works (2/3)

Branch and Bound (BnB)





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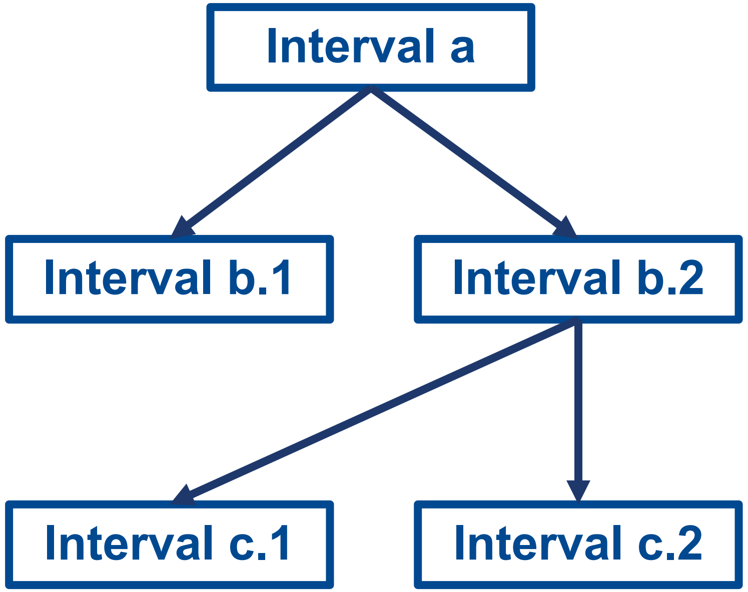
Related Works (2/3)

Branch and Bound (BnB)

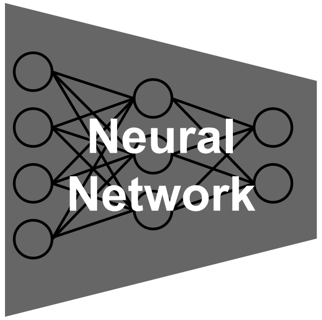


Global Optimality ***Efficiency*** ***Outlier Robustness*** ***Generalization***

[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
[2] Bazin J C, Seo Y, Pollefeys M. Globally optimal consensus set maximization through rotation search. ACCV 2012.
[3] Li H, Zhao J, Bazin J C, et al. Quasi-globally optimal and efficient vanishing point estimation in Manhattan world. ICCV 2019.
[4] Li H, Zhao J, Bazin J C, et al. Quasi-globally optimal and near/true real-time vanishing point estimation in Manhattan world. T-PAMI 2020.

Related Works (3/3)

Learning-based



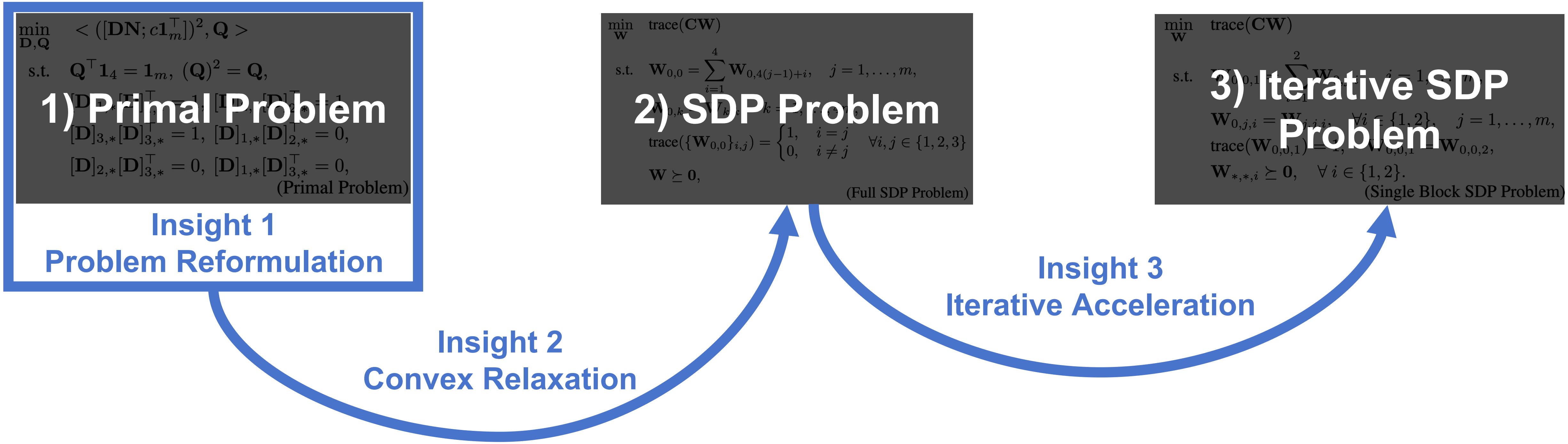
Input: **Raw Image**
Unlabeled Lines (Optional)

Output: Vanishing Points

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

[1] Kluger F, Brachmann E, Ackermann H, et al. Consac: Robust multi-model fitting by conditional sample consensus. CVPR 2020.
[2] Li H, Chen K, Kim P, et al. Learning icosahedral spherical probability map based on bingham mixture model for vanishing point estimation. ICCV 2021.
[3] Lin Y, Wiersma R, Pintea S L, et al. Deep vanishing point detection: Geometric priors make dataset variations vanish. CVPR 2022.
[4] Tong X, Ying X, Shi Y, et al. Transformer based line segment classifier with image context for real-time vanishing point detection in Manhattan world. CVPR 2022.
[5] Zhai M, Workman S, Jacobs N. Detecting vanishing points using global image context in a non-manhattan world. CVPR 2016.
[6] Zhou Y, Qi H, Huang J, et al. Neurvps: Neural vanishing point scanning via conic convolution. NeurIPS 2019.
[7] Kluger F, Rosenhahn B. PARSAC: Accelerating robust multi-model fitting with parallel sample consensus. AAAI 2024.

Ours Method: **GlobustVP**



Global Optimality ***Efficiency*** ***Outlier Robustness*** ***Generalizable***

Insight 1: Primal Problem Reformulation

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

How to represent discrete labels?

-> continuous constraint

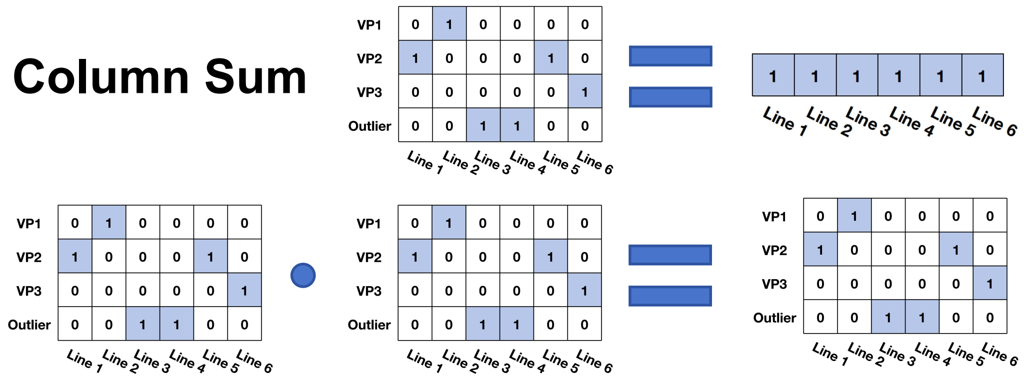
$$q = q^2 \quad \Longleftrightarrow \quad q = 1 \text{ or } q = 0$$

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

-> 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

Distance Matrix

	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 to VP Squared Distance

Maximum Inlier Threshold

⟨

	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

⟩ =

	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	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$

Insight 1: Primal Problem Reformulation

Primal Problem

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

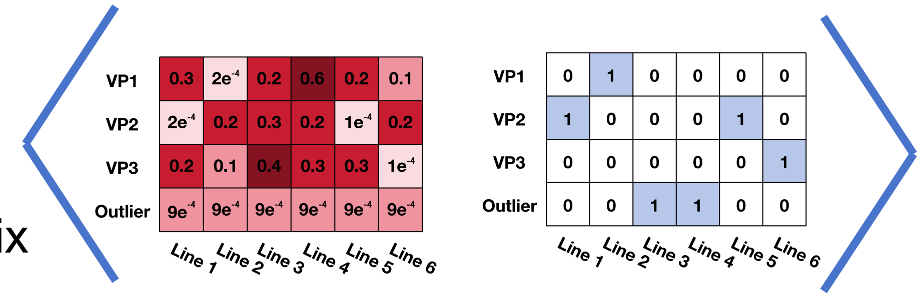
$$\text{s.t.} \quad \mathbf{Q}^\top \mathbf{1}_4 = \mathbf{1}_m, \; (\mathbf{Q})^2 = \mathbf{Q},$$

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

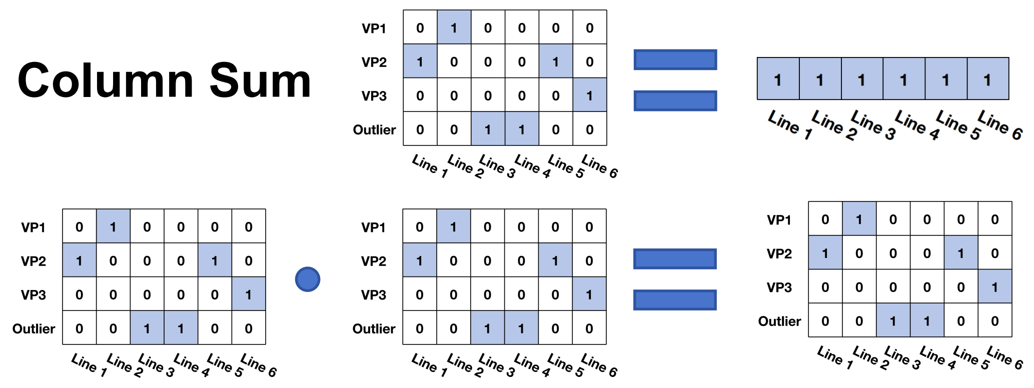
$$[\mathbf{D}]_{3,*}[\mathbf{D}]_{3,*}^\top = 1, \; [\mathbf{D}]_{1,*}[\mathbf{D}]_{2,*}^\top = 0,$$

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

min
VP1,VP2,VP3
Permutation Matrix



Column Sum



Manhattan Constraint

Our Method: **GlobustVP**

1) Primal Problem

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

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

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

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

$$[\mathbf{D}]_{2,*}[\mathbf{D}]_{3,*}^\top = 0, \; [\mathbf{D}]_{1,*}[\mathbf{D}]_{3,*}^\top = 0, \quad \text{(Primal Problem)}$$

Insight 1
Problem Reformulation

Generalizable

Insight 2: QCQP -> Convex Relaxation -> SDP

1) Primal Problem

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

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

[illegible]

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

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

(Primal Problem)

Quadratically Constrained Quadratic Program (QCQP) Problem

$$\min_{\boldsymbol{\omega}} \quad \boldsymbol{\omega}^\top \mathbf{C} \boldsymbol{\omega}$$

$$\text{s.t.} \quad \boldsymbol{\omega}_0 \boldsymbol{\omega}_0^\top = \sum^{4} \boldsymbol{\omega}_0 \boldsymbol{\omega}_{i,j}^\top, \quad j = 1, \ldots, m,$$

[illegible]

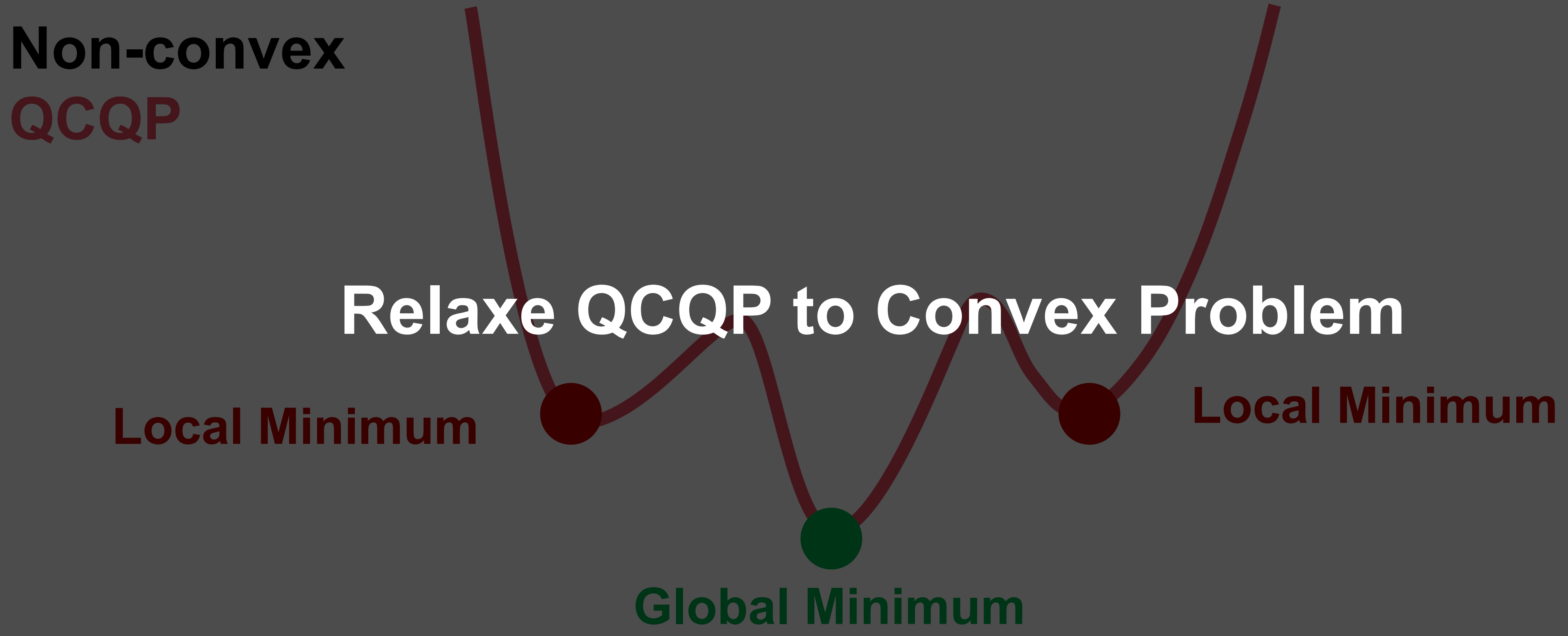
$$\{\boldsymbol{\omega}_0\}_3^\top \{\boldsymbol{\omega}_0\}_3 = 1, \quad \{\boldsymbol{\omega}_0\}_1^\top \{\boldsymbol{\omega}_0\}_2 = 0,$$

$$\{\boldsymbol{\omega}_0\}_1^\top \{\boldsymbol{\omega}_0\}_3 = 0, \quad \{\boldsymbol{\omega}_0\}_2^\top \{\boldsymbol{\omega}_0\}_3 = 0.$$

(Full QCQP Problem)

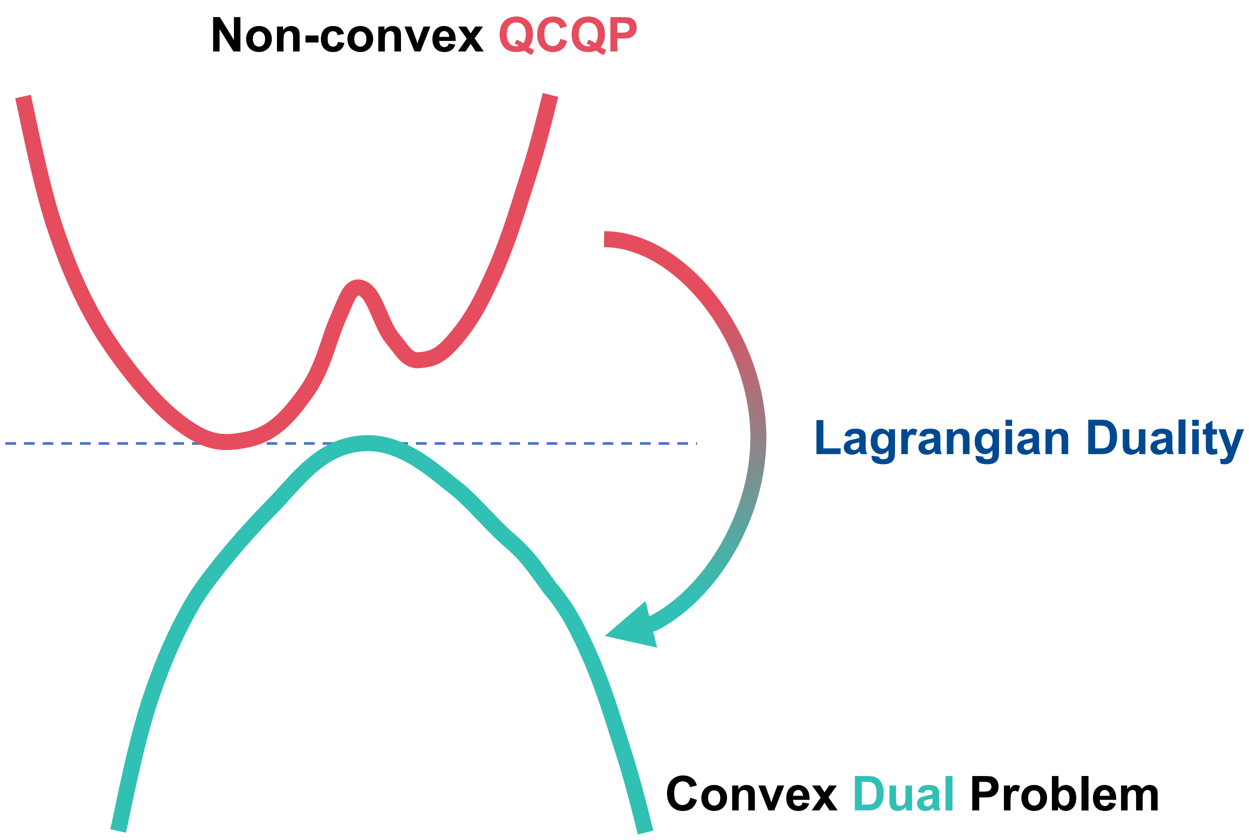
Equivalent to Higher Dimension QCQP

Insight 2: QCQP -> Convex Relaxation -> SDP

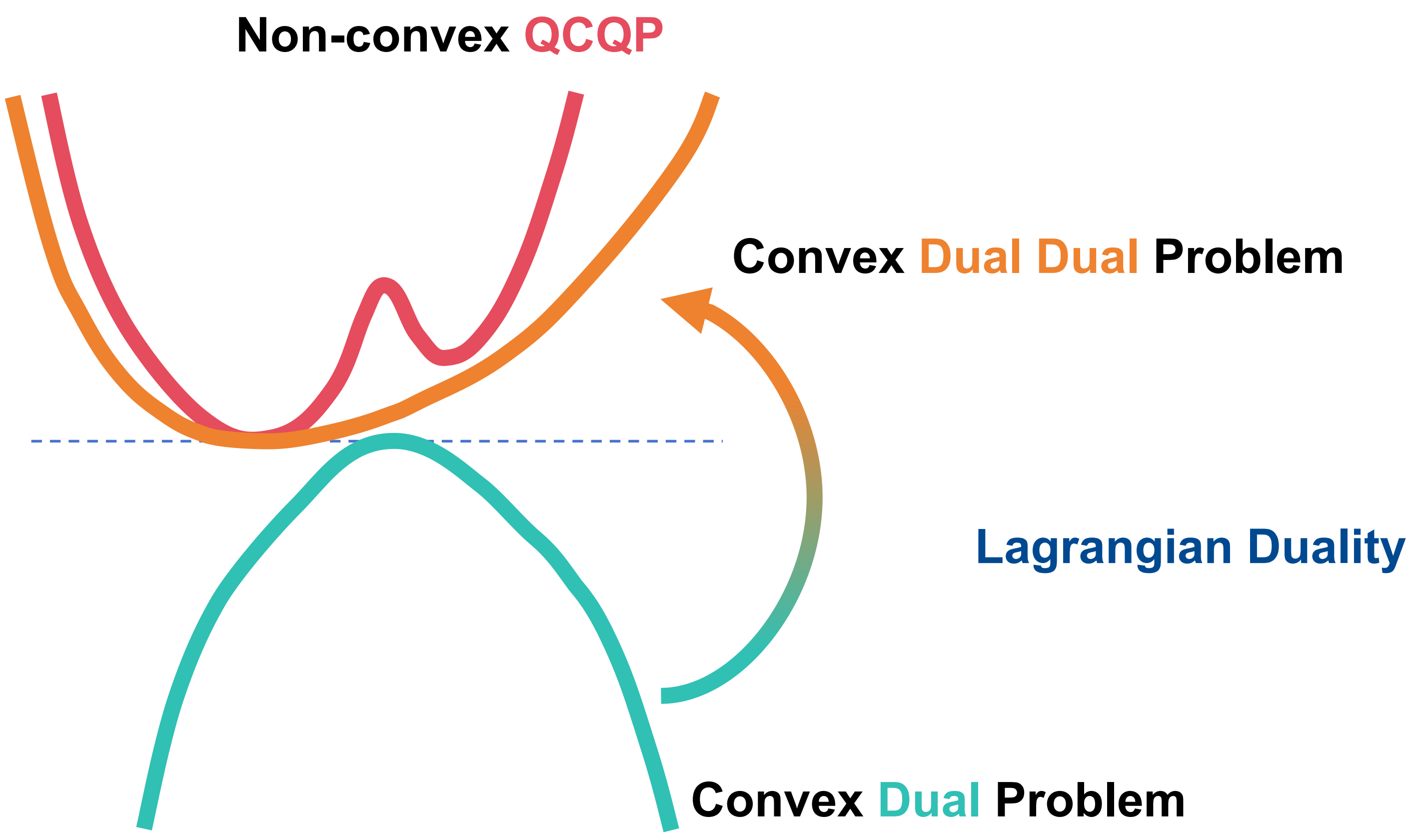


Relaxe QCQP to Convex Problem

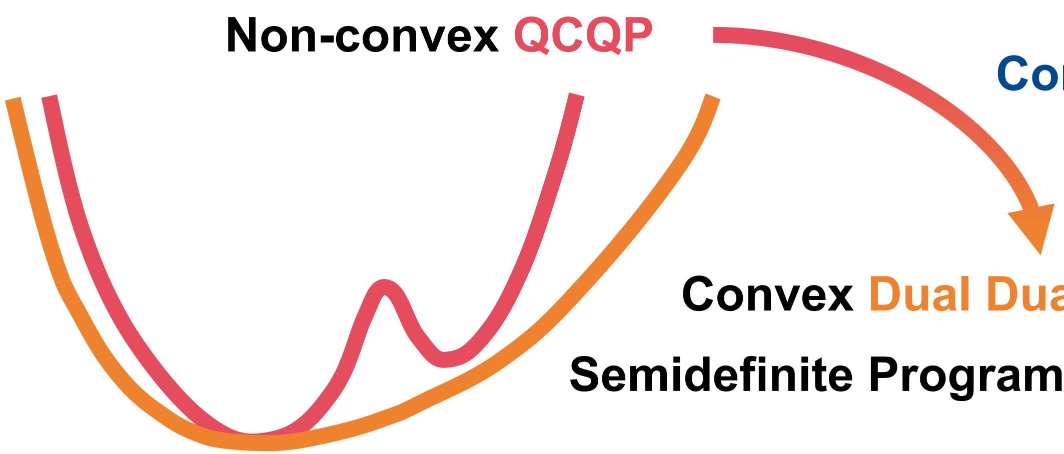
Insight 2: QCQP -> Convex Relaxation -> SDP



Insight 2: QCQP -> Convex Relaxation -> SDP



Insight 2: QCQP -> Convex Relaxation -> SDP



Convex Dual Dual Problem

Semidefinite Programming Problem (SDP)

QCQP Problem

$$\min_{\omega} \quad \omega^\top \mathbf{C} \omega$$
$$\text{s.t.} \quad \omega_0 \omega_0^\top = \sum_{i=1}^{4} \omega_0 \omega_{i,j}^\top, \quad j = 1, \ldots, m,$$
$$\{\omega_0\}_1^\top \{\omega_0\}_1 = 1, \quad \{\omega_0\}_2^\top \{\omega_0\}_2 = 1,$$
$$\{\omega_0\}_3^\top \{\omega_0\}_3 = 1, \quad \{\omega_0\}_1^\top \{\omega_0\}_2 = 0,$$
$$\{\omega_0\}_1^\top \{\omega_0\}_3 = 0, \quad \{\omega_0\}_2^\top \{\omega_0\}_3 = 0.$$

(Full QCQP Problem)

equivalent under

=

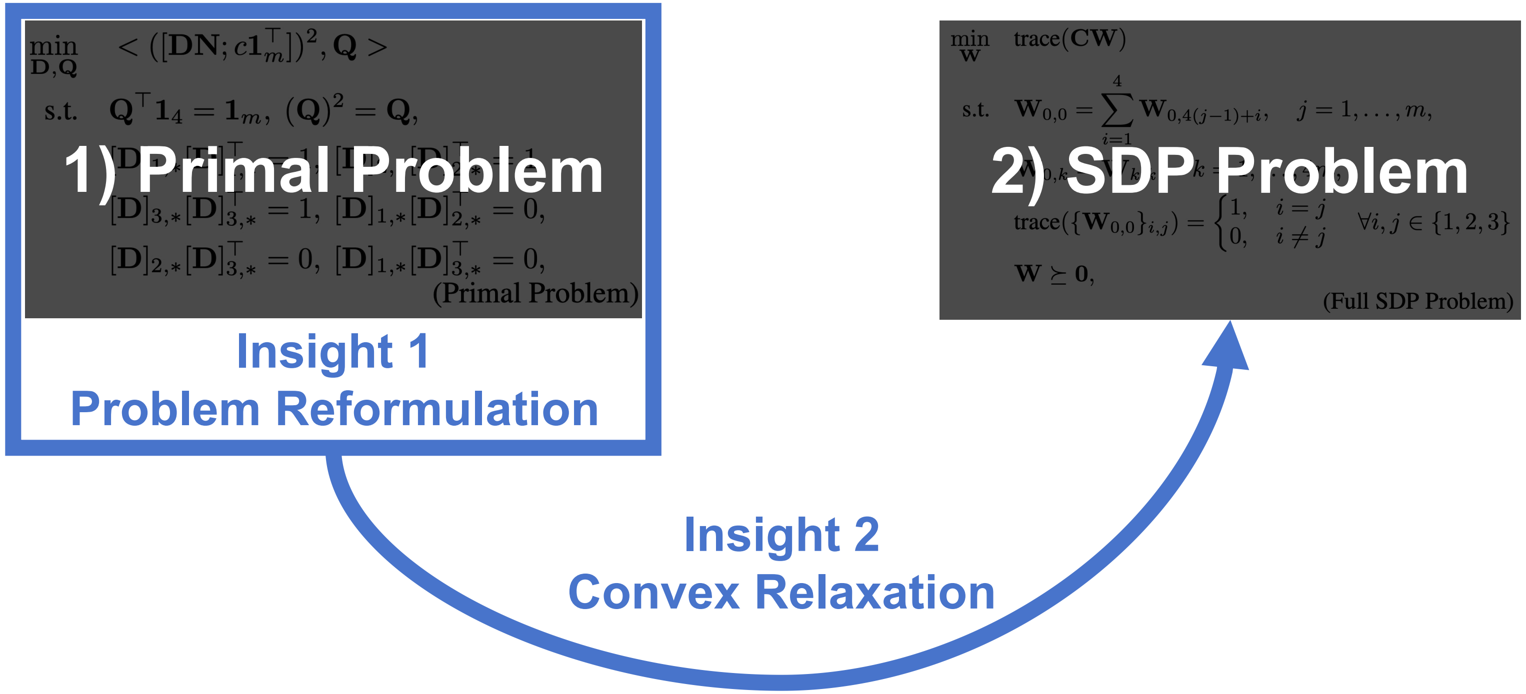
tight relaxation

SDP Problem

$$\min_{\mathbf{W}} \quad \text{trace}(\mathbf{C}\mathbf{W})$$
$$\text{s.t.} \quad \mathbf{W}_{0,0} = \sum_{i=1}^{4} \mathbf{W}_{0,4(j-1)+i}, \quad j = 1, \ldots, m,$$
$$\text{trace}(\{\mathbf{W}_{0,0}\}_{i,j}) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \quad \forall i, j \in \{1,2,3\}$$
$$\mathbf{W} \succeq \mathbf{0},$$

(Full SDP Problem)

Ours Method: **GlobustVP**

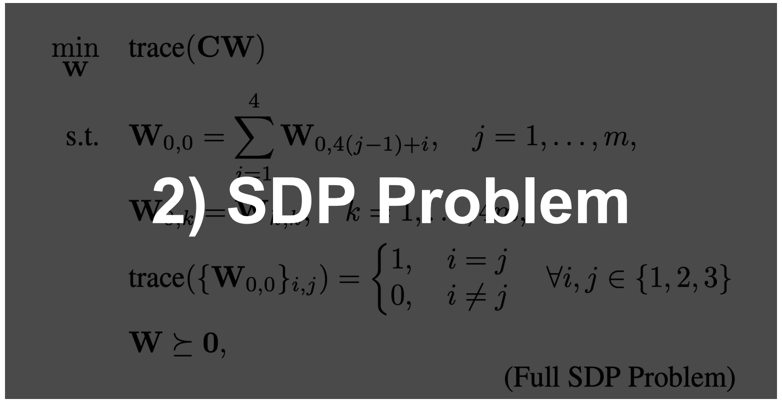


Global Optimality

Outlier Robustness

Generalizable

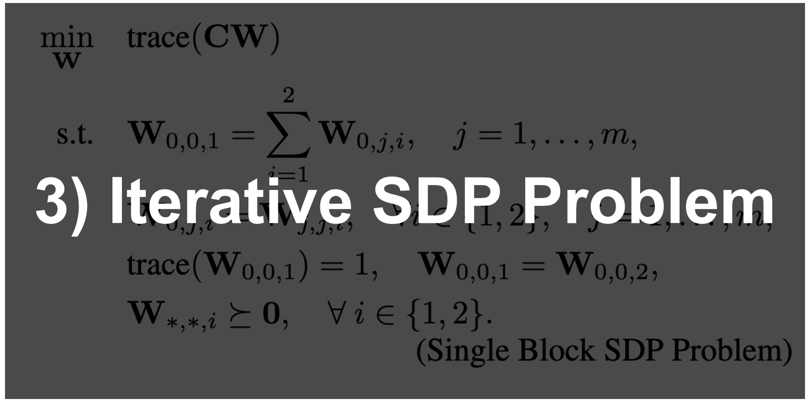
Insight 3: Iterative SDP



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

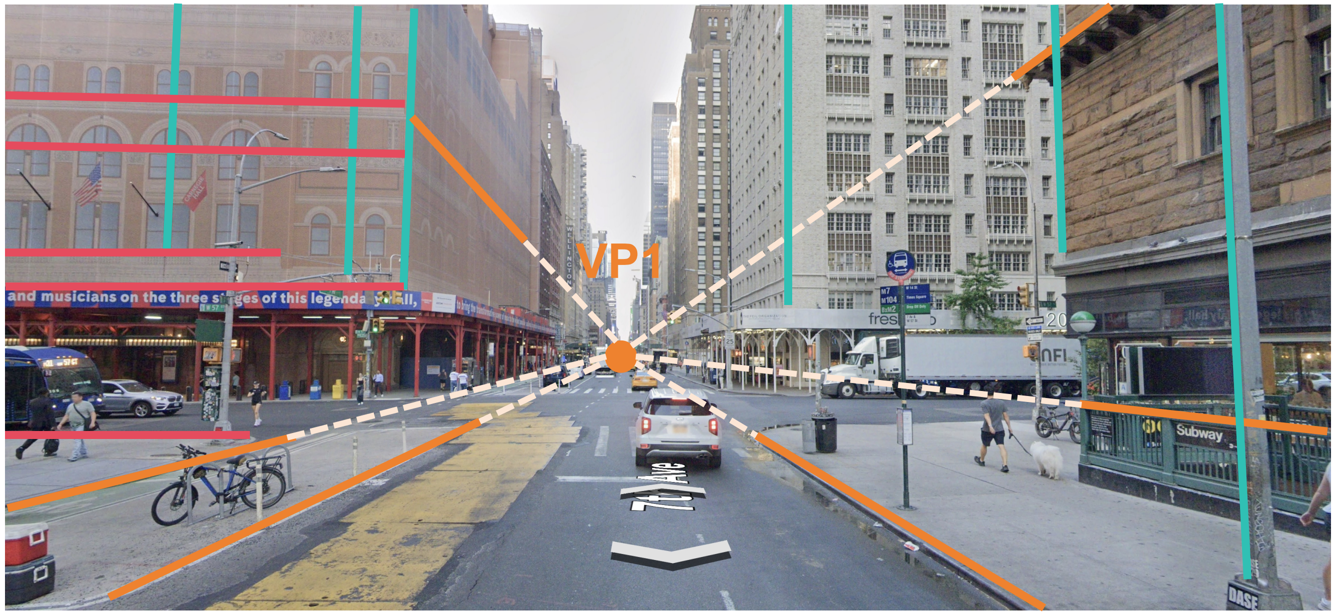


Find VPs one by one!

	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	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$	$9e^{-4}$

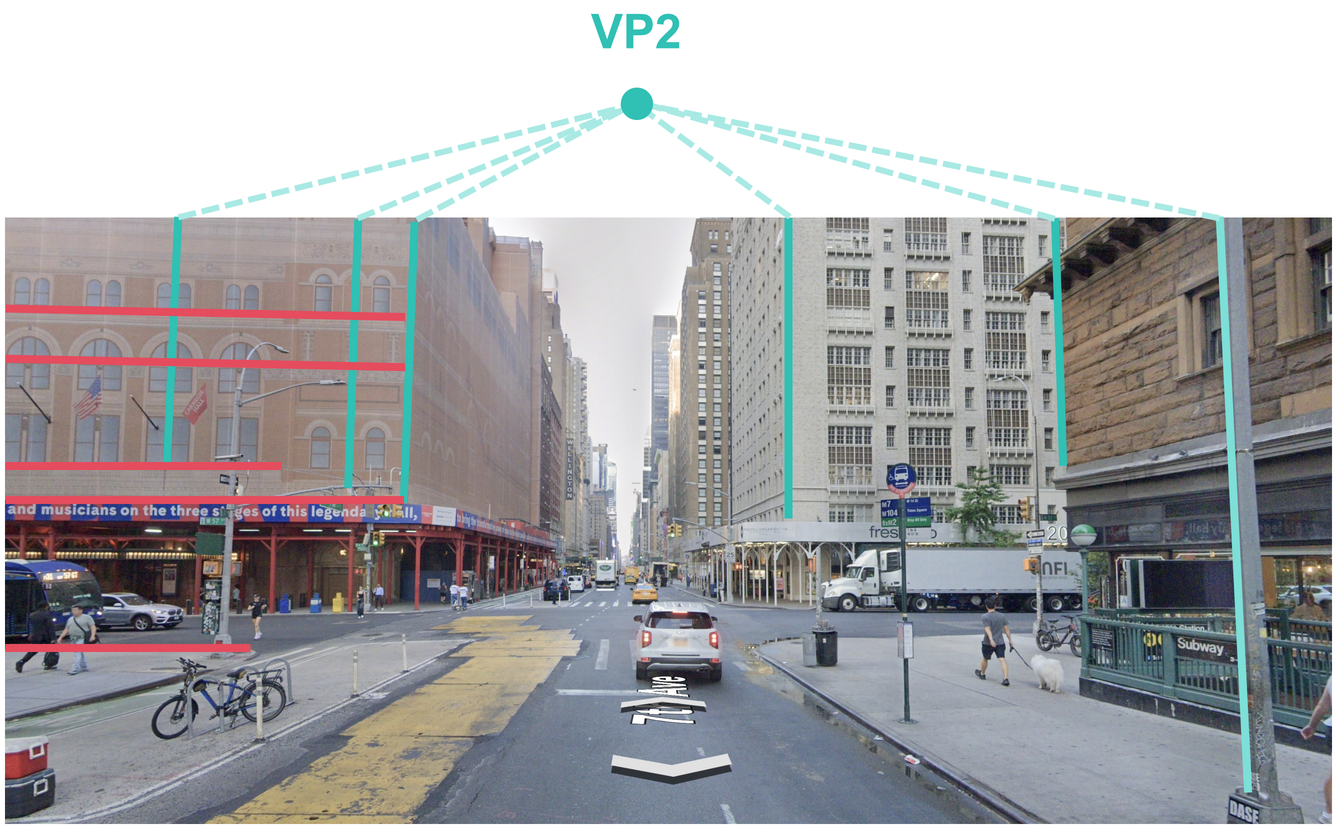
	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
VP	0	1	0	1	0	1
Outlier	1	0	1	0	1	0

Insight 3: Iterative SDP



Treat Line and Line as Outliers, find VP1

Insight 3: Iterative SDP

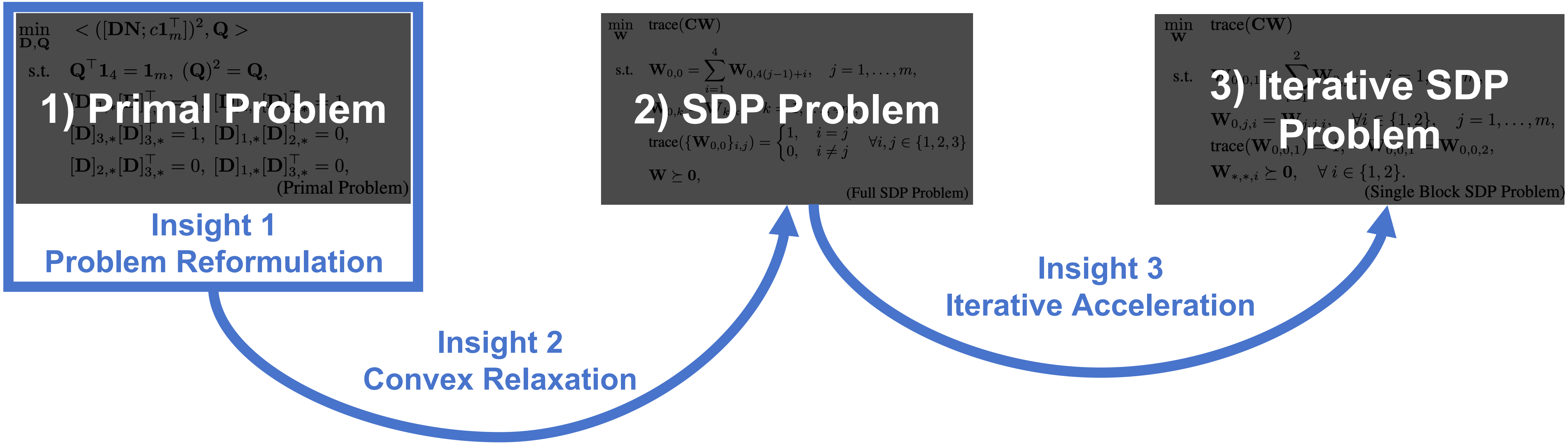


Treat Line as Outliers, find VP2

Insight 3: Iterative SDP

Find VP3

Ours Method: **GlobustVP**



Global Optimality

Efficiency

Outlier Robustness

Generalizable

Some Qualitative Results

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↓

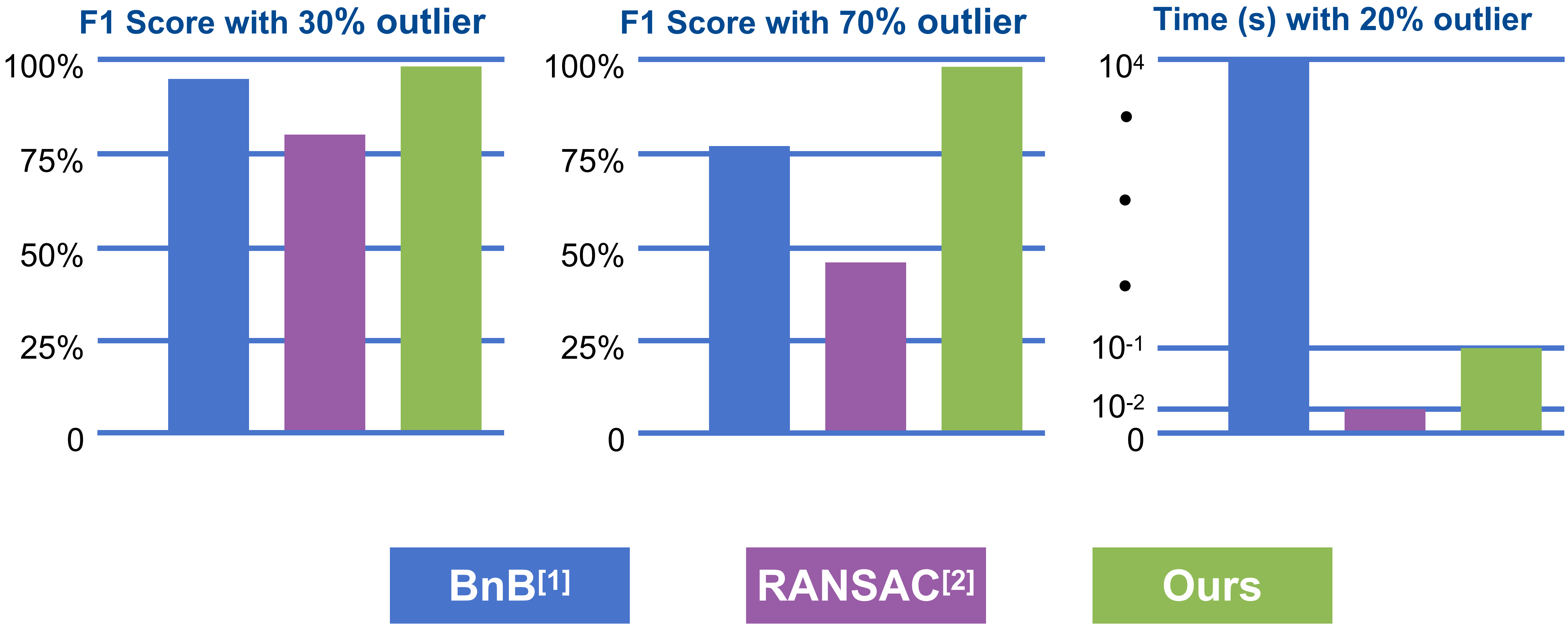
87.60%, 0.52 pix.

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.

Synthetic Comparison

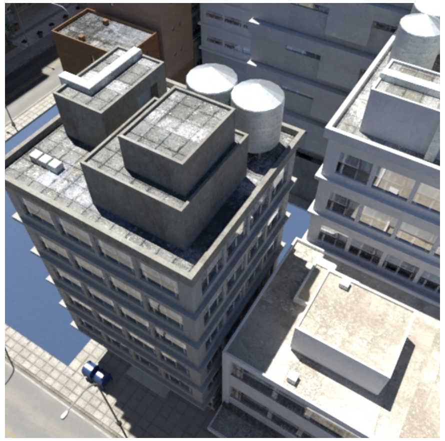


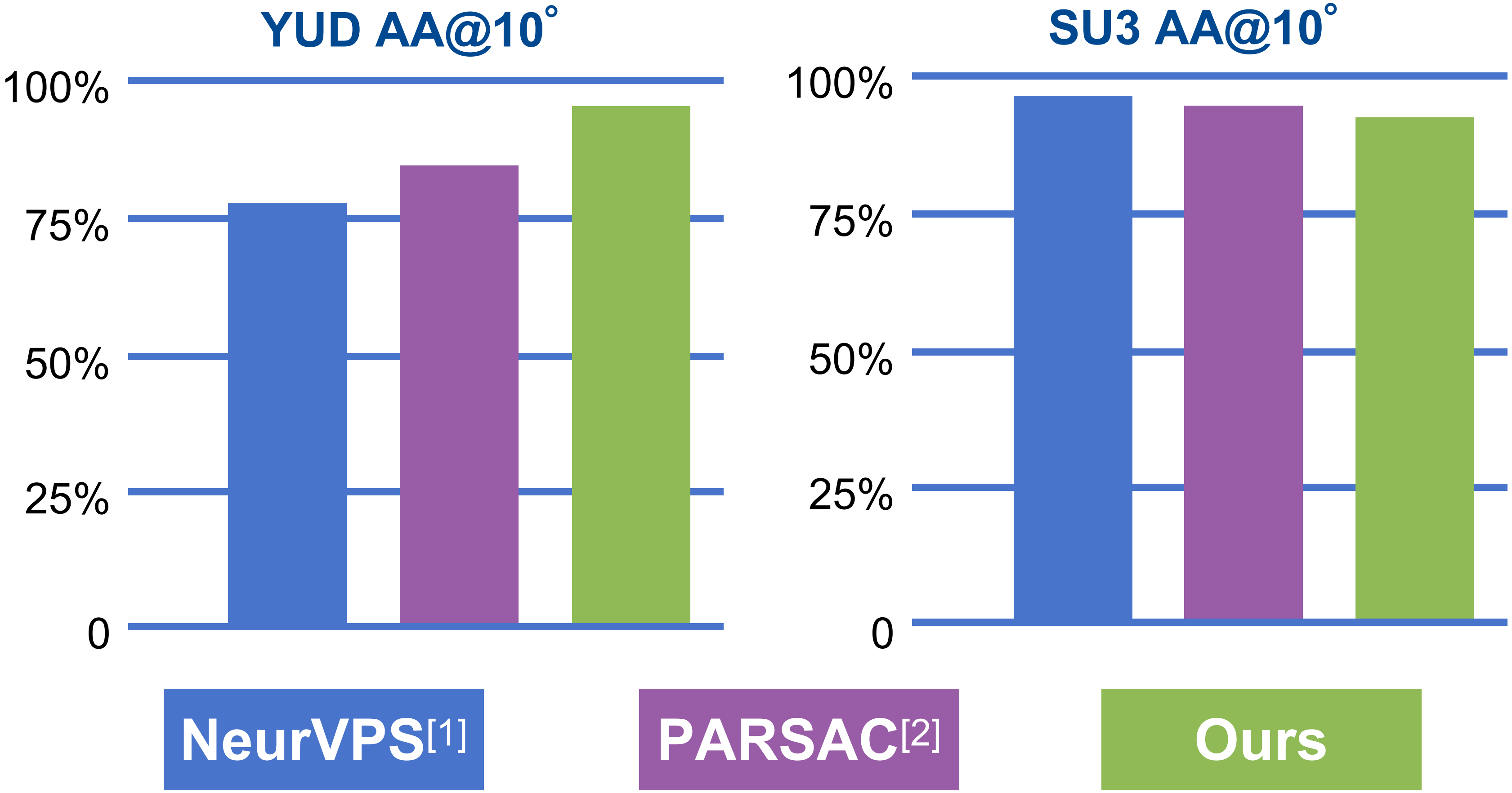
[1] Bazin J C, Seo Y, Demonceaux C, et al. Globally optimal line clustering and vanishing point estimation in manhattan world. CVPR 2012.
[2] Zhang L, Lu H, Hu X, et al. Vanishing point estimation and line classification in a manhattan world with a unifying camera model. IJCV 2016.

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.

GlobustVP = Globally Optimal Outlier-Robust Vanishing Point Solver

Global Optimality

Efficiency

Outlier Robustness

Generalizable

GitHub

https://github.com/WU-CVGL/GlobustVP/

CVPR Nashville JUNE 11-15, 2025

Thanks for watching