Learning of Global Objective for Network Flow in Multi-Object Tracking

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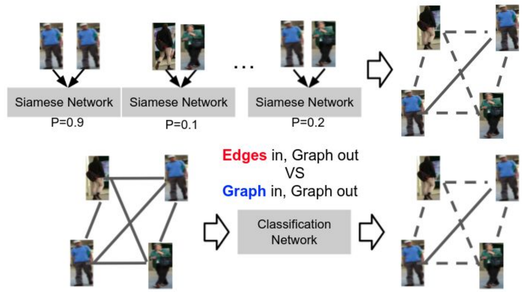
Motivation

- Network Flow[1] is well-suited for MOT problem.
- Previous work e.g.[3] do not utilize global data association results to learn matching costs for Network Flow.

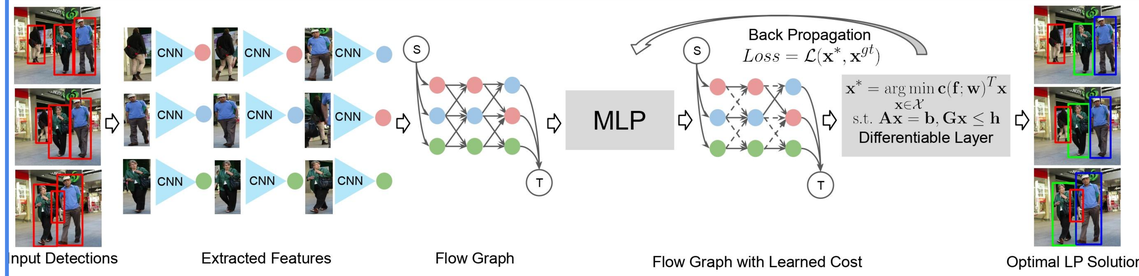


Working with graphs should improve tracking performance!

Contributions

- Novel Bi-Level optimization formulation for differentiating Linear Program (LP) through optimal **KKT** conditions[2].
- Approximation of LP as a quadratic program **(QP)** enables end-to-end training data association costs.
- Tracking performance comparable to SOTA[8], while being significantly faster.

Our Method



Training

- KKT condition of the optimization problem. $L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = f(\mathbf{x}) + \boldsymbol{\lambda}^T(\mathbf{G}\mathbf{x} - \mathbf{h}) + \boldsymbol{\nu}^T(\mathbf{A}\mathbf{x} - \mathbf{b})$
- Implicit Function Theorem.

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathcal{X}} \frac{1}{2}\mathbf{x}^T\mathbf{Q}\mathbf{x} + \mathbf{c}^T\mathbf{x} \quad \text{s.t. } \mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{G}\mathbf{x} \leq \mathbf{h} \Rightarrow \begin{bmatrix} \mathbf{Q} & \mathbf{G}^T & \mathbf{A}^T \\ diag(\boldsymbol{\lambda})\mathbf{G} & diag(\mathbf{G}\mathbf{x}-\mathbf{h}) & \mathbf{0} \\ \mathbf{A} & \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \frac{d\mathbf{x}}{d\mathbf{c}} \\ \frac{d\boldsymbol{\lambda}}{d\mathbf{c}} \\ \frac{d\boldsymbol{\nu}}{d\mathbf{c}} \end{bmatrix} = \begin{bmatrix} -\frac{d\nabla_{\mathbf{x}}L(\mathbf{x},\boldsymbol{\lambda},\boldsymbol{\nu})}{d\mathbf{c}} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \Rightarrow \frac{d\mathcal{L}}{d\mathbf{w}} = \frac{d\mathcal{L}}{d\hat{\mathbf{x}}}\frac{d\hat{\mathbf{x}}}{d\mathbf{c}}\frac{d\mathbf{c}}{d\mathbf{w}}$$

Able to learn the cost function end-to-end!

Inference

Polynomial-time algorithm for Network Flow ⇨ $\mathbf{x}^* = \arg\min_{\mathbf{x}\in\mathcal{X}} \mathbf{c}^T\mathbf{x}$ s.t. $\mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{G}\mathbf{x} \leq \mathbf{h}$ ⇨ Set of tracks

References

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Results

Tracking results on MOT17(Top) and MOT20(Bottom)

Method	Mode	MOTA	IDF1	MT	ML	IDS
[6]	Online	53.7	53.8	19.4	36.6	1947
[5]	Online	56.3	55.1	21.2	35.5	1987
[9]	Online	57.3	56.3	24.2	**33.4**	1911
[4]	Offline	50.7	47.2	20.8	36.9	2314
[7]	Offline	58.8	61.7	**28.8**	33.5	**1185**
[8]	Offline	**60.5**	**65.6**	27.0	33.6	1189
Ours	Offline	57.3	57.7	23.2	36.9	1424

Method	Mode	MOTA	IDF1	MT	ML	IDS
[5]	Online	52.6	52.7	29.4	26.7	1648
[10]	Online	53.6	51.0	31.6	28.1	**1531**
[9]	Online	54.5	49.0	32.8	25.5	2038
[11]	Offline	**58.9**	**56.5**	**41.3**	**21.3**	2241
Ours	Offline	57.9	53.5	39.0	22.8	1827