# A Natural Quadratic Approach to the Generalized Graph Layering Problem 

Sven Mallach

Department of Mathematics \& Computer Science
University of Cologne, Germany
Graph Drawing \& Network Visualization
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## Layered Drawings of Directed Graphs



Drawing Restictions:

- Vertices on consecutive layers
- No two adjacent vertices on the same layer
- (Major) Common arc direction


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Drawing Restictions:

- Vertices on consecutive layers
- No two adjacent vertices on the same layer
- (Major) Common arc direction
- Aesthetic layering objectives:
- 'Compactness' (Width $\mathcal{W}$, Height $\mathcal{H}$, Total Arc Length),
- Few Arc Reversals


## Sugiyama-Style Drawings of Directed Graphs



Classic Approach (Sugiyama et al. [1981]):

1. Cycle Removal
2. Vertex Layering
3. Crossing Minimization
4. Horizontal Coordinates \& Arc Routing

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Limitations w.r.t. steps $1 \& 2$ :
Longest path may impede 'compactness' / good aspect ratio from the very beginning.

## Visual effects of poor and good aspect ratios

Two drawings of a graph, the right of which has two arcs reversed.



## Area-Adaptive Graph Layering

Rüegg et al. [2017]: Adapt Layering w.r.t. target drawing area.
Input: (Relative) Area width $r_{W}$ and height $r_{H}$, denoted $r_{W}: r_{H}$.
Goal: Maximum Resolution or Scaling Factor $\mathcal{S}:=\min \left\{\frac{r_{w}}{\mathcal{W}}, \frac{r_{H}}{\mathcal{H}}\right\}$ (plus possibly minimum edge length / number of reversed arcs).


$1: 1$
$2: 1$

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## Maximum-Scale Generalized Layering Problem (GLP-MS)

Given $G=(V, A), r_{W}$, and $r_{H}$, find a feasible layering $L: V \mapsto \mathbb{N}_{+}$ minimizing

$$
\omega_{\text {len }}\left(\sum_{u v \in A}|L(v)-L(u)|\right)+\omega_{\text {rev }}|\{u v \in A \mid L(v)<L(u)\}|-\omega_{\text {scl }} \mathcal{S}
$$

## Graph Layering - Evolution of Optimization Problems

Name
DLP $\quad \sum_{u v \in A}(L(v)-L(u))$
DLP-W $\quad \sum_{u v \in A} \omega_{\text {len }}(L(v)-L(u))+\omega_{\text {wid }} \mathcal{W}$
GLP

$$
\begin{aligned}
& \sum_{u v \in A} \omega_{\text {len }}|L(v)-L(u)|+ \\
& \omega_{\text {rev }}|\{u v \in A \mid L(v)<L(u)\}|
\end{aligned}
$$

GLP-W

$$
\sum_{u v \in A} \omega_{\text {len }}|L(v)-L(u)|+
$$

$$
\omega_{\text {rev }}|\{u v \in A \mid L(v)<L(u)\}|+\omega_{\text {wid }} \mathcal{W} \quad \text { Jabrayilov et al. [GD 2016] }
$$

GLP-MS* $\quad \sum_{u v \in A} \omega_{\text {len }}|L(v)-L(u)|+$
$\omega_{\text {rev }}|\{u v \in A \mid L(v)<L(u)\}|+\omega_{\text {scl }} \overline{\mathcal{S}} \quad$ Rüegg et al. [JGAA 2017] $\left(\overline{\mathcal{S}}:=\frac{1}{\mathcal{S}}\right)$

## Graph Layering and Mixed-Integer Linear Programming

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Assignment variables: $x_{v, k}:= \begin{cases}1, & \text { if } L(v)=k \\ 0, & \text { otherwise }\end{cases}$
Ordering variables: $y_{k, v}:= \begin{cases}1, & \text { if } L(v)>k \\ 0, & \text { otherwise }\end{cases}$

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- Easy if arc directions are fixed (DLP cases).
- DLP-W: Dummy vertex variables:

$$
d_{u v, k}:= \begin{cases}1, & \text { if } u v \in A \text { spans layer } k \\ 0, & \text { otherwise }\end{cases}
$$

- Additional option to "count" edge lengths.


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- Need to model dummy vertices based on two possible arc directions.
- Case Distinctions: More and weaker linear constraints to enforce correct values on $r_{u v}$ and $d_{u v, k}$.


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- There is a stronger and compact linearization technique.
- For any arc $u v \in A$, there is exactly one pair of layers $k$ and $\ell$, $k \neq \ell$, such that $x_{u, k} \cdot x_{v, \ell}=1$. All other products are zero.


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- There is a stronger and compact linearization technique.
- For any arc $u v \in A$, there is exactly one pair of layers $k$ and $\ell$, $k \neq \ell$, such that $x_{u, k} \cdot x_{V, \ell}=1$. All other products are zero.
- Assignment variables more intuitive than ordering variables.


## A Quadratic Assignment Perspective on Graph Layering

If there are $Y$ layers, the length of $u v \in A$ thus equals

$$
\sum_{\ell=2}^{Y} \sum_{k=1}^{\ell-1}\left((\ell-k) \cdot\left(x_{u, \ell} \cdot x_{v, k}+x_{u, k} \cdot x_{V, \ell}\right)\right)
$$



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An arc $u v \in A$ is reversed if and only if the expression

$$
\sum_{\ell=2}^{Y}\left(x_{u, \ell} \cdot \sum_{k=1}^{\ell-1} x_{v, k}\right)
$$

evaluates to one. Otherwise, the expression is zero.

## A Quadratic Assignment Perspective on Graph Layering

An arc $u v \in A$ causes a dummy vertex on layer $k \in\{2, \ldots, Y-1\}$ if and only if $k$ is between the layers of $u$ and $v$, i.e., if

$$
\sum_{\ell=1}^{k-1} \sum_{m=k+1}^{Y}\left(x_{u, \ell} \cdot x_{v, m}+x_{u, m} \cdot x_{v, \ell}\right)
$$

evaluates to one. Again, the term will be zero otherwise.

$$
\begin{cases}O_{u} & \ell \\ & k-1 \\ k & k+1 \\ & k=\end{cases}
$$

## A Basic Quadratic Layer Assignment Model (QLA)

Replace the product $x_{u, k} \cdot x_{v, \ell}$ by variables $p_{u, k, v, \ell}$ for all $u v \in A$ and all $k, \ell \in\{1, \ldots, Y\}$.

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Replace the product $x_{u, k} \cdot x_{v, \ell}$ by variables $p_{u, k, v, \ell}$ for all $u v \in A$ and all $k, \ell \in\{1, \ldots, Y\}$.

Then a feasible layering is characterized by the restrictions:

$$
\begin{array}{lll}
\sum_{k=1}^{Y} x_{v, k} & =1 & \text { for all } v \in V \\
\sum_{\ell=1}^{Y} p_{u, k, v, \ell} & =x_{u, k} & \\
\text { for all } u v \in A, k \in\{1, \ldots, Y\} \\
\sum_{k=1}^{Y} p_{u, k, v, \ell} & =x_{v, \ell} & \\
\text { for all } u v \in A, \ell \in\{1, \ldots, Y\} \\
p_{u, k, v, k} & =0 & \\
x_{v, k} & \in\{0,1\} & \text { for all } u v \in A, k \in\{1, \ldots, Y\} \\
p_{u, k, v, \ell} & \in[0,1] & \\
\text { for all } v \in V, k \in\{1, \ldots, Y\} \\
& & \\
& \\
x_{l} \in A, k, \ell \in\{1, \ldots, Y\}
\end{array}
$$

## Computational Study

Two runtime competitions:
QLA-W vs. CGL-W (Jabrayilov et al. [2016])
QLA-MS* vs. CGL-MS* (Rüegg et al. [2017])

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CGL-W/MS* $\approx|V| \cdot Y+|A| \cdot Y$ variables
QLA-W/MS* $\quad \approx|V| \cdot Y+|A| \cdot Y^{2}$ variables

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CGL-W $\approx(4|A|+|V|) \cdot Y+4|A|$ constraints
QLA-W $\quad \approx(2|A|) \cdot Y+|V|$ constraints
QLA-/CGL-MS* versions: $|V|$ more constraints each.

## GLP and GLP-W - Results ATTar (Di Battista et al. [1997])

Two experiments (Gurobi 8, timeout at 1800s (30 min.)):
(1) Almost no width emphasis (GLP setting)
(2) Major emphasis on width minimization

$\times$ QLA-W
CGL-W

Intel Core i7-3770T (2.5 GHz), 1 Thread, 8 GB RAM, Linux

## GLP-MS* - Results ATTar (Di Battista et al. [1997])

Three experiments (Gurobi 8, timeout at 1800s (30 min.)):

- $r_{W}: r_{H}$ ratios $1: 2,1: 1$, and $2: 1$.
- Major emphasis on maximum scaling factor.

$\times$ QLA-MS* $\times$ CGL-MS*

Intel Core i7-3770T (2.5 GHz), 1 Thread, 8 GB RAM, Linux

