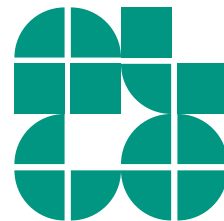


# Algorithmen zur Visualisierung von Graphen

## Automatisches Zeichnen von Linienplänen

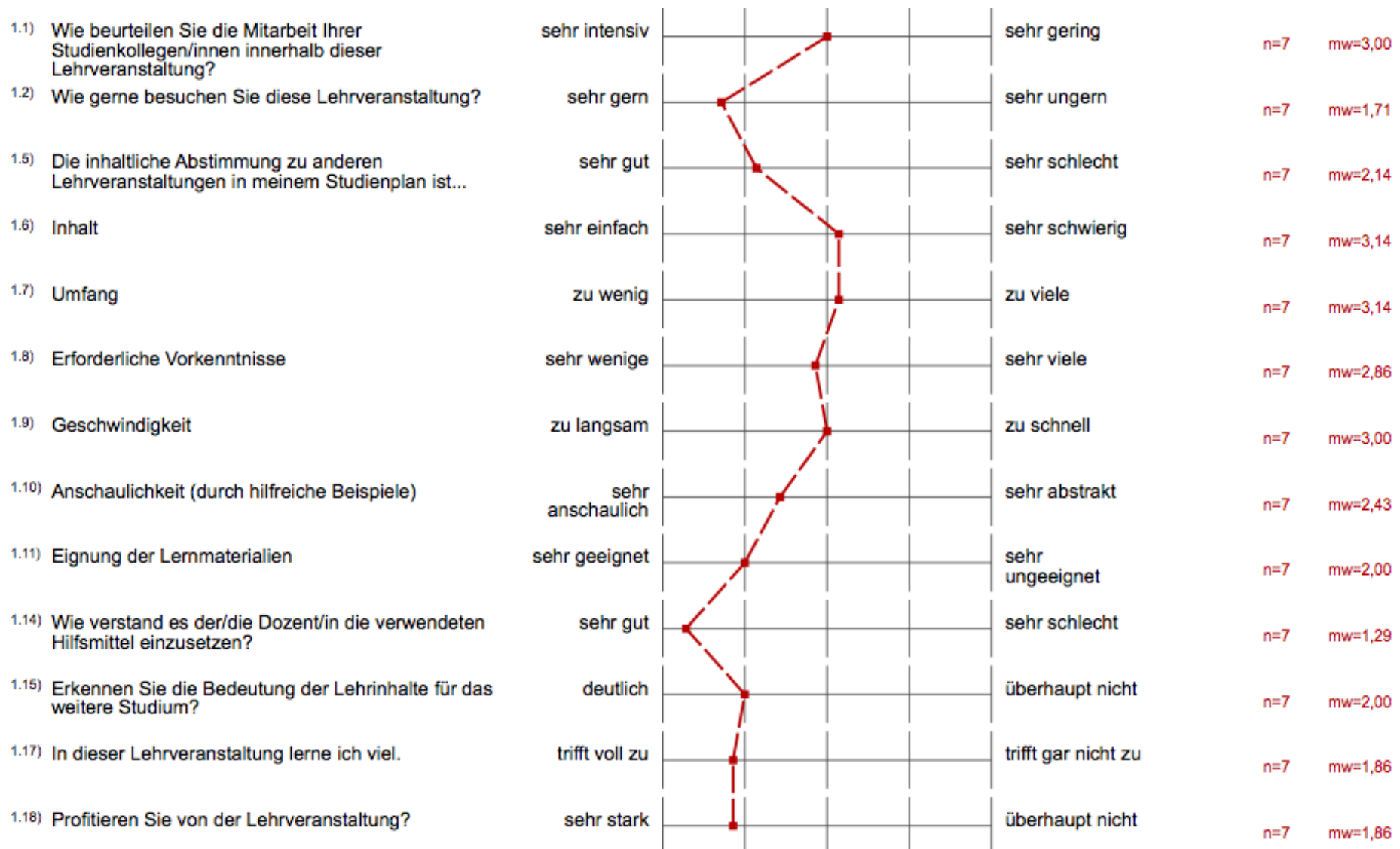
INSTITUT FÜR THEORETISCHE INFORMATIK · FAKULTÄT FÜR INFORMATIK

Tamara Mchedlidze · **Martin Nöllenburg**  
28.01.2014

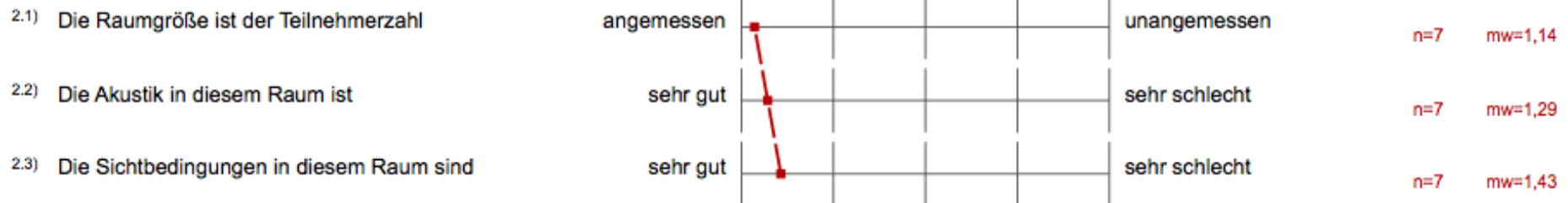


# Evaluationsergebnisse

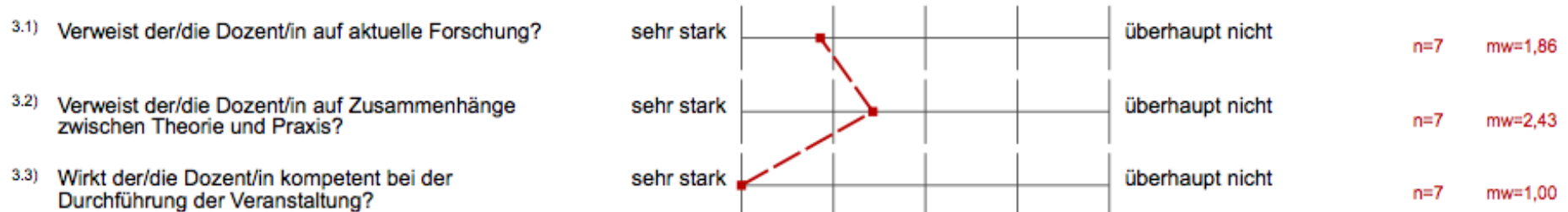
## 1. Fragen zur Lehrveranstaltung



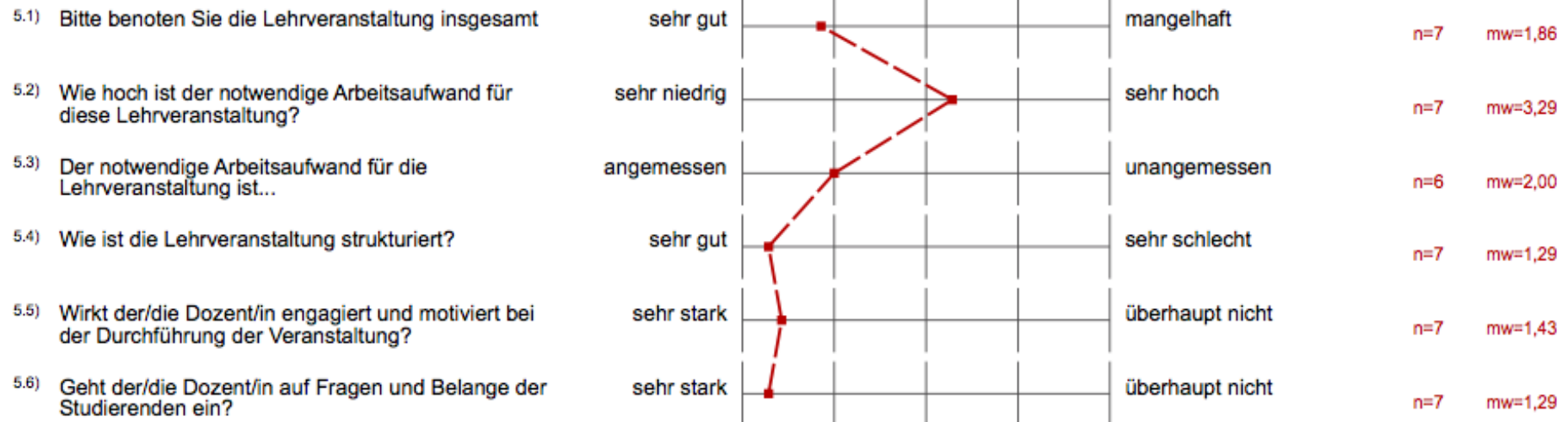
## 2. Fragen zur Bewertung der Raumbedingungen



## 3. Fragen zum/zur Dozenten/in

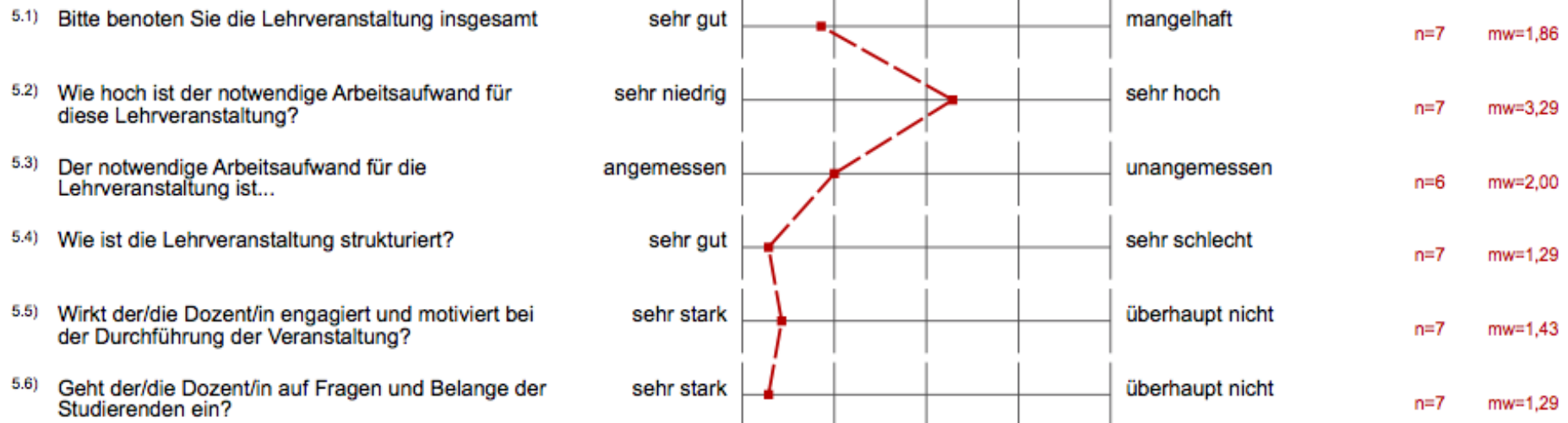


## 5. Monitoring





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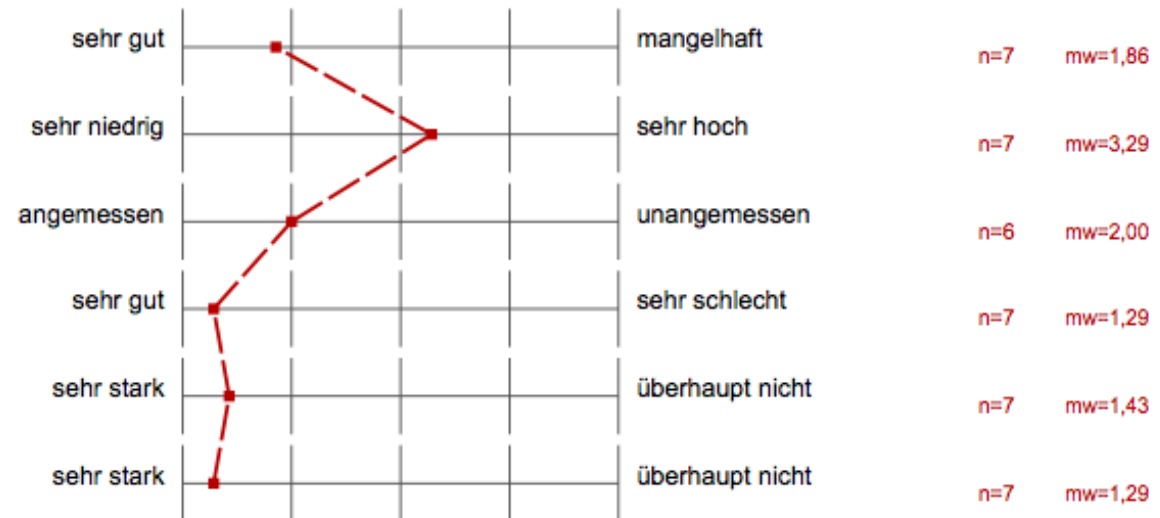


## gut gefallen:

- Projekt (2-mal)
- Folien + Tafel
- Folien + Skript
- Beweise

## 5. Monitoring

- 5.1) Bitte benoten Sie die Lehrveranstaltung insgesamt
- 5.2) Wie hoch ist der notwendige Arbeitsaufwand für diese Lehrveranstaltung?
- 5.3) Der notwendige Arbeitsaufwand für die Lehrveranstaltung ist...
- 5.4) Wie ist die Lehrveranstaltung strukturiert?
- 5.5) Wirkt der/die Dozent/in engagiert und motiviert bei der Durchführung der Veranstaltung?
- 5.6) Geht der/die Dozent/in auf Fragen und Belange der Studierenden ein?



## gut gefallen:

- Projekt (2-mal)
- Folien + Tafel
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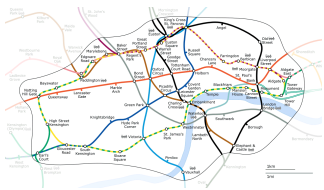
## weniger gut gefallen:

- Musterlösungen für Übungsblätter (2-mal)
- Stoff sehr theoretisch
- Übungstermin

- 1 Modeling the Metro Map Problem
  - What is a Metro Map?
  - Hard and Soft Constraints
- 2 NP-Hardness: Bad News—Nice Proof
  - Rectilinear vs. Octilinear Drawing
  - Reduction from PLANAR 3-SAT
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# What is a Metro Map?

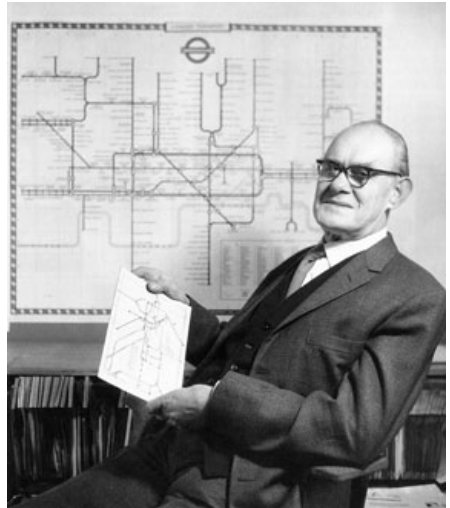


- schematic diagram for public transport
- visualizes lines and stations
- goal: ease navigation for passengers
  - “How do I get from A to B?”
  - “Where to get off and change trains?”
- distorts geometry and scale
- improves readability
- compromise between  
schematic road map ↔ abstract graph



# Why Automate Drawing Metro Maps?

- current maps designed manually



# Why Automate Drawing Metro Maps?

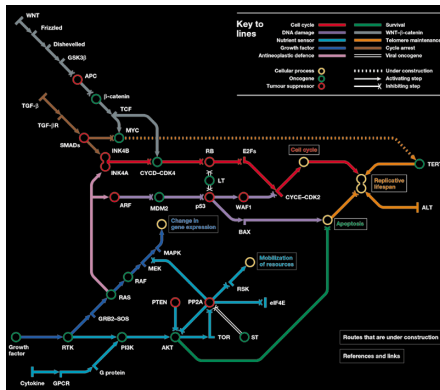
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  - metabolic pathways

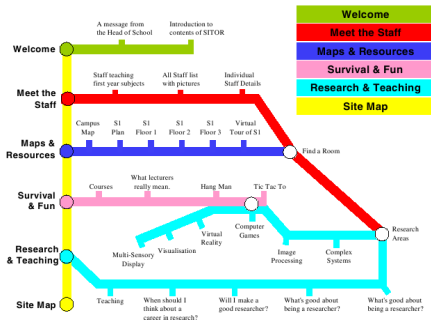
[Hahn, Weinberg '02]





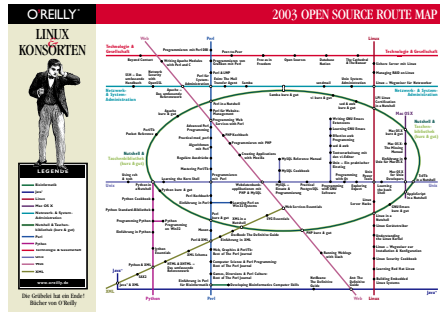
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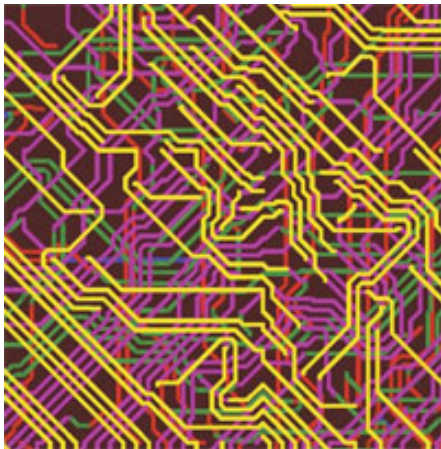
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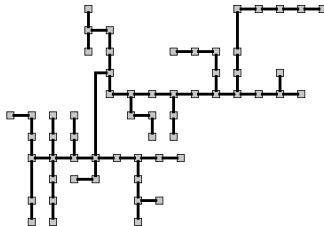
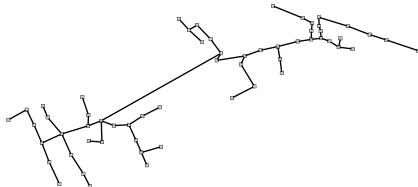
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- VLSI: X-architecture
- redrawing sketches [Brandes et al. '03]



## The Metro Map Problem

- Given: planar embedded graph  $G = (V, E)$ ,  $V \subset \mathbb{R}^2$ ,  
line cover  $\mathcal{L}$  of paths or cycles in  $G$  (the metro lines),
- Goal: draw  $G$  and  $\mathcal{L}$  **nicely**.

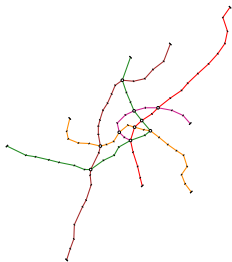
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Goal: draw  $G$  and  $\mathcal{L}$  **nicely**.

- What is a **nice** drawing?
- Look at real-world metro maps drawn by graphic designers and model their design principles as
  - *hard* constraints – must be fulfilled,
  - *soft* constraints – should hold as tightly as possible.

# Hard Constraints

(H1) preserve embedding of  $G$



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i.e. horizontal, vertical or diagonal (45 degrees)





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i.e. horizontal, vertical or diagonal (45 degrees)
- (H3) draw each edge  $e$  with length  $\geq \ell_e$
- (H4) keep edges  $d_{\min}$  away from non-incident edges ( $\rightarrow$  no crossings)



# Soft Constraints

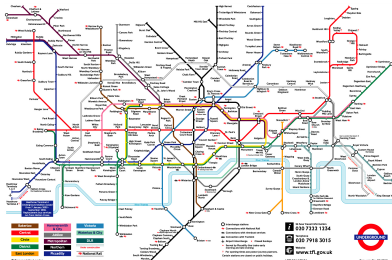
(S1) draw metro lines with few bends



# Soft Constraints

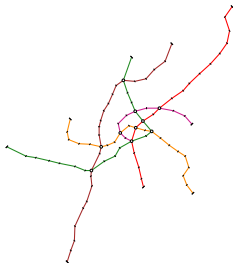
(S1) draw metro lines with few bends

(S2) keep total edge length small



# Soft Constraints

- (S1) draw metro lines with few bends
- (S2) keep total edge length small
- (S3) draw each octilinear edge similar to its geographical orientation:  
keep **relative position** of adjacent vertices



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# A Related Problem

## RECTILINEARGRAPHDRAWING Decision Problem

Given a planar embedded graph  $G$  with max degree 4.

Is there a drawing of  $G$  that

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- uses straight-line edges,
- is rectilinear?

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## Proof.

By reduction to a flow problem. □

## METROMAPLAYOUT Decision Problem

Given a planar embedded graph  $G$  with max degree 8.

Is there a drawing of  $G$  that

- preserves the embedding,
- uses straight-line edges,
- is **octilinear**?

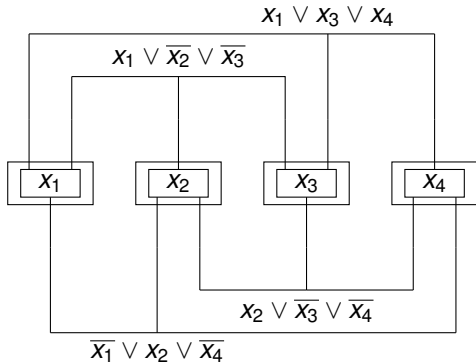
## Theorem

METROMAPLAYOUT is **NP-hard**.

## Proof.

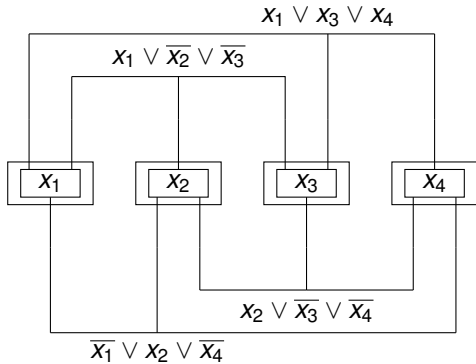
By Reduction from PLANAR 3-SAT to METROMAPLAYOUT. □

# Outline of the Reduction



Input: planar 3-SAT formula  $\varphi = (x_1 \vee x_3 \vee x_4) \wedge (x_1 \vee \bar{x}_2 \vee \bar{x}_3) \wedge \dots$

# Outline of the Reduction

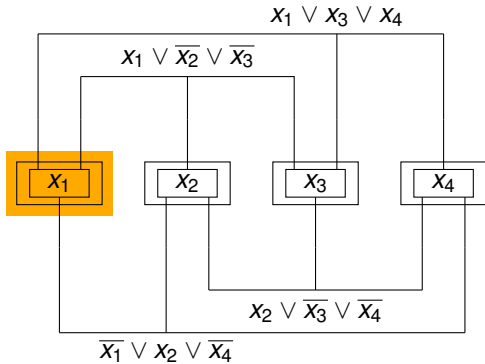


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Goal: planar embedded graph  $G_\varphi$  with:

$G_\varphi$  has a metro map drawing  $\Leftrightarrow \varphi$  satisfiable.

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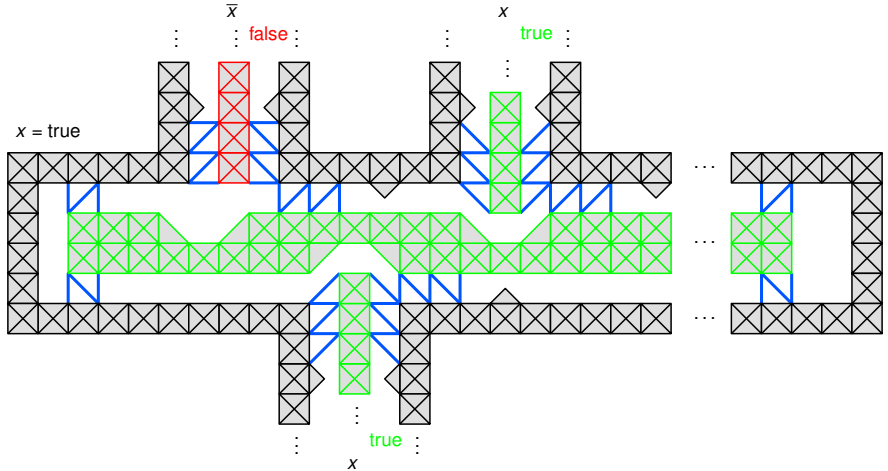


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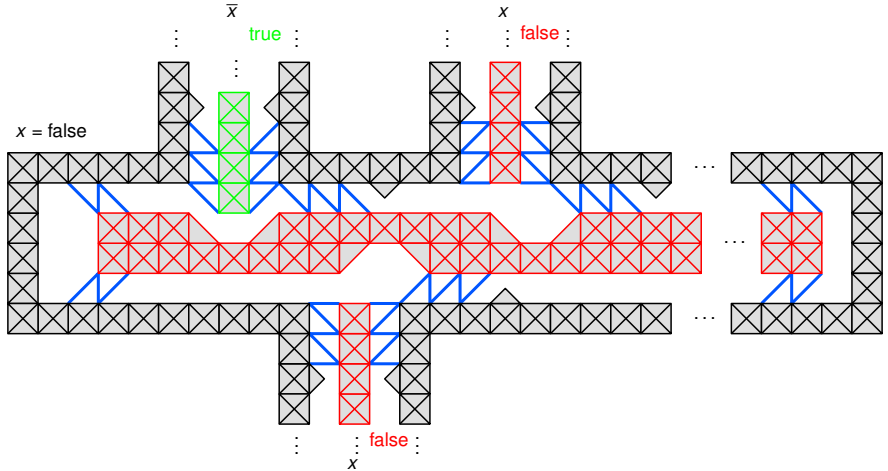
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# Variable Gadget

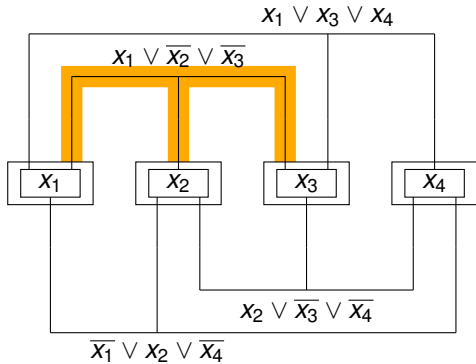


# Variable Gadget





# Outline of the Reduction

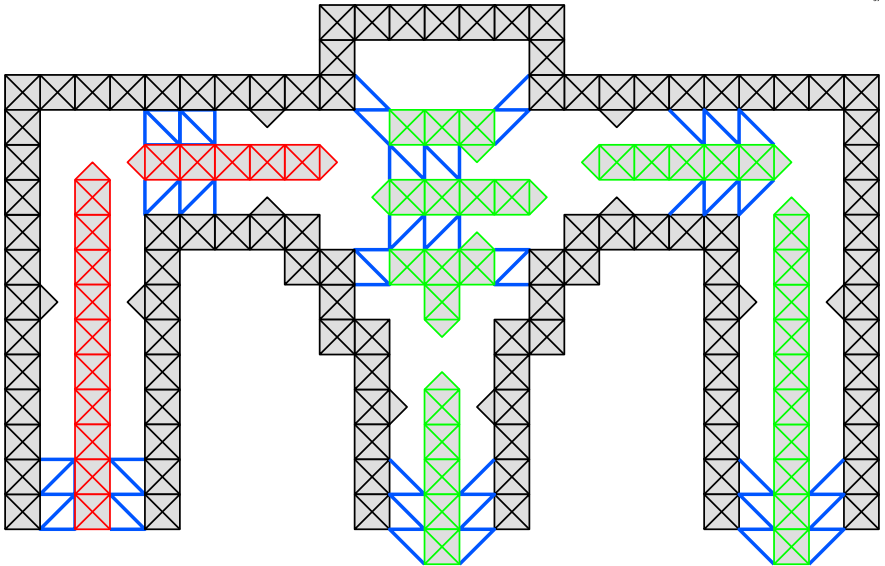


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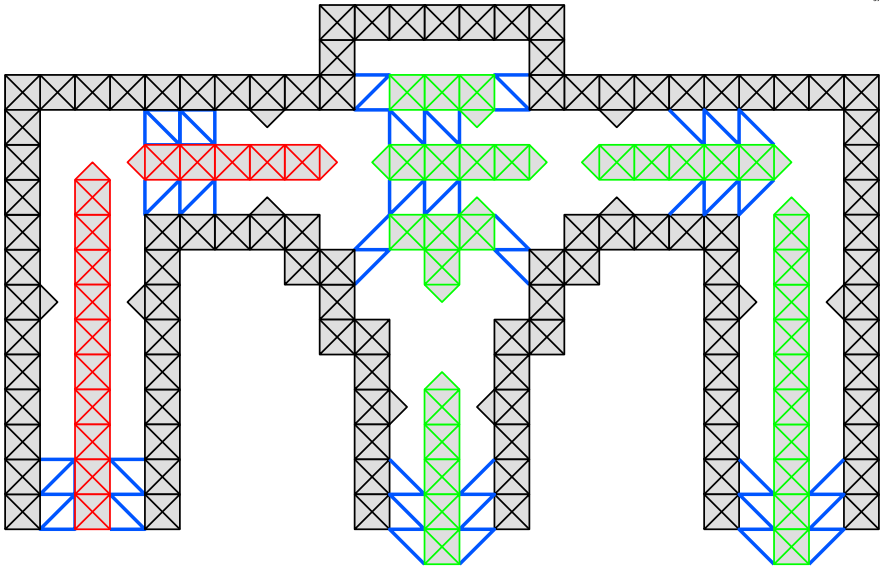
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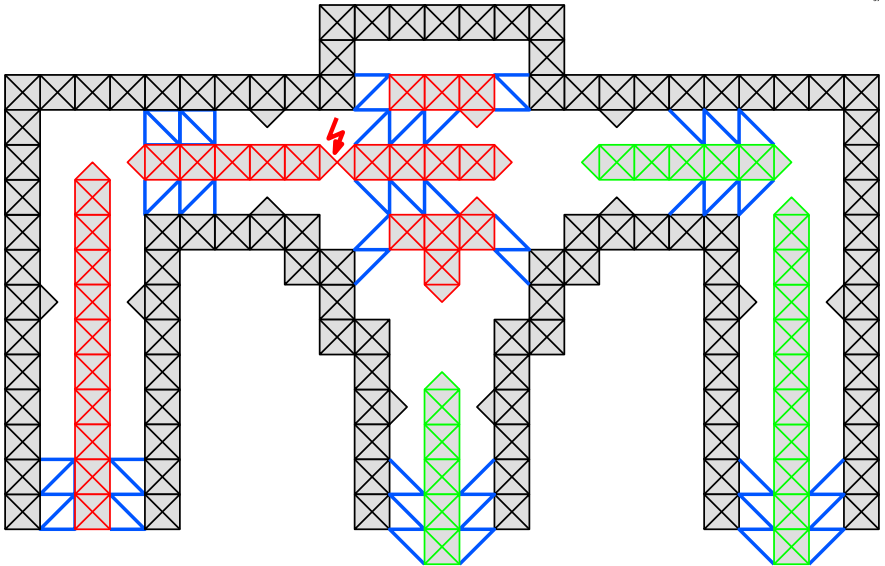
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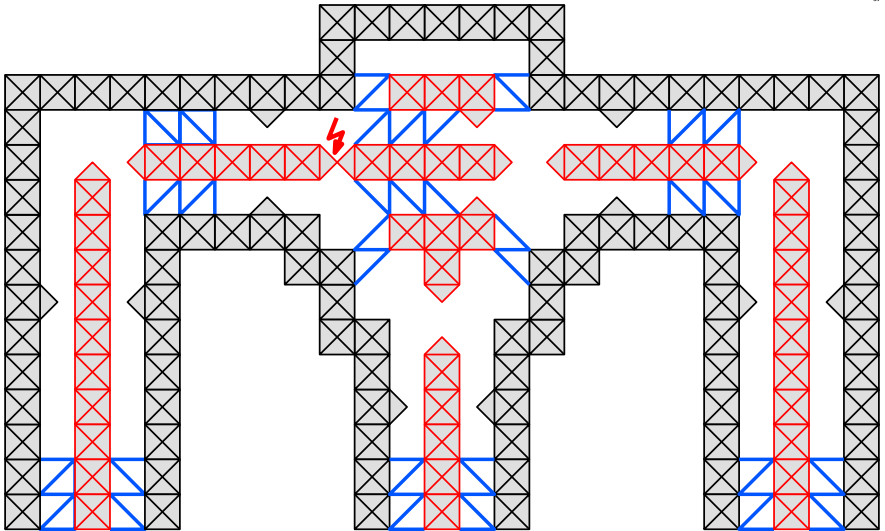
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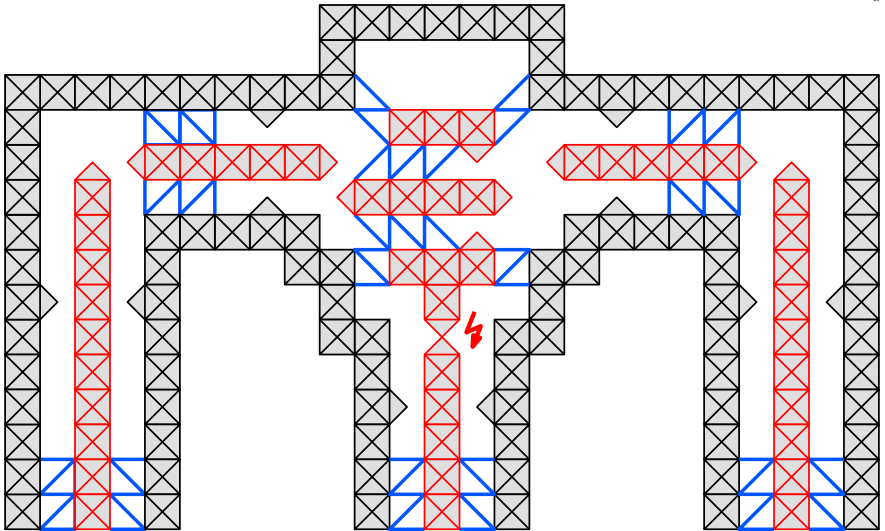
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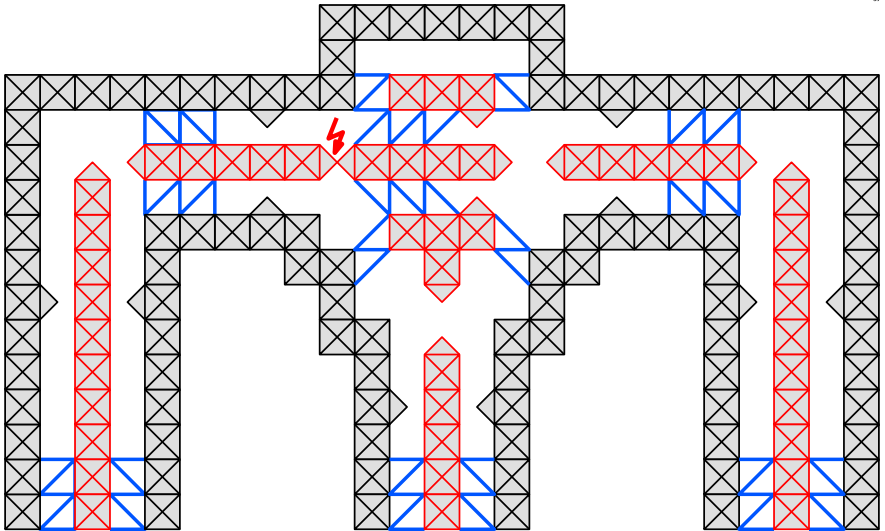
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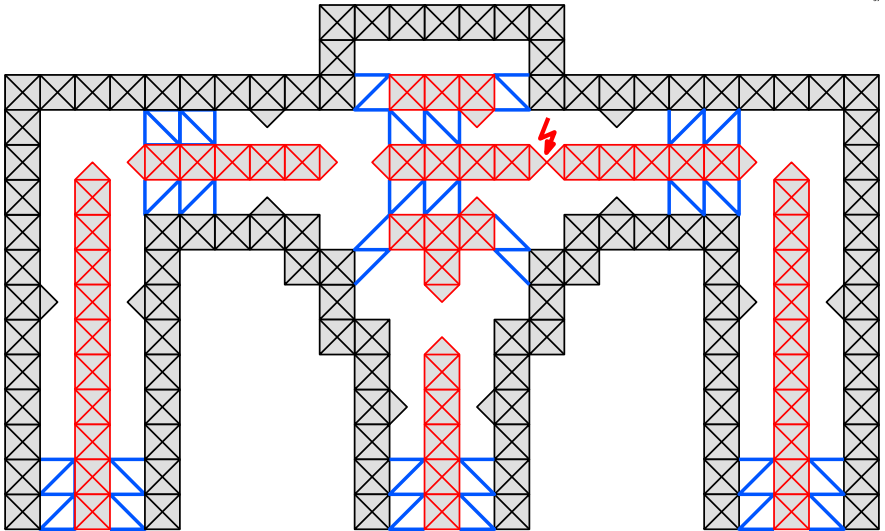
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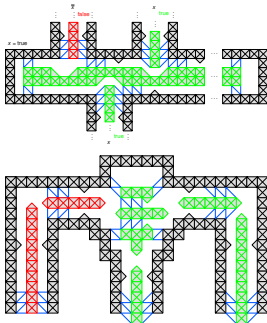
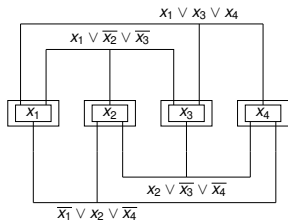


# Clause Gadget





# Summary of the Reduction

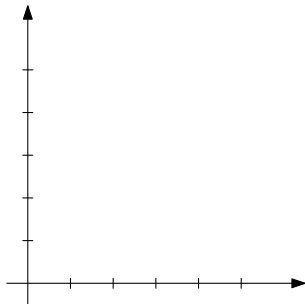


## ■ Indeed we have:

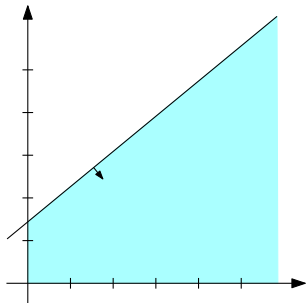
- $\varphi$  satisfiable  $\Rightarrow$  corresponding MM drawing of  $G_\varphi$
- $G_\varphi$  has MM drawing  $\Rightarrow$  satisfying truth assignment of  $\varphi$

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  - linear constraints
  - linear objective function
  - real-valued variables



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 $maximize\ x + 2y$   
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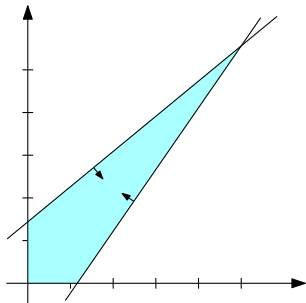
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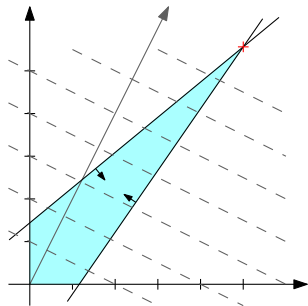
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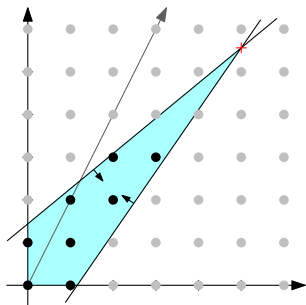
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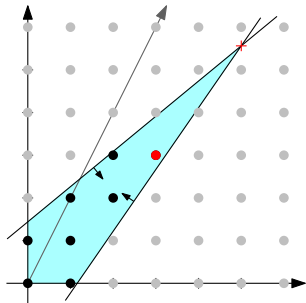
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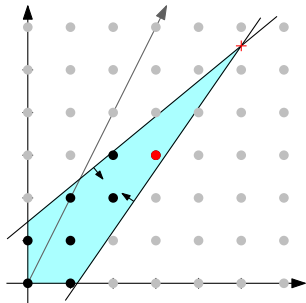


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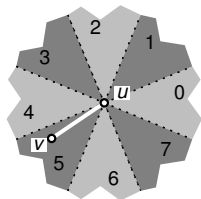


## Theorem

*The metro map layout problem can be formulated as a MIP s.th.*

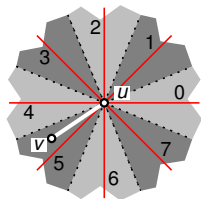
*hard constraints* → *linear constraints*

*soft constraints* → *objective function*



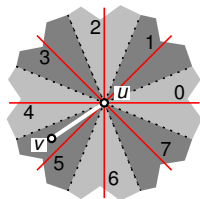
## Sectors

- for each vtx.  $u$  partition plane into sectors 0–7
  - here:  $\text{sec}(u, v) = 5$  (input)



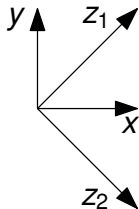
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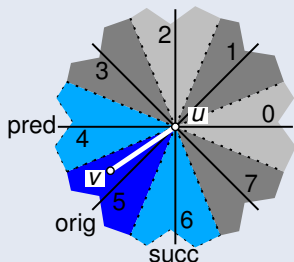


## Coordinates

assign  $z_1$ - and  $z_2$ -coordinates to each vertex  $v$ :

- $z_1(v) = x(v) + y(v)$
- $z_2(v) = x(v) - y(v)$

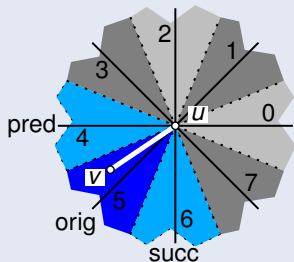
## Goal



Draw edge  $uv$

- octilinearly
- with minimum length  $\ell_{uv}$
- restricted to 3 directions

## Goal

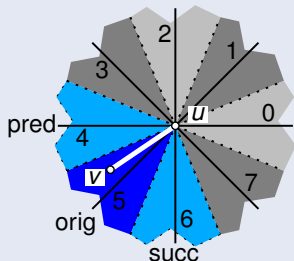


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How to model this using linear constraints?

## Goal



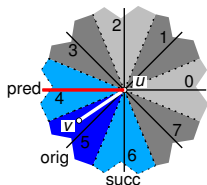
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## Binary Variables

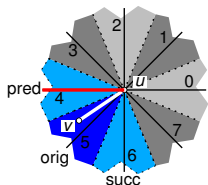
$$\alpha_{\text{pred}}(u, v) + \alpha_{\text{orig}}(u, v) + \alpha_{\text{succ}}(u, v) = 1$$



## Predecessor Sector

$$\begin{aligned}y(u) - y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ -y(u) + y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ x(u) - x(v) &\geq -M(1 - \alpha_{\text{pred}}(u, v)) + \ell_{uv}\end{aligned}$$

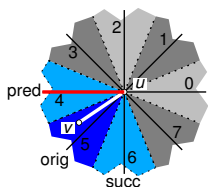




## Predecessor Sector

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How does this work?



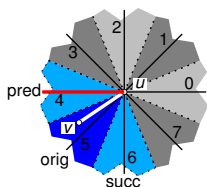
## Predecessor Sector

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## How does this work?

Case 1:  $\alpha_{\text{pred}}(u, v) = 0$

$$\begin{aligned}y(u) - y(v) &\leq M \\ -y(u) + y(v) &\leq M \\ x(u) - x(v) &\geq \ell_{uv} - M\end{aligned}$$



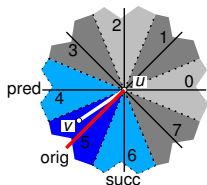
## Predecessor Sector

$$\begin{aligned}y(u) - y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ -y(u) + y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ x(u) - x(v) &\geq -M(1 - \alpha_{\text{pred}}(u, v)) + \ell_{uv}\end{aligned}$$

## How does this work?

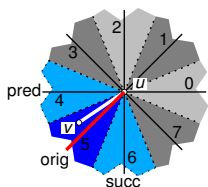
Case 2:  $\alpha_{\text{pred}}(u, v) = 1$

$$\begin{aligned}y(u) - y(v) &\leq 0 \\ -y(u) + y(v) &\leq 0 \\ x(u) - x(v) &\geq \ell_{uv}\end{aligned}$$



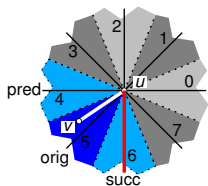
## Original Sector

$$\begin{aligned}z_2(u) - z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\ -z_2(u) + z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\ z_1(u) - z_1(v) &\geq -M(1 - \alpha_{\text{orig}}(u, v)) + 2\ell_{uv}\end{aligned}$$



## Original Sector

$$\begin{aligned} z_2(u) - z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\ -z_2(u) + z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\ z_1(u) - z_1(v) &\geq -M(1 - \alpha_{\text{orig}}(u, v)) + 2\ell_{uv} \end{aligned}$$



## Successor Sector

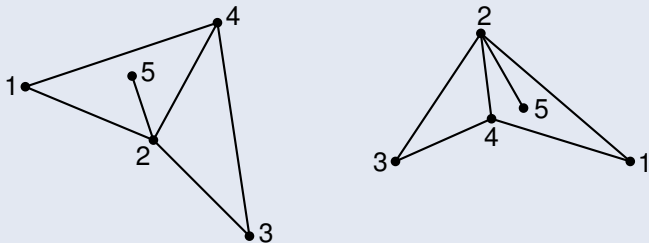
$$\begin{aligned} x(u) - x(v) &\leq M(1 - \alpha_{\text{succ}}(u, v)) \\ -x(u) + x(v) &\leq M(1 - \alpha_{\text{succ}}(u, v)) \\ y(u) - y(v) &\geq -M(1 - \alpha_{\text{succ}}(u, v)) + \ell_{uv} \end{aligned}$$

# Preserving the Embedding (H1)

## Definition

Two planar drawings of  $G$  have the same *embedding* if the induced orderings on the neighbors of each vertex are equal.

## Same Embedding

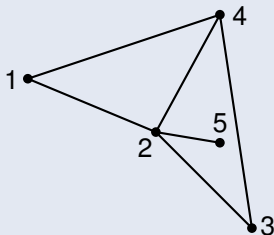
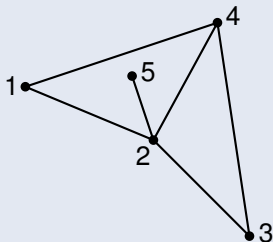


# Preserving the Embedding (H1)

## Definition

Two planar drawings of  $G$  have the same *embedding* if the induced orderings on the neighbors of each vertex are equal.

## Different Embeddings



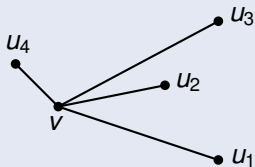
## Constraints (Example)

- $N(v) = \{u_1, u_2, u_3, u_4\}$
- circular input order:  $u_1 < u_2 < u_3 < u_4 < u_1$

All but one of the following inequalities must hold

$$\text{dir}(v, u_1) < \text{dir}(v, u_2) < \text{dir}(v, u_3) < \text{dir}(v, u_4) < \text{dir}(v, u_1)$$

## Input





# Preserving the Embedding (H1)

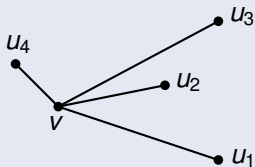
## Constraints (Example)

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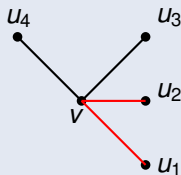
All but one of the following inequalities must hold

$$\text{dir}(v, u_1) \not< \text{dir}(v, u_2) < \text{dir}(v, u_3) < \text{dir}(v, u_4) < \text{dir}(v, u_1)$$

### Input



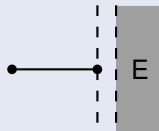
### Output



## Observation

For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

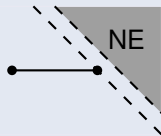
- east, northeast, north, northwest, west, southwest, south, or southeast



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For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

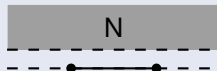
- east, **northeast**, north, northwest, west, southwest, south, or southeast



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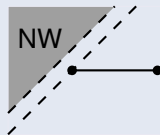
- east, northeast, **north**, northwest, west, southwest, south, or southeast



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For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

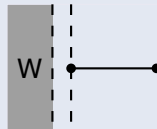
- east, northeast, north, **northwest**, west, southwest, south, or southeast



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For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

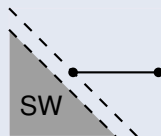
- east, northeast, north, northwest, **west**, southwest, south, or southeast



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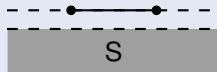
- east, northeast, north, northwest, west, **southwest**, south, or southeast



## Observation

For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

- east, northeast, north, northwest, west, southwest, **south**, or southeast

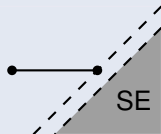




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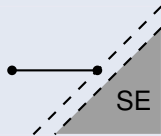
- east, northeast, north, northwest, west, southwest, south, or **southeast**



## Observation

For octilinear, straight edge  $e_1$  non-incident edge  $e_2$  must be placed  $d_{\min}$  to the

- east, northeast, north, northwest, west, southwest, south, or southeast



## Constraints

- model as MIP with binary variables

$$\alpha_E + \alpha_{NE} + \alpha_N + \alpha_{NW} + \alpha_W + \alpha_{SW} + \alpha_S + \alpha_{SE} \geq 1$$

- required for each pair of non-incident edges

## Objective Function

- corresponds to soft constraints (S1)–(S3)
- weighted sum of individual cost functions

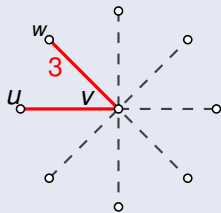
$$\text{minimize } \lambda_{\text{bends}} \text{cost}_{\text{bends}} + \lambda_{\text{length}} \text{cost}_{\text{length}} + \lambda_{\text{relpos}} \text{cost}_{\text{relpos}}$$

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## Line Bends (S1)



Edges  $uv$  and  $vw$  on a metro line  $L \in \mathcal{L}$

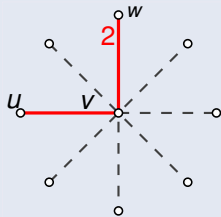
- draw as straight as possible
- increase  $\text{cost}_{\text{bend}}(u, v, w)$  for increasing acuteness of  $\angle(\overline{uv}, \overline{vw})$

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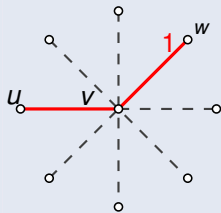
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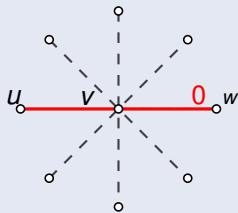
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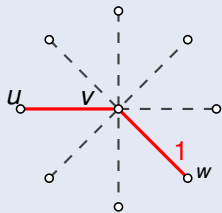
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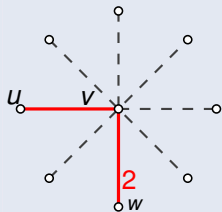


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Edges  $uv$  and  $wv$  on a metro line  $L \in \mathcal{L}$

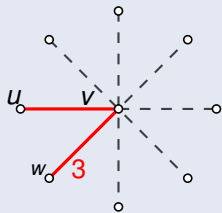
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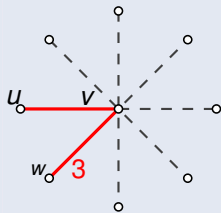
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## Line Bends (S1)



Edges  $uv$  and  $vw$  on a metro line  $L \in \mathcal{L}$

- draw as straight as possible
- increase cost  $\text{bend}(u, v, w)$  for increasing acuteness of  $\angle(\overline{uv}, \overline{vw})$

$$\text{cost}_{\text{bends}} = \sum_{L \in \mathcal{L}} \sum_{uv, vw \in L} \text{bend}(u, v, w)$$

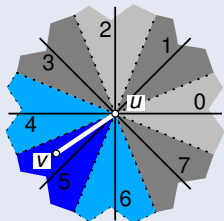
## Total Edge Length (S2)

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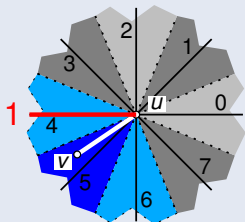


- only three directions possible

## Total Edge Length (S2)

$$\text{cost}_{\text{length}} = \sum_{uv \in E} \text{length}(\overline{uv})$$

## Relative Position (S3)

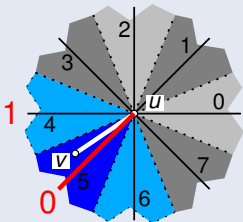


- only three directions possible
- charge 1 if edge deviates from original sector

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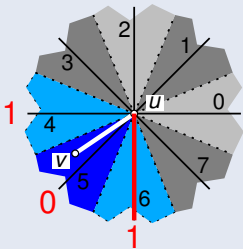


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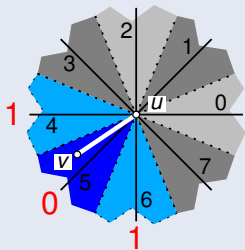
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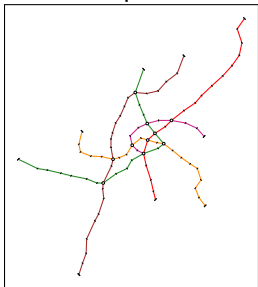
$$\text{cost}_{\text{relpos}} = \sum_{uv \in E} \text{relpos}(uv)$$

## Objective Function

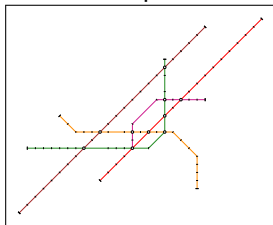
- corresponds to soft constraints (S1)–(S3)
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$$\text{minimize } \lambda_{\text{bends}} \text{cost}_{\text{bends}} + \lambda_{\text{length}} \text{cost}_{\text{length}} + \lambda_{\text{relpos}} \text{cost}_{\text{relpos}}$$

Input



Output

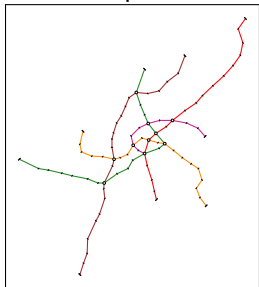


## Objective Function

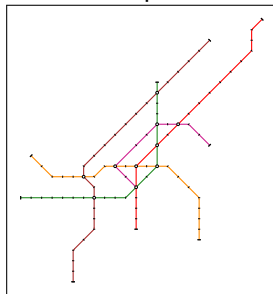
- corresponds to soft constraints (S1)–(S3)
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$$\text{minimize } \lambda_{\text{bends}} \text{ COST}_{\text{bends}} + \lambda_{\text{length}} \text{ COST}_{\text{length}} + \lambda_{\text{relpos}} \text{ COST}_{\text{relpos}}$$

Input



Output

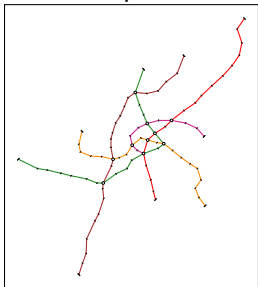


## Objective Function

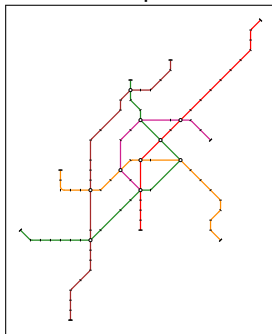
- corresponds to soft constraints (S1)–(S3)
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**minimize**  $\lambda_{\text{bends}} \text{COST}_{\text{bends}} + \lambda_{\text{length}} \text{COST}_{\text{length}} + \lambda_{\text{relpos}} \text{COST}_{\text{relpos}}$

Input



Output



# Summary of the MIP

- hard constraints:
  - orthogonality
  - minimum edge length
  - (partially) relative position
  - preservation of embedding
  - planarity

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  - octilinearity
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- models METROMAPLAYOUT as MIP

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- models METROMAPLAYOUT as MIP
- in total  $O(|V|^2)$  constraints and variables



# Summary of the MIP

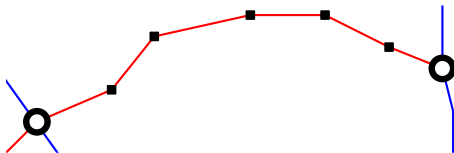
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- soft constraints:

$$\text{minimize } \lambda_{\text{bends}} \text{cost}_{\text{bends}} + \lambda_{\text{length}} \text{cost}_{\text{length}} + \lambda_{\text{relpos}} \text{cost}_{\text{relpos}}$$

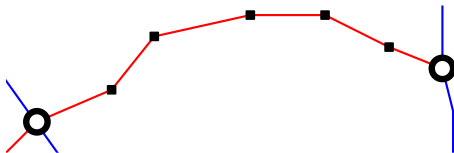
- models METROMAPLAYOUT as MIP
- in total  $O(|V|^2)$  constraints and variables

# Speeding Up: Reduce Graph Size



- metro graphs have many degree-2 vertices
- want to optimize line straightness

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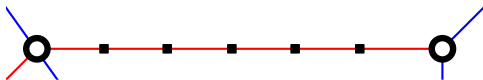
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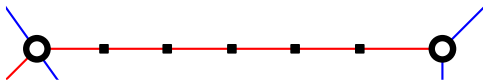
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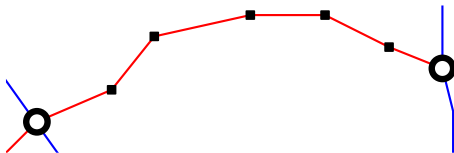


- metro graphs have many degree-2 vertices
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- low flexibility

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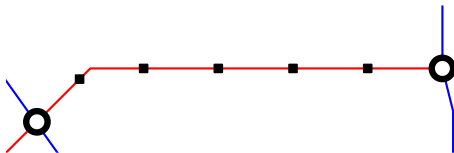
- metro graphs have many degree-2 vertices
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Idea 1 collapse all degree-2 vertices

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Idea 2 keep two *joints*

# Speeding Up: Reduce Graph Size



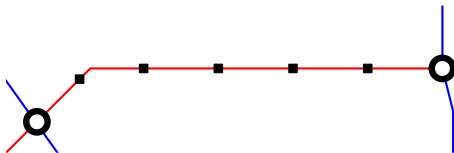
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# Speeding Up: Reduce Graph Size



- metro graphs have many degree-2 vertices
- want to optimize line straightness

Idea 1 collapse all degree-2 vertices

- low flexibility

Idea 2 keep two *joints*

- higher flexibility
- more similar to input

# Speeding Up: Reduce MIP Size

- $O(|V|^2)$  planarity constraints (for each pair of edges...)
- in practice 95–99% of constraints

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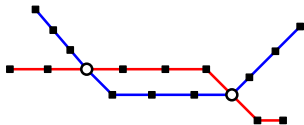
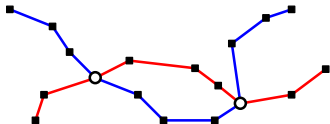
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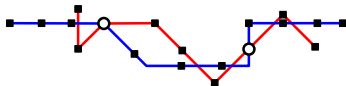
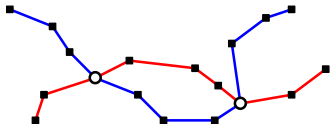
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# Speeding Up: Callback Functions

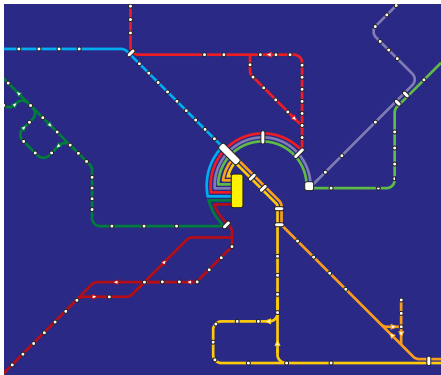
- MIP optimizer CPLEX offers advanced callback functions
- add required planarity constraints on the fly

## Algorithm

- 1 start solving MIP without planarity constraints
- 2 for each new solution
  - 1 interrupt CPLEX
  - 2 if solution is not planar
    - add planarity constraints for intersecting edges
    - reject solution
  - else
    - accept solution
- 3 continue solving the MIP (until optimal)

# Labeling

- unlabeled metro map of little use in practice



# Labeling

- unlabeled metro map of little use in practice
- labels
  - occupy space
  - may not overlap



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- labels
  - occupy space
  - may not overlap
- static edge labeling is NP-hard

[Tollis, Kakoulis '01]



# Labeling

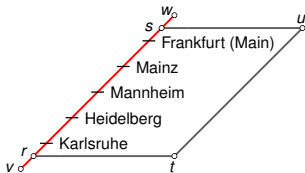
- unlabeled metro map of little use in practice
- labels
  - occupy space
  - may not overlap
- static edge labeling is NP-hard  
[Tollis, Kakoulis '01]
- combine layout and labeling for better results



# Modeling Labels

Model labels as special metro lines:

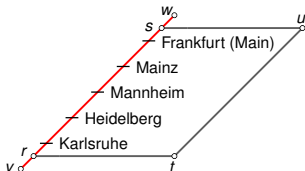
- put all labels between each pair of interchange stations into one parallelogram,



# Modeling Labels

Model labels as special metro lines:

- put all labels between each pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,

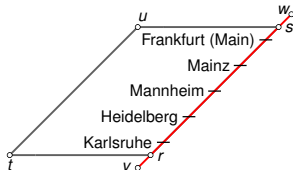




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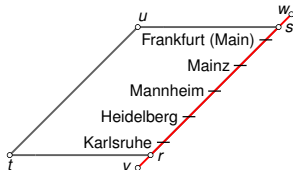
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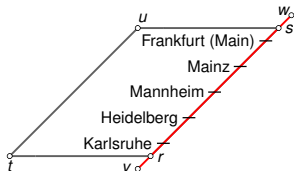
- put all labels between each pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,
- **bad news**: a **lot** more planarity constraints



# Modeling Labels

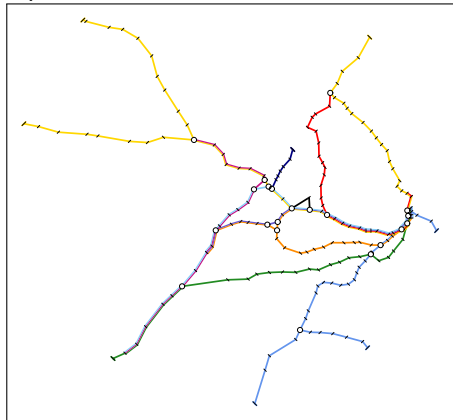
Model labels as special metro lines:

- put all labels between each pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,
- **bad news**: a **lot** more planarity constraints
- **good news**: callback method helps



## Results – Sydney unlabeled

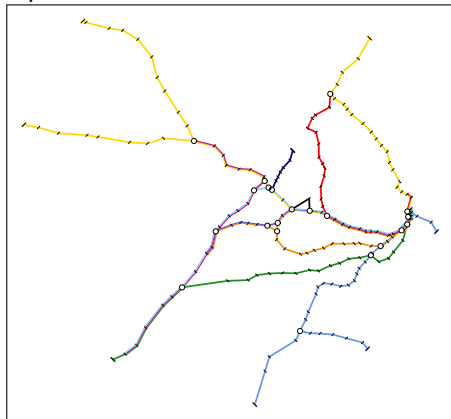
Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
full	174	183	11	10
reduced	88	97		

# Results – Sydney unlabeled

Input



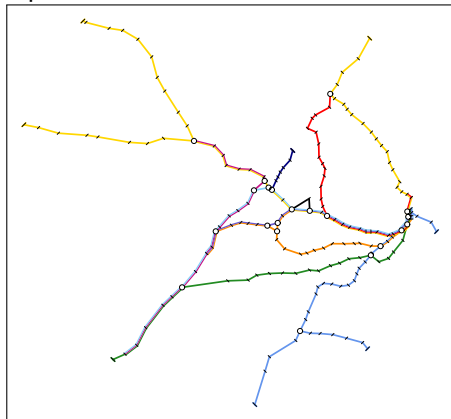
Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
full	174	183	11	10
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MIP	constr.	var.
full	152,194	37,802
callback	3,529	4,834
skipped	3,034	1,642

# Results – Sydney unlabeled

Input



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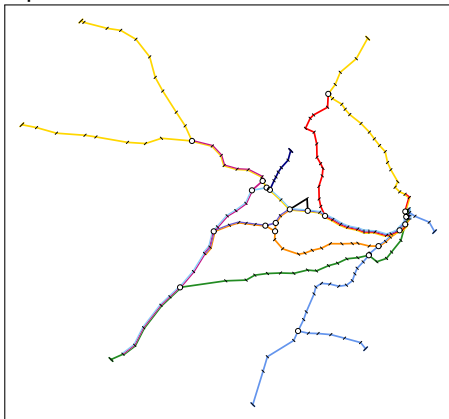
↓

MIP	constr.	var.
full	152,194	37,802
callback*	3,529	4,834
skipped	3,034	1,642

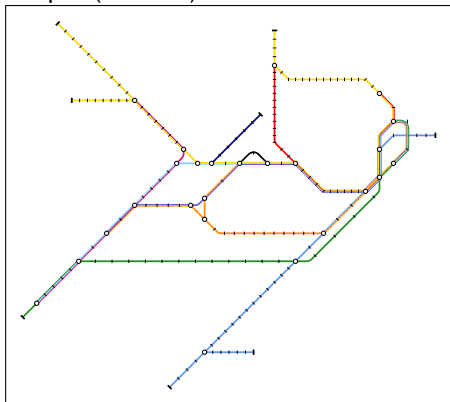
\* ) 23 minutes w/o proof of opt.  
constr. of 3 edge pairs added

# Results – Sydney unlabeled

Input

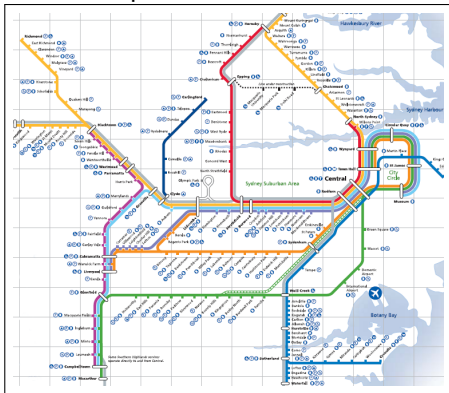


Output (23 min.)

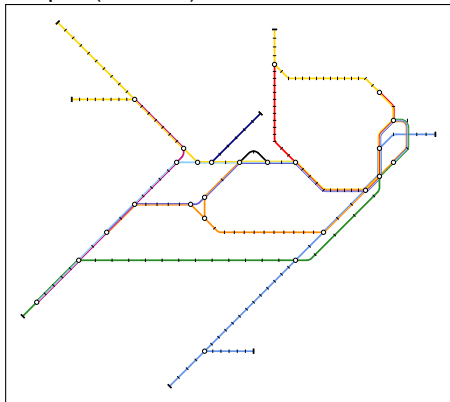


# Results – Sydney unlabeled

Official map



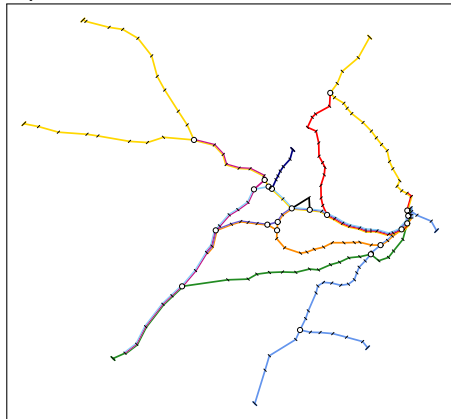
Output (23 min.)





## Results – Sydney labeled

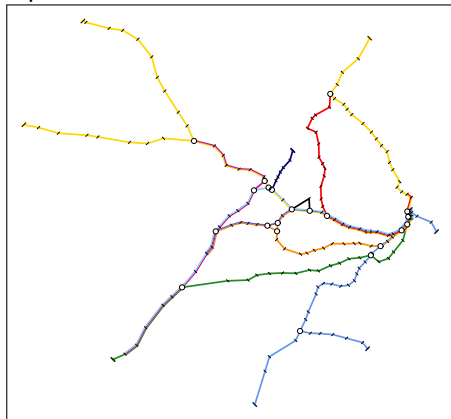
Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
full	174	183	11	10
reduced	88	97		
labeled	242	270	30	

# Results – Sydney labeled

Input



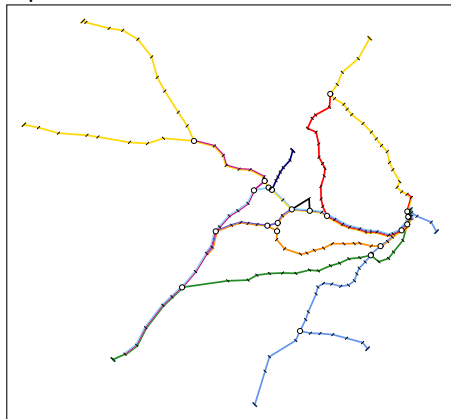
Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
full	174	183	11	10
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<b>labeled</b>	242	270	30	



MIP	constr.	var.
full	1,191,406	290,137
callback	21,988	92,681
skipped	6,838	2,969

# Results – Sydney labeled

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
full	174	183	11	10
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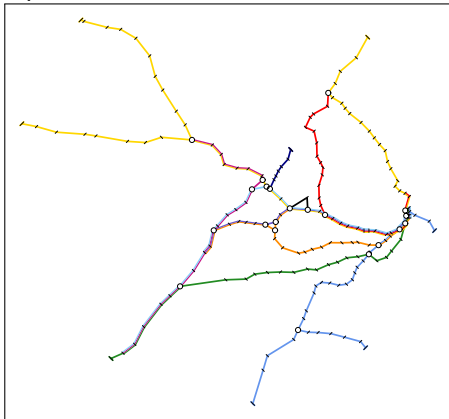
↓

MIP	constr.	var.
full	1,191,406	290,137
<b>callback*</b>	21,988	92,681
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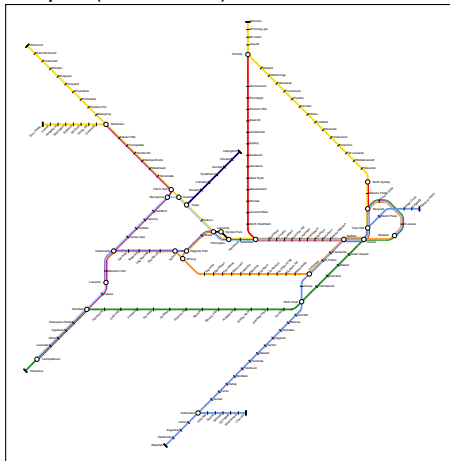
\* ) 10:30 hours w/o proof of opt.  
add constr. of 123 edge pairs

# Results – Sydney labeled

Input

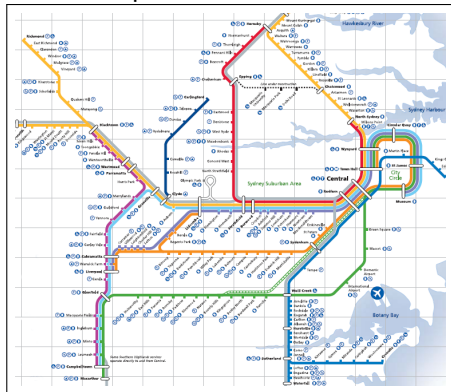


Output (10:30 hrs.)

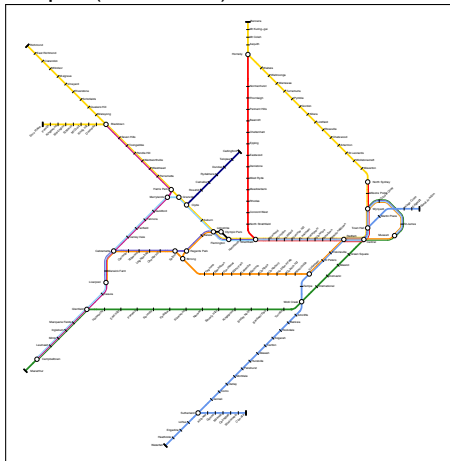


# Results – Sydney labeled

Official map

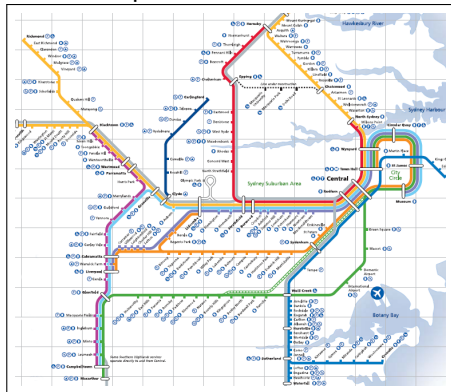


Output (10:30 hrs.)

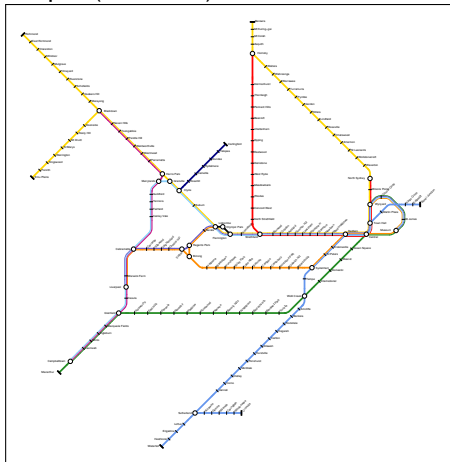


# Results – Sydney labeled

Official map

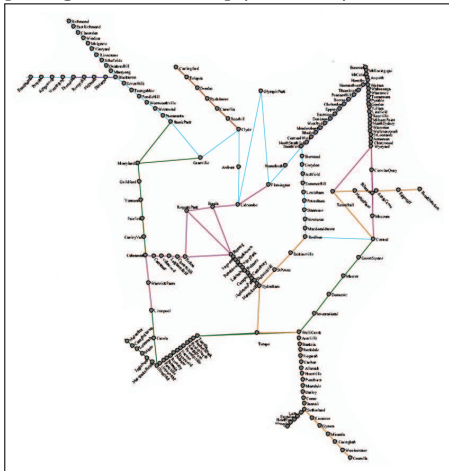


Output (1:40 hrs.)

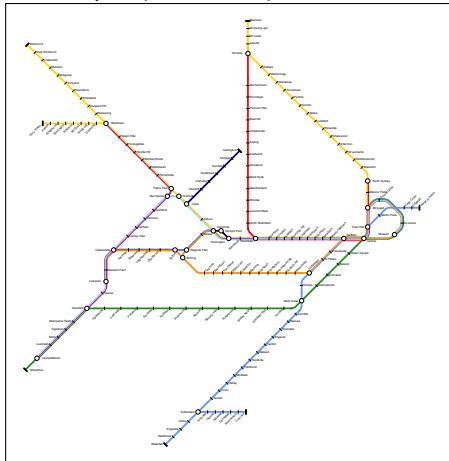


# Sydney: Related Work

[Hong et al. GD'04] (7.6 sec.)

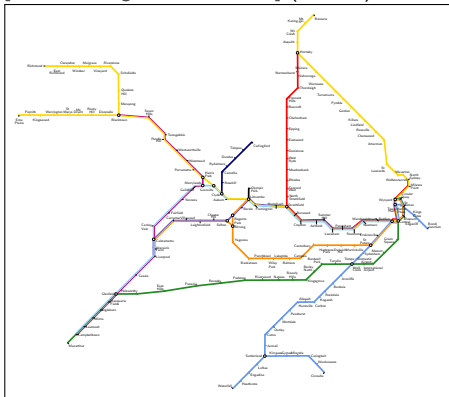


Our output (10:30 hrs.)

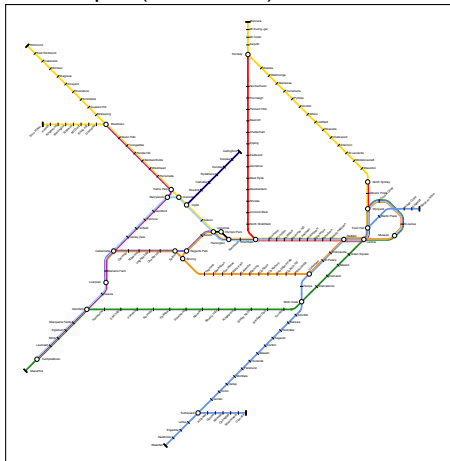


# Sydney: Related Work

[Stott, Rodgers TVCG'10] (2 hrs.)



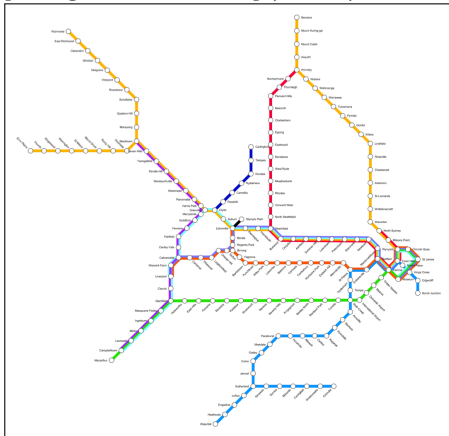
Our output (10:30 hrs.)



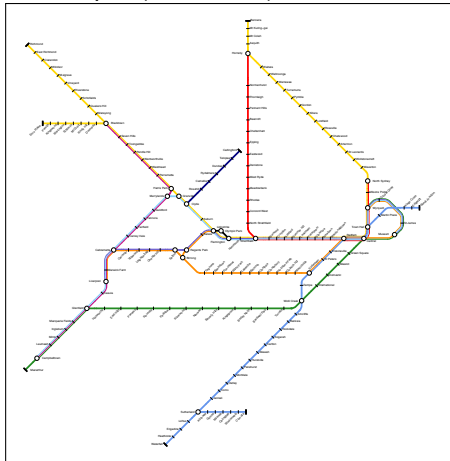


# Sydney: Related Work

[Wang, Chi TVCG'11] (1 sec.)

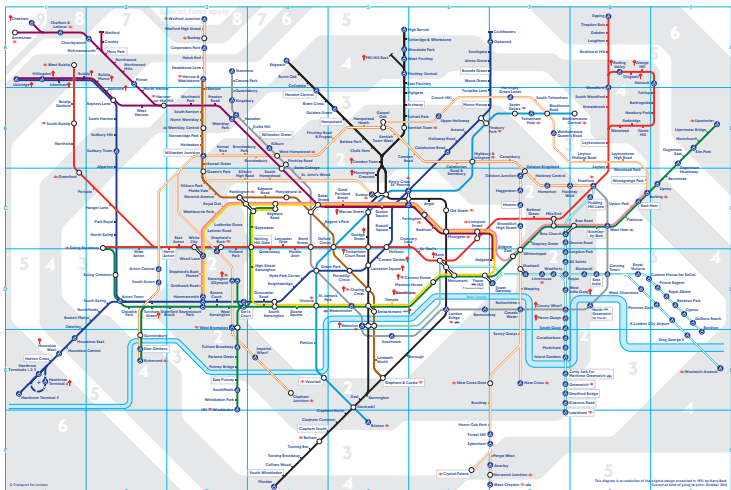


Our output (10:30 hrs.)



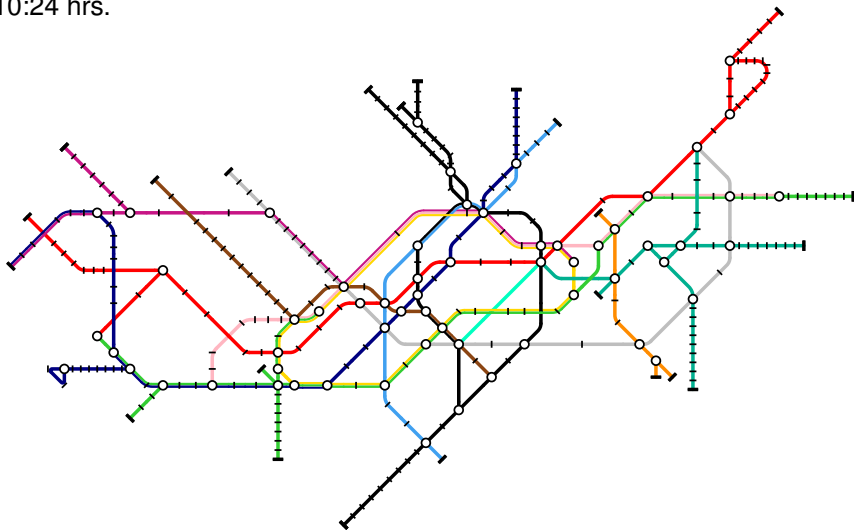
# Large Example: London

## Tube map



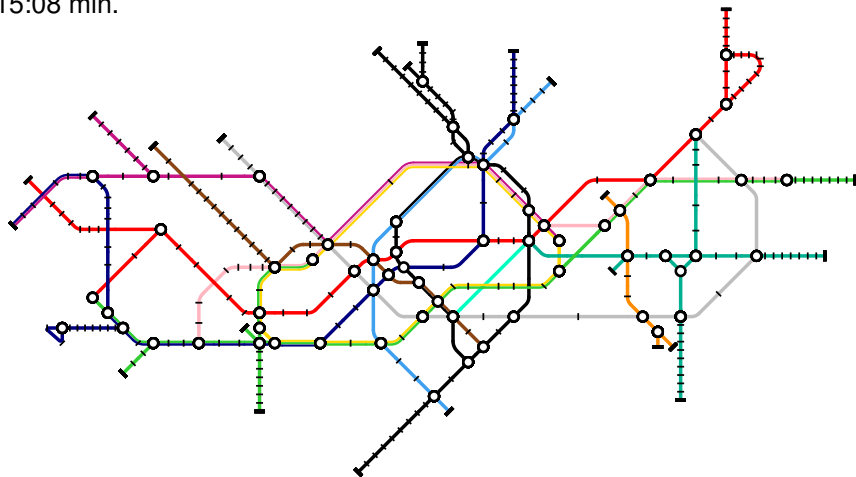
# Large Example: London

10:24 hrs.

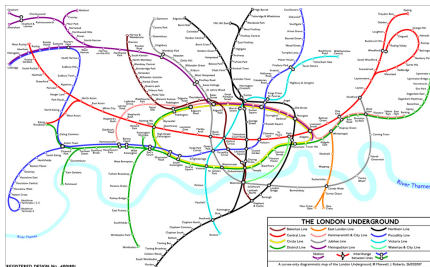
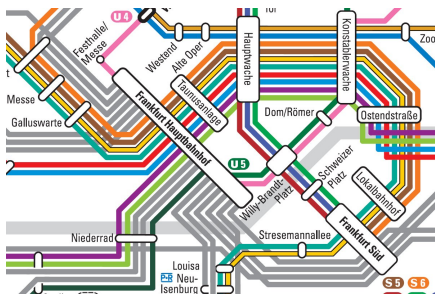


# Large Example: London

15:08 min.



# Problem solved?



## Open questions

- more user interaction
- how to handle large stations and many parallel lines?
- formulate global aesthetics like symmetry and balance
- use of curves for metro layouts (see [Fink et al. GD'12])

# Summary

- METROMAPLAYOUT is NP-hard
- formulation of hard and soft constraints as MIP
- combined layout and labeling
- MIP size & runtime reductions
- high-quality results
- MIP can schematize *any* kind of graph sketch

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For more info see:

M. Nöllenburg and A. Wolff. *Drawing and labeling high-quality metro maps by mixed-integer programming*. IEEE Trans. Visualization and Computer Graphics 17(5):626–641, 2011.