# Embedding Formulations and Complexity for Unions of Polyhedra

#### Juan Pablo Vielma

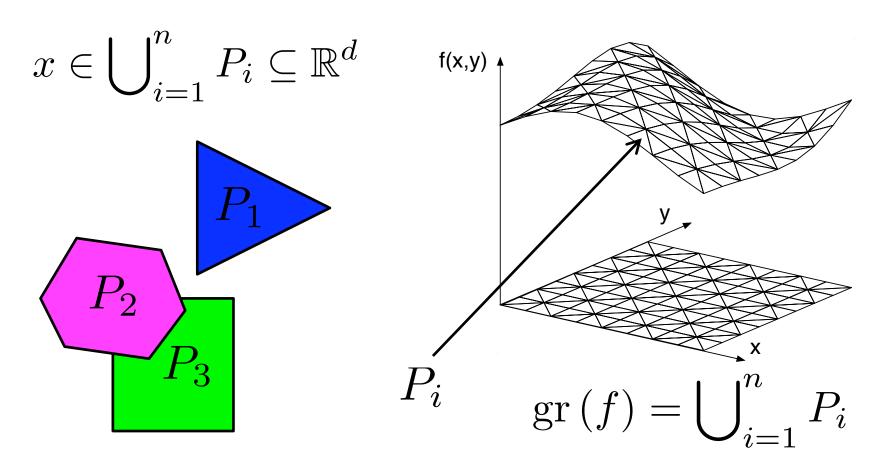
Massachusetts Institute of Technology

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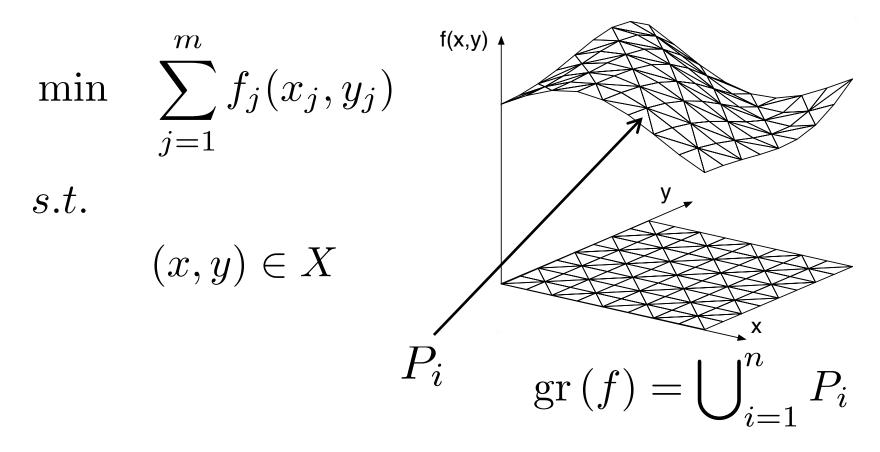
#### (Linear) Mixed <u>0-1</u> Integer Formulations

Modeling Finite Alternatives = Unions of Polyhedra



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#### Outline

- Introduction
  - Classical Formulations v/s Specialized Branching
- Encoding Formulations
  - Role of Binary Variables and Specialized Branching
- Embedding Formulations
  - Smallest Strong Formulations

### **Strong** Extended Formulations for $x \in \bigcup_{i=1}^n P_i$

Balas, Jeroslow and Lowe '70s early '80s

$$P_i = \left\{ x \in \mathbb{R}^d : A^i x \le b^i \right\}$$

$$A^{i}x^{i} \leq b^{i}y_{i} \quad \forall i$$

$$\sum_{i=1}^{n} x^{i} = x$$

$$\sum_{i=1}^{n} y_{i} = 1$$

$$y \in \{0, 1\}^{n}$$

 $\mathcal{H}$ -formulation

$$\sum_{i=1}^{n} \sum_{v \in \text{ext}(P_i)} v \lambda_v^i = x$$

$$\sum_{v \in \text{ext}(P_i)} \lambda_v^i = y_i \quad \forall i$$

$$\sum_{i=1}^{n} y_i = 1$$

$$\lambda^i \in \mathbb{R}_+^{\text{ext}(P_i)}$$

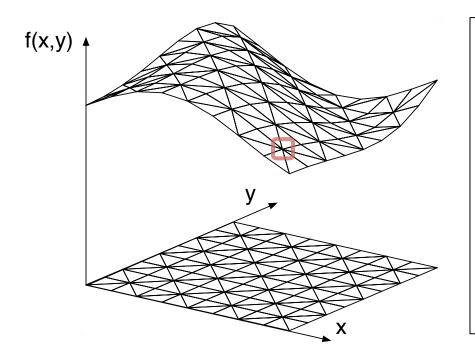
$$y \in \{0, 1\}^n$$

 $\mathcal{V}$ -formulation

- Convex Hull (Sharp) = LP relaxation projects to  $conv \left( \bigcup_{i=1}^{n} P_i \right)$
- Integral (Locally Ideal) = LP relaxation has integral extreme points (y)

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### "Strong" Extended Formulations for $x \in \bigcup_{i=1}^n P_i$

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$$Ax \le \sum_{i=1}^{n} b^{i} y_{i}$$

$$\sum_{i=1}^{n} y_{i} = 1$$

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 $\mathcal{H}$ -formulation

Lee and Wilson late '90s

$$V := \bigcup_{i=1}^{n} \operatorname{ext}\left(P_{i}\right)$$

$$\sum_{v \in V} v \lambda_v = x$$

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$$\sum_{i=1}^n y_i = 1$$

$$y \in \{0,1\}^n, \quad \lambda \in \mathbb{R}_+^V$$

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Sometimes

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# "Strong" Extended Formulations for $x \in \bigcup_{i=1}^n P_i$

- Balas, Blair and Jeroslow late '80s
- f(x,y)

  y

  X
- Lee and Wilson late '90s

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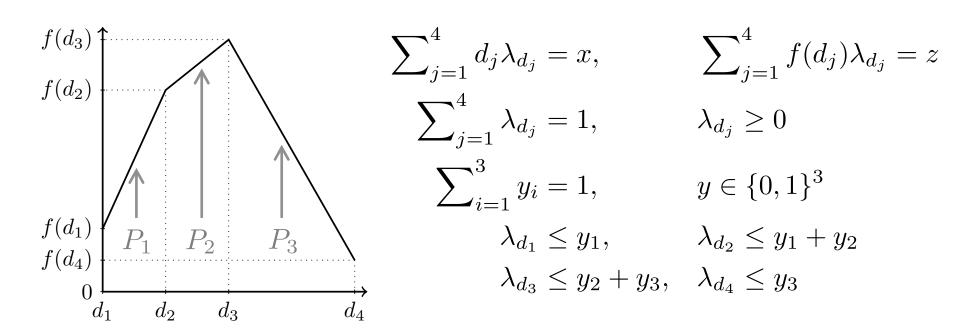
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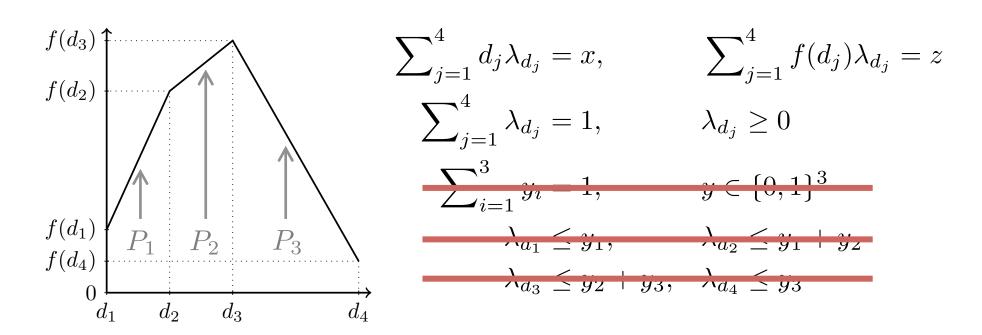
#### **Projected Formulation for Univariate Functions**



- Convex Hull, but not Integral
- Branching is very ineffective (unbalanced B&B tree)

$$-y_{i_0}=1$$
  $\Rightarrow$   $y_i=0$   $\forall i \neq i_0$   $y_{i_0}=0$  does not imply much (anything)

#### Projected Formulation for Univariate Functions

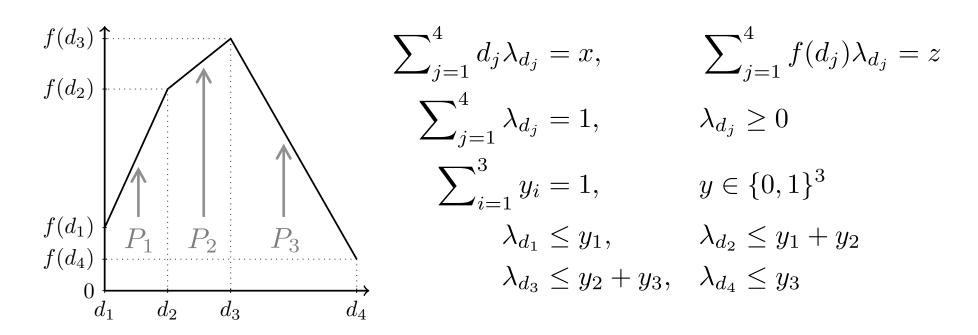


One solution = SOS2 branching (Beale and Tomlin '70):

$$- \lambda_{d_i} = 0 \quad \forall i \le i_0 - 1$$

$$-\lambda_{d_i} = 0 \quad \forall i \ge i_0 + 1$$

#### Projected Formulation for Univariate Functions



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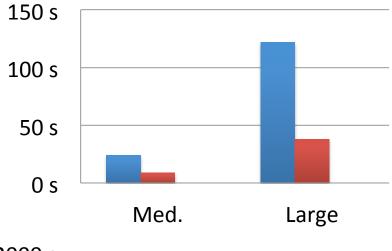
$$-\lambda_{d_i} = 0 \quad \forall i \le i_0 - 1 \qquad y_i = 0 \quad \forall i \le i_0 - 1$$

$$-\lambda_{d_i} = 0 \quad \forall i \ge i_0 + 1 \qquad y_i = 0 \quad \forall i \ge i_0$$

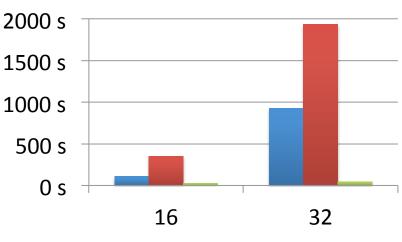
$$y_i = 0 \quad \forall i \ge i_0$$

#### MIP Formulations v/s Specialized Branching

CPLEX 9: Basic SOS2
 branching implementation
 (Nemhauser, Keha and V. '08)



CPLEX 11: Improved SOS2
 branching implementation
 (Nemhauser, Ahmed and V. '10)



Embedding

Projected

SOS2

### Encoding Formulations: The Role of Binary Variables

#### **Encodings to Induce Specialized Branching**

• Discrete alternatives ( $P_i = \{v^i\}$ ):

$$\sum_{i=1}^{n} y_i v^i = x, \quad \sum_{i=1}^{n} y_i = 1$$
$$y \in \{0, 1\}^n$$

#### **Encodings to Induce Specialized Branching**

• Discrete alternatives ( $P_i = \{v^i\}$ ):

$$\sum_{i=1}^{n} y_i v^i = x, \qquad \sum_{i=1}^{n} y_i = 1$$

$$g \in \{0, 1\}^n \quad y \in \mathbb{R}_+^n$$

$$\sum_{i=1}^{n} y_i h^i = w, \quad w \in \{0, 1\}^k$$

- Pick  $\left\{h^i\right\}_{i=1}^n \subseteq \left\{0,1\right\}^k$ ,  $h^i \neq h^j$  Encoding
- Li and Lu '09, Adams and Henry '11, V. and Nemhauser '08 for  $k = \log_2 n$ . Also in the folklore, e.g. Sommer, TIMS '72

#### Different Encodings = Different Branching

• Unary encoding :  $\{h^i\}_{i=1}^n = \{e^i\}_{i=1}^n$ 

$$\sum_{i=1}^{8} y_i = 1, \quad y \in \mathbb{R}_+^8$$

$$\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix} y = \begin{pmatrix}
w_1 \\
w_2 \\
w_3 \\
w_4 \\
w_5 \\
w_6 \\
w_7 \\
w_8
\end{pmatrix}, \quad w \in \{0, 1\}^8$$

$$\Rightarrow y_i = w_i$$

#### Different Encodings = Different Branching

•Binary encoding :  $\left\{h^i\right\}_{i=1}^n = \left\{0,1\right\}^{\log_2 n}$ 

$$\sum_{i=1}^{8} y_{i} = 1, \quad y \in \mathbb{R}^{8}_{+}$$

$$\begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} y = \begin{pmatrix} w_{1} \\ w_{2} \\ w_{3} \end{pmatrix}, \quad w \in \{0, 1\}^{3}$$

#### Discrete Alternatives to Unions of Polyhedra

Adapt extended  $\mathcal{V}$ -formulation:

$$\sum_{i=1}^{n} \sum_{v \in \text{ext}(P_i)} v \lambda_v^i = x$$

$$\sum_{v \in \text{ext}(P_i)} \lambda_v^i = y_i \ \forall i$$

$$\sum_{i=1}^{n} y_i = 1$$

$$\lambda^i \in \mathbb{R}_+^{\text{ext}(P_i)}$$

$$y \in \{0, 1\}^n$$

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Adapt extended  $\mathcal{V}$ -formulation:

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$$\sum_{i=1}^{n} \sum_{v \in \text{ext}(P_i)} \lambda_v^i = 1 \quad \forall i$$

$$\sum_{i=1}^{n} h^i \sum_{v \in \text{ext}(P_i)} \lambda_v^i = w$$

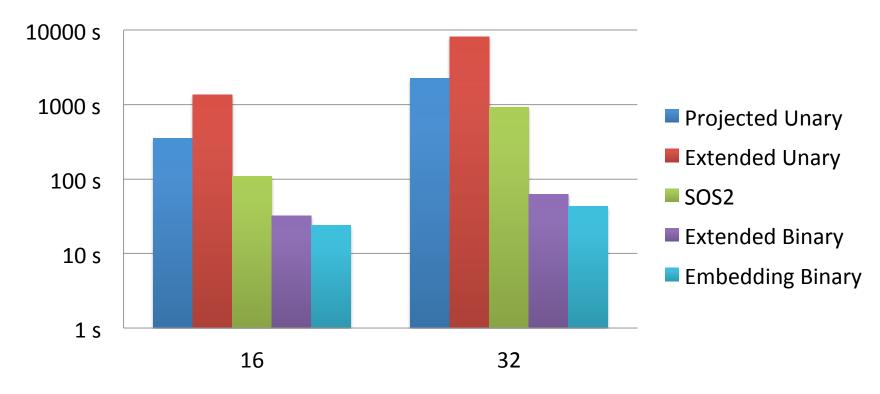
$$\lambda^i \in \mathbb{R}_+^{\text{ext}(P_i)}$$

$$w \in \{0, 1\}^k$$

V., Ahmed and Nemhauser 2010; Yıldız and V. 2013; V. 2014

#### Performance for Univariate Functions

Results from Nemhauser, Ahmed and V. '10 using CPLEX 11



 Multivariate functions: Embedding Binary is 6 times faster than Extended Binary

### Embedding Formulations: Strong Projected Formulations

#### Polyhedra as MIP Formulations

$$\lambda \in \bigcup_{i=1}^{n} P_{i}, \qquad P_{i} = \left\{\lambda \in \mathbb{R}^{d} : A^{i}\lambda \leq b^{i}\right\}$$

$$Q = \left\{(\lambda, y) \in \mathbb{R}^{d} \times \mathbb{R}^{n} : 1 = \sum_{i=1}^{n} y_{i} \\ y_{i} \geq 0 \\ y \in \mathbb{Z}^{n} \right\}$$

$$\left(\lambda, e^{i}\right) \in Q \quad \Leftrightarrow \quad \lambda \in P_{i}$$

#### **Embedding Formulations for Union of Polyhedra**

- **Projected** MIP formulation of  $\lambda \in \bigcup_{i=1}^n P_i \subseteq \mathbb{R}^V$ :
  - Encoding  $\left\{h^i\right\}_{i=1}^n \subseteq \left\{0,1\right\}^k, \quad h^i \neq h^j$
  - Polyhedron  $Q \subseteq \mathbb{R}^V \times \mathbb{R}^k$ , s.t.

$$(\lambda, h^i) \in Q \quad \Leftrightarrow \quad \lambda \in P_i$$

• **Embedding formulation** = strongest polyhedron:

Cayley 
$$\longrightarrow Q = \operatorname{conv}\left(\bigcup_{i=1}^{n} P_i \times \left\{h^i\right\}\right)$$

For unary encoding:

$$h^i = e^i$$

**Cayley Embedding** 

#### **Embedding Formulations for Union of Polyhedra**

- **Projected** MIP formulation of  $\lambda \in \bigcup_{i=1}^n P_i \subseteq \mathbb{R}^V$ :
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$$(\lambda, h^i) \in Q \quad \Leftrightarrow \quad \lambda \in P_i$$

• **Embedding formulation** = strongest polyhedron:

$$Q = \operatorname{conv}\left(\bigcup_{i=1}^{n} P_i \times \left\{h^i\right\}\right)$$

size(Q) := # of facets of Q (usually function of n)

#### Binary v/s Unary Encodings

$$Q = \text{conv}\left(\bigcup_{i=1}^{n} P_i \times \{h^i\}\right), \ \{h^i\}_{i=1}^{n} \subseteq \{0, 1\}^k$$

- Unary better than Binary?
  - •Formulation contains convex hull through **projection**:

• 
$$\operatorname{Proj}_{\lambda}(Q) = \operatorname{conv}\left(\bigcup_{i=1}^{n} P_{i}\right)$$

• size 
$$(\operatorname{Proj}_{\lambda}(Q)) \leq \binom{\operatorname{size}(Q)}{\operatorname{size}(Q)-k-1}$$

- •Binary encoding has  $k = \log_2 n$ :
  - Size of projection is at most quasipolynomial in size of formulation
- •Unary encoding has k=n:
  - •Size of projection can be exponential in size of formulation

#### Binary v/s Unary Encodings

$$Q = \text{conv}\left(\bigcup_{i=1}^{n} P_i \times \{h^i\}\right), \ \{h^i\}_{i=1}^{n} \subseteq \{0, 1\}^k$$

- Binary better than Unary?
  - •Formulation contains Minkowski sum through sections:
    - For unary encoding

$$\left(\lambda, \frac{1}{n} \sum_{i=1}^{n} e^{i}\right) \in \mathbb{Q} \quad \Leftrightarrow \quad \lambda \in \frac{1}{n} P_{1} + \ldots + \frac{1}{n} P_{n}$$

- •Unary encoding formulation can be large even if convex hull is simple(x)
- •Binary encoding seems to only contain partial sums of  $\log_2 n$  polytopes

#### Simple Case: Combinatorial Part of $\mathcal{V}$ -formulation

• 
$$\Delta^{V} := \left\{ \lambda \in \mathbb{R}_{+}^{V} : \sum_{v \in V} \lambda_{v} = 1 \right\}, \operatorname{ext}(P_{i}) = T_{i} \subseteq V$$

• 
$$P_i = \{ \lambda \in \Delta^V : \lambda_v \le 0 \quad \forall v \notin T_i \}$$

$$\lambda \in \bigcup_{i=1}^{n} P_i \qquad \Leftrightarrow \qquad$$

$$\sum_{v \in V} v \lambda_v = x$$

$$\sum_{v \in V} \lambda_v = 1$$

$$\lambda_v \le \sum_{i:v \in \text{ext}(P_i)} y_i$$

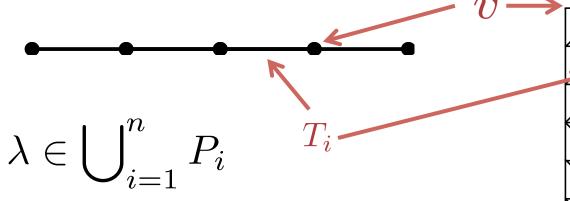
$$\sum_{i=1}^n y_i = 1$$

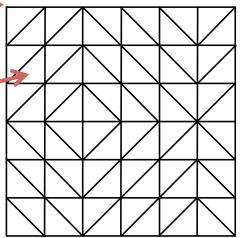
$$y \in \{0, 1\}^n, \quad \lambda \in \mathbb{R}_+^V$$

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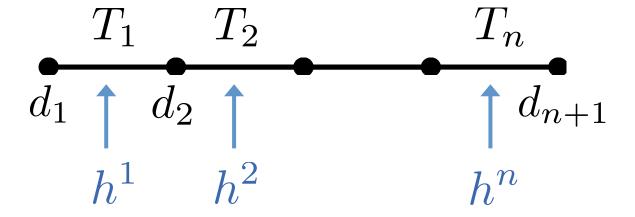




• conv 
$$\left(\bigcup_{i=1}^{n} P_i\right) = \Delta^V$$

#### Message 1: The Devil is in the Detail

Choice of binary encoding is crucial



#### Formulation Size for Univariate case

- Simple facets:  $\lambda_v \geq 0$ 
  - Only sometimes are facets
  - "Zero" computational cost and at most n of them
- All other facets:  $\sum_{v \in V} \alpha_v \lambda_v \leq \sum_{i=1}^k \beta_i y_i$
- Unary encoding (Padberg, Lee and Wilson, early 00's):
  - 2n facets (2n + 2 including bounds)
- Binary encoding with Gray code (V. and Nemhauser, 08, 11):
  - $-\log_2 n \text{ facets } (\leq 2\log_2 n + n \text{ including bounds})$

#### High Binary Complexity? Gray v/s Anti-Gray

• Assumption:  $n=2^k$ 

$$-\left\{h^{i}\right\}_{i=1}^{n} = \left\{0,1\right\}^{k}, \quad H := \left\{h^{i} - h^{i+1}\right\}_{i=1}^{n-1} \subseteq \left\{-1,0,1\right\}^{k}$$

- # facets =twice the # of **linear** hyperplanes spanned by  $oldsymbol{H}$
- Gray code:  $\{h^i h^{i+1}\}_{i=1}^{n-1} \equiv \{e^i\}_{i=1}^k$ 
  - # hyperplanes :  $k = \log_2 n$  , # facets  $\leq 2 \log_2 n + n$
- One kind of Anti-Gray code:  $\left\{h^i-h^{i+1}\right\}_{i=1}^{n-1}$  " $\supseteq$ "  $\left\{-1,1\right\}^k$ 
  - # hyperplanes = # affine hyperplanes spanned by  $\left\{0,1\right\}^{k-1}$
  - Using believed growth rate (e.g. Aichholzer and Auremacher '96):
    - # facets =  $\Theta\left(n^{\log_2 n}\right)$

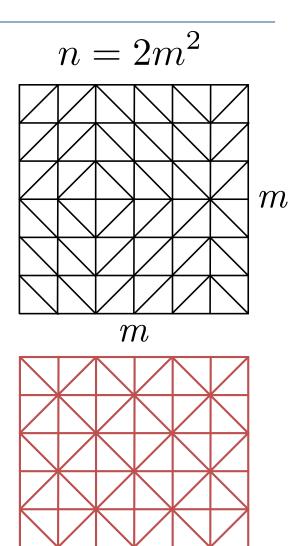
#### Message 2 : Binary Encoding = Smaller Formulation

• Size of unary formulation is at least (Lee and Wilson '01):

$$\binom{2\sqrt{n/2}}{\sqrt{n/2}} + \underbrace{\left(\sqrt{n/2} + 1\right)^2}_{\text{Non-negativity}}$$

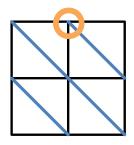
 Size of best binary formulation for union jack triangulation is at most (V. and Nemhauser '08):

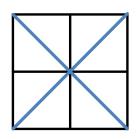
$$4\log_2\sqrt{n/2} + 2 + \underbrace{\left(\sqrt{n/2} + 1\right)^2}_{\text{Non-negativity}}$$



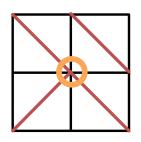
#### Beyond Union Jack: Exploit Redundancy

 Embedding-like formulation for triangulations with "even degree outside the boundary"











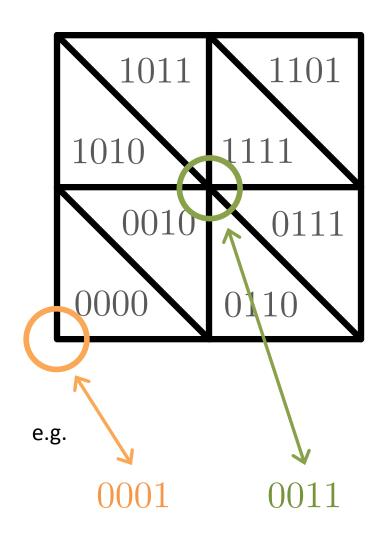
•Formulation size at most two larger than for union jack:

$$4\log_2\sqrt{n/2} + 4 + \left(\sqrt{n/2} + 1\right)^2$$

•Formulation fits **independent branching** framework (V. and Nemhauser '08)

#### Independent Branching = Embedding + Redundancy

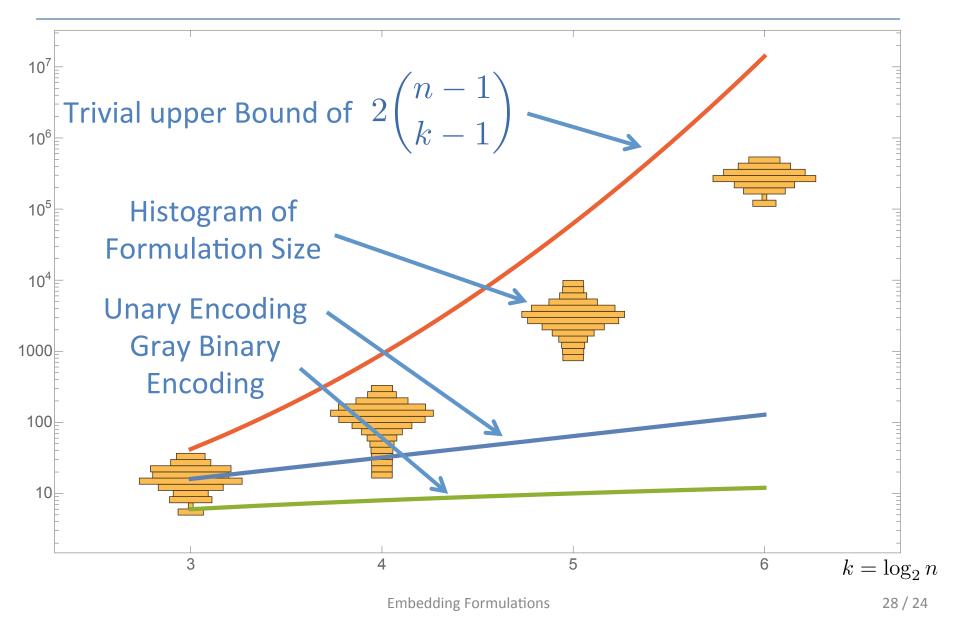
- Triangle ← binary vector
- More vectors than triangles
  - Ind. Branch ≠ Embedding
  - Embedding size is larger (17)
- Ind. Branching solution:
  - Add redundant single-vertex polytopes with remaining 8 binary vectors
- Unary cannot reduce size through redundancy



#### Summary

- Embedding Formulations = Systematic procedure
  - Encoding can significantly affect size
  - Redundancy can help for binary encodings
- Complexity of Union of Polyhedra beyond convex hull
  - Embedding Complexity (Integral Formulation)
  - MIP formulation complexity
- More on encoding properties
  - All gray codes yield the same size, but not combinatorially equivalent polytopes
- Can help discover strong (non-integral) formulations
  - Facility layout problem (Huchette, Dey, V. '14)

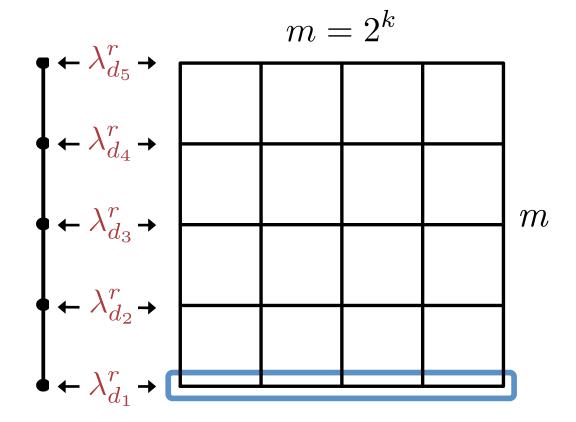
#### Formulation Size for all Binary Encodings



$$\lambda_{(i,j)} \geq 0 \quad i,j \in [m+1] \\ \\ \lambda_{(2,1)} \\ \\ \lambda_{(1,1)} \\ \\ \end{pmatrix} m = 2^k$$

$$\lambda_{(i,j)} \ge 0 \quad i, j \in [m+1]$$

$$\lambda_{d_i}^r = \sum_{j=1}^{m+1} \lambda_{(i,j)}$$



$$(\lambda^r, y^r) \in Q \subseteq \mathbb{R}^m \times \mathbb{R}^k$$
Univariate Gray Code Formulation

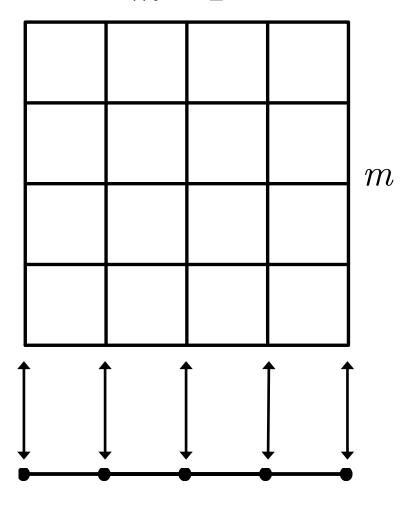
$$\lambda_{(i,j)} \ge 0 \quad i, j \in [m+1]$$

$$\lambda_{d_i}^r = \sum_{j=1}^{m+1} \lambda_{(i,j)}$$

$$\lambda_{d_i}^c = \sum_{i=1}^{m+1} \lambda_{(i,j)}$$

$$(\lambda^r, y^r) \in Q \subseteq \mathbb{R}^m \times \mathbb{R}^k$$
  
 $(\lambda^c, y^c) \in Q \subseteq \mathbb{R}^m \times \mathbb{R}^k$ 

$$m = 2^{k}$$

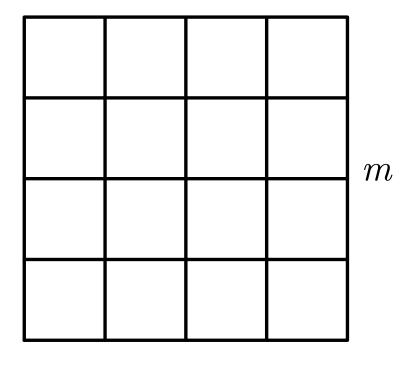


$$\lambda_{(i,j)} \ge 0 \quad i, j \in [m+1]$$

$$\lambda_{d_i}^r = \sum_{j=1}^{m+1} \lambda_{(i,j)}$$

$$\lambda_{d_i}^c = \sum_{i=1}^{m+1} \lambda_{(i,j)}$$

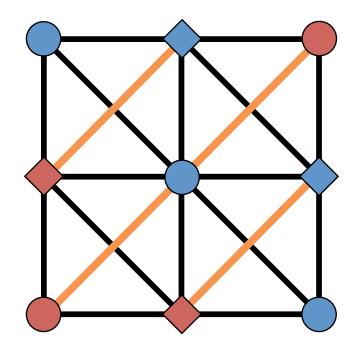
$$m=2^k$$



$$\begin{pmatrix} \boldsymbol{\lambda}^r, y^r \end{pmatrix} \in Q \subseteq \mathbb{R}^m \times \mathbb{R}^k \\
(\boldsymbol{\lambda}^c, y^c) \in Q \subseteq \mathbb{R}^m \times \mathbb{R}^k \end{pmatrix} 4 \log_2 m$$

#### Beyond Union Jack: Part II = Selecting Triangles

- 1. Add "Dual" Triangulation
- 2. Color vertices following diagonal arcs:
  - Keep color for original arcs
  - Change color for dual arcs
- 3. Add binary  $y_1^t$  and constraints:



$$\sum_{(i,j) \text{ colored red}} \lambda_{(i,j)} \leq y_1^t \quad \text{ and } \quad \sum_{(i,j) \text{ colored blue}} \lambda_{(i,j)} \leq 1 - y_1^t$$

4. May need to repeat coloring once more

#### Independent Branching = Embedding + Redundancy

- Triangle ← binary vector
- More vectors than triangles
  - Ind. Branch ≠ Embedding
  - Embedding size is larger (17)
- Ind. Branching solution:
  - Add redundant single-vertex polytopes with remaining 8 binary vectors
- Unary cannot reduce size through redundancy

