

Yibo Lin

**Peking University** 

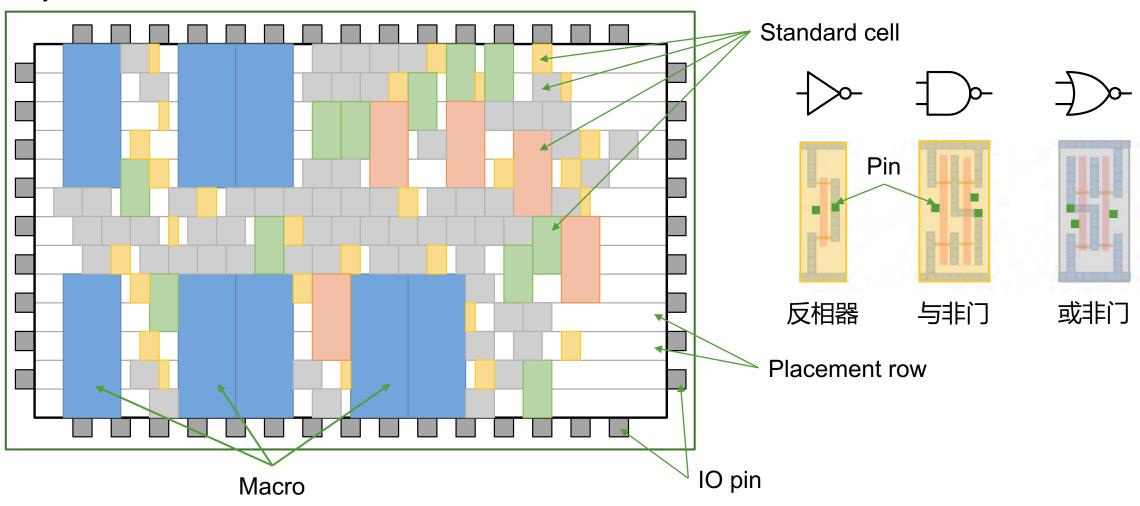
#### Outline

- What is placement
- History of placement algorithms
- Global placement
  - Simulated annealing: DRAGON
  - Partitioning: CAPO
  - Quadratic placement: FastPlace & SimPL
  - Nonlinear placement: NTUplace & ePlace
- Legalization
  - Tetris
  - Row-based algorithms: Abacus, DP, LP, MCF
  - Integer linear programming

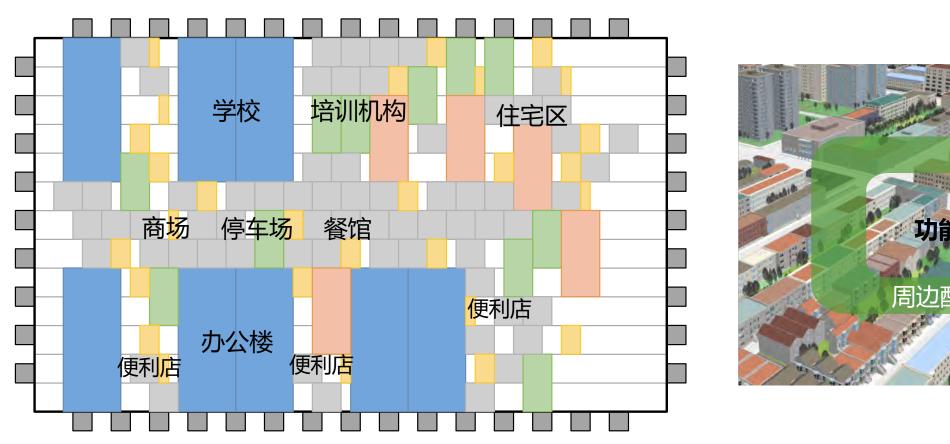
- Detailed placement
  - Global move & swap
  - Independent set matching
  - Local reordering
  - Row-based algorithms: DP, LP, MCF
- Other topics
  - Routability-driven placement
  - Timing-driven placement
  - Macro placement

## What is Placement

#### Layout



# Analog to Urban Planning

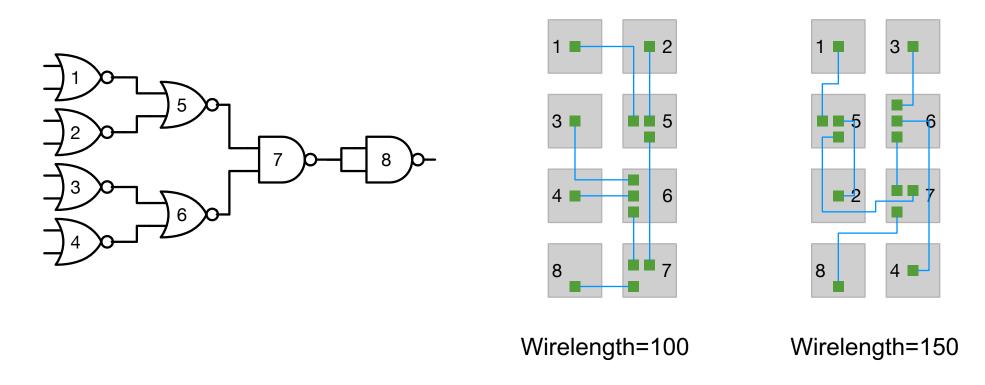




好的城市规划应使功能关联建筑之间的距离尽可能小

#### Metrics for Placement

Wirelength: length of physical wires connecting cells



好的布局应使相连Cell之间的距离尽可能小

#### Problem Formulation for Placement

#### Input

- Blocks (standard cells and macros) B<sub>1</sub>, ... , B<sub>n</sub>
- Shapes and Pin Positions for each block B<sub>i</sub>
- Nets  $N_1$ , ...,  $N_m$

#### Output

- Coordinates (x<sub>i</sub>, y<sub>i</sub>) for block B<sub>i</sub>.
- No overlaps between blocks within a fixed layout area

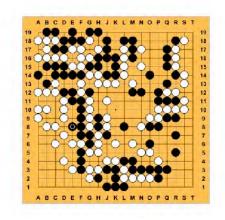
#### Objective

- The total wirelength is minimized
- Other objectives: timing, routability, clock, buffering

### How Difficult Placement is



#states: ~10<sup>123</sup>



#states: ~10<sup>360</sup>

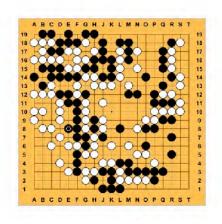
Google AlphaGo Train 40 days using 176 GPUs

#### How Difficult Placement is

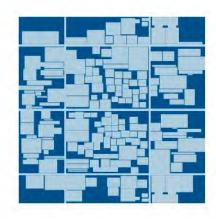
- Huge problem sizes : tens of millions of cells
- Huge solution space : larger than  $1K \times 1K$  grids in a layout



#states: ~10<sup>123</sup>



#states: ~10<sup>360</sup>



#states: >10<sup>100,000</sup>

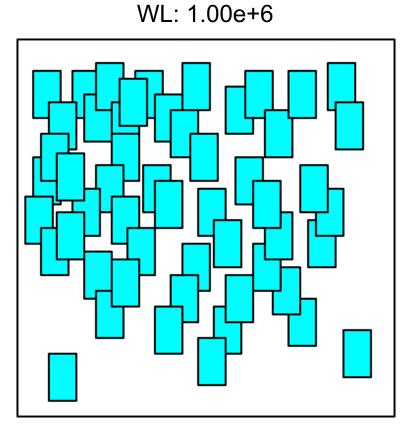
Google AlphaGo Train 40 days using 176 GPUs

#### Good Placement vs Bad Placement

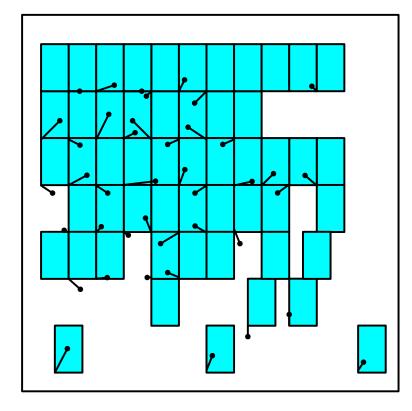
230 cells in FPGA (design e64 in the MCNC benchmark suite)

Random Initial Final Solution **Routing Solution** WL = 5.47e + 4WL = 6.73e + 3

# Typical Placement Flow



WL: 1.05e+6



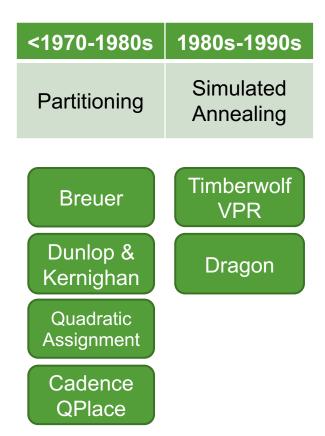
WL: 1.02e+6

Global placement

Legalization

**Detailed Placement** 

# The History of Placement Algorithms



# The History of Placement Algorithms

<1970-1980s	1980s-1990s	1990s-2010s			>2010s	
Partitioning	Simulated Annealing	Min-Cut (Multi-level)	Analytic		Analytic	
			Quadratic	Nonlinear	Quadratic	Nonlinear
Breuer	Timberwolf VPR	FengShui	GORDIAN	APlace	POLAR	ePlace RePlAce
Dunlop & Kernighan	Dragon	Саро	BonnPlace	Naylor Synopsis	SimPL ComPLx	DREAMPlace
Quadratic Assignment		Capo +Rooster	mFar	NTUplace	MAPLE	
Cadence QPlace			Kraftwerk	mPL6		
			FastPlace			
			Warp3			

#### Outline

- What is placement
- History of placement algorithms
- Global placement
  - Simulated annealing: DRAGON
  - Partitioning: CAPO
  - Quadratic placement: FastPlace & SimPL
  - Nonlinear placement: NTUplace & ePlace
- Legalization
  - Tetris
  - Row-based algorithms: Abacus, DP, LP, MCF
  - Integer linear programming

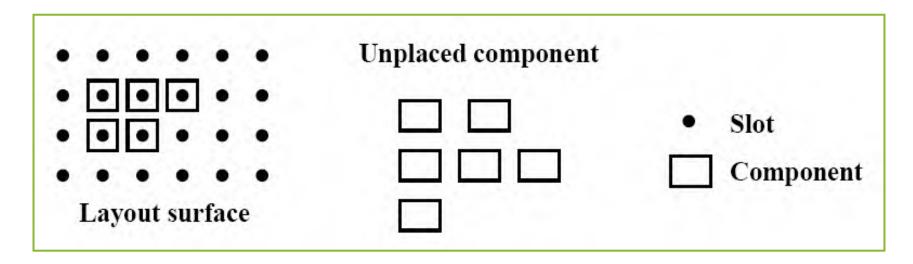
- Detailed placement
  - Global move & swap
  - Independent set matching
  - Local reordering
  - Row-based algorithms: DP, LP, MCF
- Other topics
  - Macro placement
  - Flip-Flop placement
  - Routability-driven placement
  - Timing-driven placement

# Simulated Annealing

- Timberwolf package [JSSC-85, DAC-86]
  - Sechen, Carl, and Alberto Sangiovanni-Vincentelli. "The TimberWolf placement and routing package." *IEEE Journal of Solid-State Circuits* 20.2 (1985): 510-522.
  - Sechen, Carl, and Alberto Sangiovanni-Vincentelli. "TimberWolf3. 2: A new standard cell placement and global routing package." 23rd ACM/IEEE Design Automation Conference. IEEE, 1986.
- Dragon [ICCAD-00]
  - Yang, Xiaojian, and Majid Sarrafzadeh. "Dragon2000: Standard-cell placement tool for large industry circuits." IEEE/ACM International Conference on Computer Aided Design. ICCAD-2000. IEEE/ACM Digest of Technical Papers (Cat. No. 00CH37140). IEEE, 2000.

#### A Down-to-the-Earth Method

- Select unplaced components and place them in slots
- SELECT: choose the unplaced component that is most strongly connected to all (or any single) of the placed component
- PLACE: place the selected component at a slot such that a certain "cost" of the partial placement is minimized
- Simple and fast: ideal for initial placement



#### TimberWolf

#### Stage 1

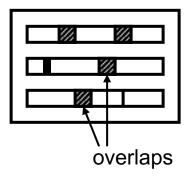
- Modules are moved between different rows as well as within the same row
- Module overlaps are allowed
- When the temperature is reduced below a certain value, stage 2 begins

#### Stage 2

- Remove overlaps
- Annealing process continues, but only interchanges adjacent modules within the same row

# Solution Space

■ All possible arrangements of modules into rows possibly with overlaps



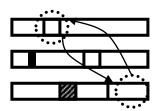
# **Neighboring Solutions**

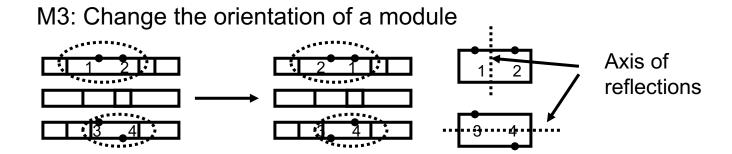
#### Three types of moves:

M1: Displace a module to a new location



M2: Interchange two modules





#### **Move Selection**

- Timber wolf first try to select a move betwee M1 and M2
  - Prob(M1) = 4/5
  - Prob(M2) = 1/5

M1: Displacement

M2: Interchange

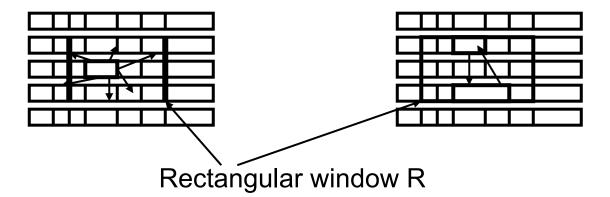
M3: Reflection

- If a move of type M1 is chosen (for certain module) and it is rejected, then a move of type M3 (for the same module) will be chosen with probability 1/10
- Restriction on:
  - How far a module can be displaced
  - What pairs of modules can be interchanged

#### Move Restriction

#### Range Limiter

- At the beginning, R is very large, big enough to contain the whole chip
- Window size shrinks slowly as the temperature decreases. In fact, height and width of  $R \propto \log(T)$
- Stage 2 begins when window size are so small that no inter-row modules interchanges are possible



#### **Cost Function**

$$\Psi = C_1 + C_2 + C_3$$

$$\square \qquad \square \qquad \square$$

$$C_1 : \sum_{i} (\alpha_i w_i + \beta_i h_i)$$

$$\square \qquad \square \qquad \square$$

$$W_i$$

 $\alpha_{\text{i}},\,\beta_{\text{i}}$  are horizontal and vertical weights, respectively

 $\alpha_i$  =1,  $\beta_i$  =1  $\Rightarrow$ 1/2 •perimeter of bounding box

- $\mbox{\$}$  Critical nets: Increase both  $\alpha_i$  and  $\beta_i$
- **Preferred metal layer routing: if vertical wirings** are "cheaper" than horizontal wirings, we can use smaller vertical weights, i.e.  $\beta_i < \alpha_i$

# Cost Function (Cont'd)

C<sub>2</sub>: Penalty function for module overlaps

O(i,j) = amount of overlaps in the X-dimension between modules i and j

$$C_2 = \sum_{i \neq j} (O(i,j) + \alpha)^2$$

 $\alpha$  — offset parameter to ensure  $C_2 \rightarrow 0$  when  $T \rightarrow 0$ 

C<sub>3</sub>: Penalty function that controls the row lengths

Desired row length = d(r)

l(r) = sum of the widths of the modules in row r

$$C_3 = \sum_r \beta |l(r) - d(r)|$$

## Annealing Schedule

- $T_k = r(k) \cdot T_{k-1}$  k= 1, 2, 3, ....
- r(k) increase from 0.8 to max value 0.94 and then decrease to 0.1
- At each temperature, a total number of K•n attempts is made
- n= number of modules
- K= user specified constant

## Dragon2000

- Simulated annealing based
  - 1.9x faster than iTools 1.4.0 (commerical version of TimberWolf)
  - Comparable wirelength to iTools (i.e., very good)
  - Performs better for larger circuits
  - Still very slow compared with than other approaches
  - Also shown to have good routability
- Top-down hierarchical approach
  - hMetis to recursively quadrisect into 4<sup>h</sup> bins at level h
  - Swapping of bins at each level by SA to minimize WL
  - Terminates when each bin contains < 7 cells</li>
  - Then swap single cells locally to further minimize WL
- Detailed placement is done by greedy algorithm

#### Partition based Methods

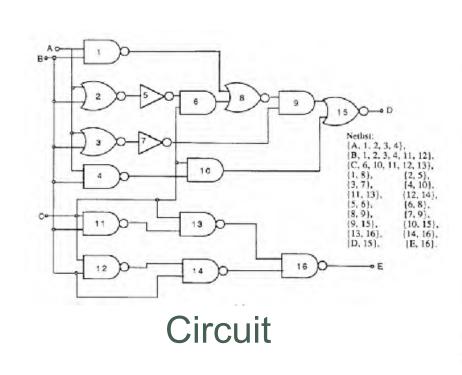
- Partitioning methods (already covered in previous lectures)
  - -FM
  - Multilevel techniques, e.g., hMetis
- Two academic open source placement tools
  - Capo (UCLA/UCSD/Michigan): multilevel FM
  - Feng-shui (SUNY Binghamton): use hMetis
- Pros and cons
  - Fast
  - Not stable

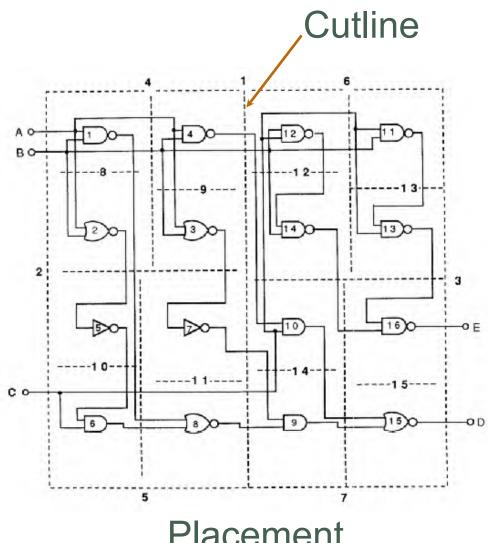
## Partitioning-based Approach

- Try to group closely connected modules together.
- Repetitively divide a circuit into sub-circuits such that the cut value is minimized.
- Also, the placement region is partitioned (by <u>cutlines</u>) accordingly.
- Each sub-circuit is assigned to one partition of the placement region.

Note: Also called min-cut placement approach.

# An Example





**Placement** 

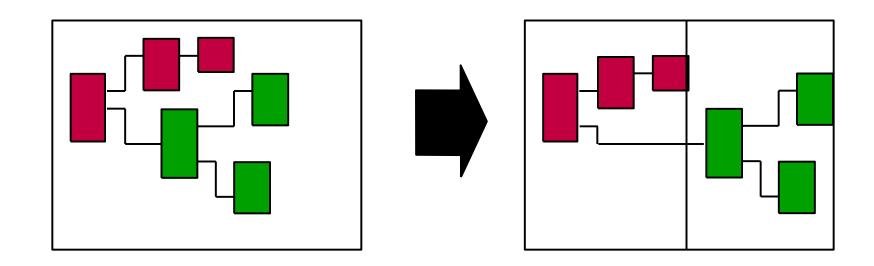
#### **Variations**

- There are many variations in the partitioning-based approach. They are different in:
  - The objective function used.
  - The partitioning algorithm used.
  - The selection of cutlines.

# Partitioning

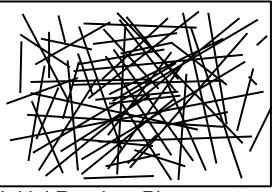
#### Objective:

 Given a set of interconnected blocks, produce two sets that are of equal size, and such that the number of nets connecting the two sets is minimized.

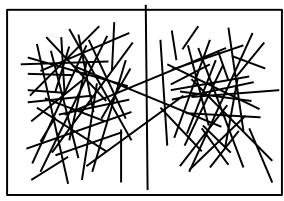


# FM Partitioning

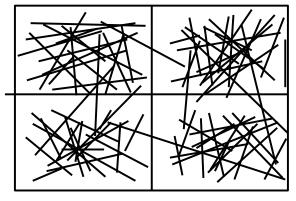
```
list_of_sets = entire_chip;
while(any_set_has_2_or_more_objects(list_of_sets))
{
    for_each_set_in(list_of_sets)
    {
        partition_it();
    }
    /* each time through this loop the number of */
    /* sets in the list doubles. */
}
```



**Initial Random Placement** 



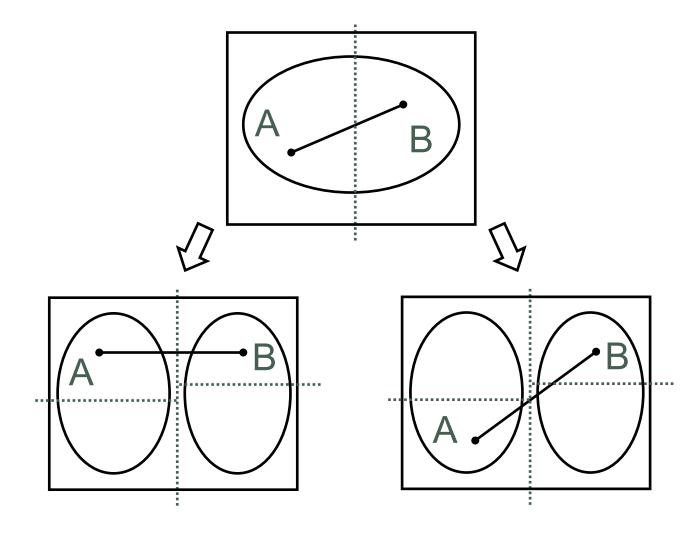
After Cut 1



After Cut 2

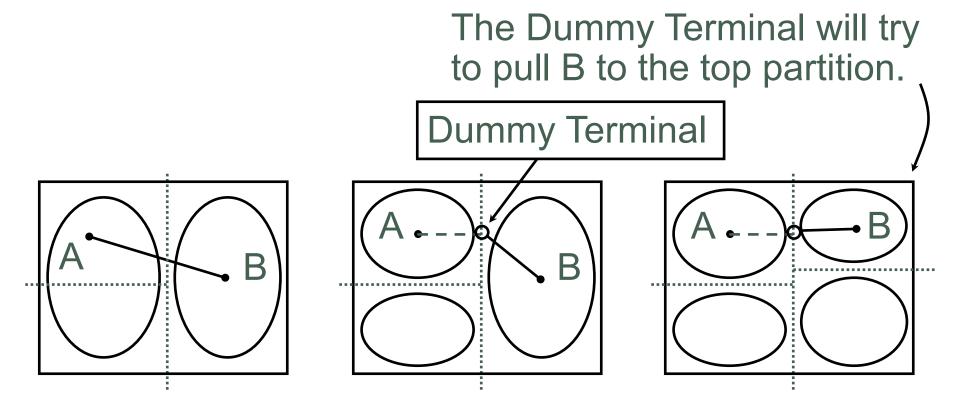
# Problem of Partitioning Subcircuits

Cost of these 2 partitionings are not the same.

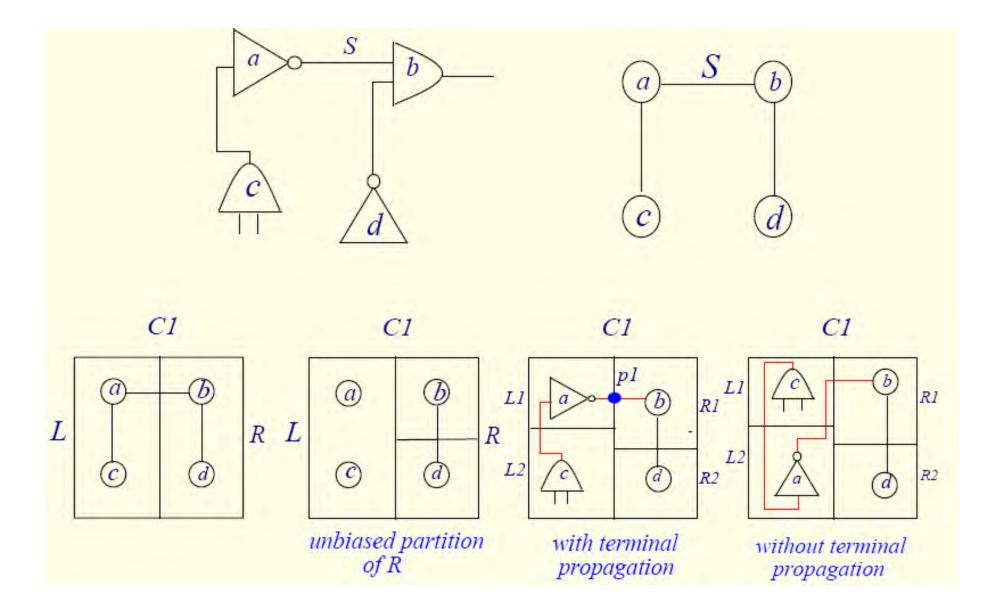


## **Terminal Propagation**

- Need to consider nets connecting to external terminals or other modules as well.
- Do partitioning in a breath-first manner (i.e., finish all higher-level partitioning first).



# **Terminal Propagation**



# Capo: Can Recursive Bisection Alone Produce Routable Placement

- Standard cell placement, Fixed-die context
- Pure recursive bisectioning placer
  - Several minor techniques to produce good bisections
- Produce good results mainly because:
  - Improvement in mincut bisection using multi-level idea in the past few years
  - Pay attention to details in implementation
- Implementation with good interface (LEF/DEF and GSRC bookshelf) available on web

## Capo Approach

- Recursive bisection framework:
  - Multi-level FM for instances with >200 cells
  - Flat FM for instances with 35-200 cells
  - Branch-and-bound for instances with <35 cells</li>
- Careful handling partitioning tolerance:
  - Uncorking: Prevent large cells from blocking smaller cells to move
  - Repartitioning: Several FM calls with decreasing tolerance
  - Block splitting heuristics: Higher tolerance for vertical cut
  - Hierarchical tolerance computation: Instance with more whitespace can have a bigger partitioning tolerance

## Summary for Partition Based Placement

#### Pros

- Very fast
- Great quality
- Scales nearly linearly with problem size

#### Cons

- Non-trivial to implement
- Very directed algorithm, but this limits the ability to deal with miscellaneous constraints
- Not stable (if there is minor change)

## Summary for Partition Based Placement

- Improvement in mincut partitioning are conducive to better wirelength and congestion
- Routable placements can be produced in most cases without explicit congestion management
  - Explicit congestion control may still be useful in some cases
- Better weighted wirelength often implies better routed wirelength, but not always

## The History of Placement Algorithms

<1970-1980s	1980s-1990s	1990s-2010s			>2010s	
Partitioning	Simulated	Min-Cut	Analytic		Analytic	
r artitioning	Annealing	(Multi-level)	Quadratic	Nonlinear	Quadratic	Nonlinear
Breuer	Timberwolf VPR	FengShui	GORDIAN	APlace	POLAR	ePlace RePlAce
Dunlop & Kernighan	Dragon	Саро	BonnPlace	Naylor Synopsis	SimPL ComPLx	DREAMPlace
Quadratic Assignment		Capo +Rooster	mFar	NTUplace	MAPLE	
Cadence QPlace			Kraftwerk	mPL6		
Low quality	Low efficiency	/	FastPlace			
			Warp3			

## Quadratic Placement

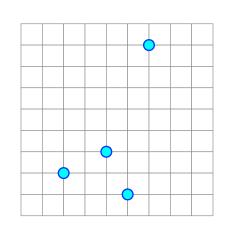
- Viswanathan, Natarajan, and CC-N. Chu. "<u>FastPlace: Efficient analytical placement</u> using cell shifting, iterative local refinement, and a hybrid net model." IEEE TCAD 2005
- ► Kim, Myung-Chul, Dong-Jin Lee, and Igor L. Markov. "SimPL: An effective placement algorithm." IEEE TCAD 2011
- Lin, Tao, et al. "POLAR: A high performance mixed-size wirelengh-driven placer with density constraints." IEEE TCAD 2015.

## Quadratic Placement

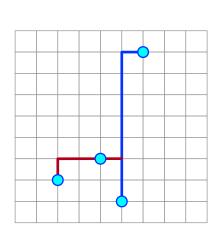
- Placement problem
  - Task: determine the locations of blocks
  - Objective: minimize wirelength
  - Constraints : no overlap between blocks
- Iterative optimization



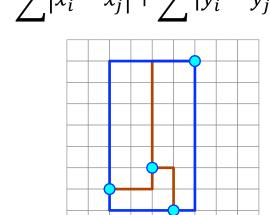
- How to compute wirelength
  - Consider how a net is routed



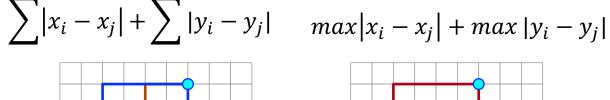


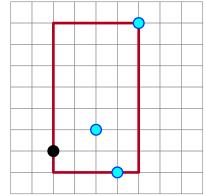


Optimal: min. Steiner tree



Clique model

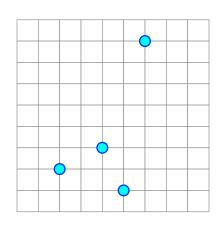




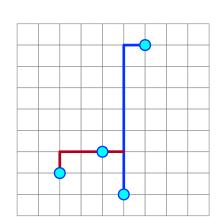
**HPWL** 

Manhattan-distance model

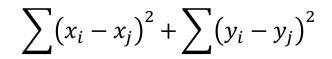
- How to compute wirelength
  - Consider how a net is routed

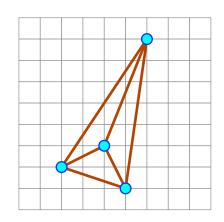


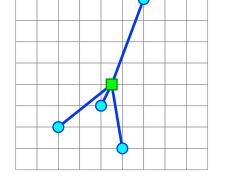
4-pin net



Optimal: min. Steiner tree







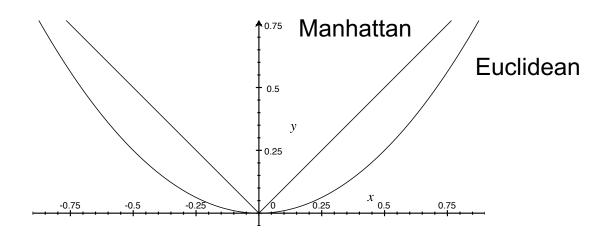
Clique model

Star model

Euclidean-distance model

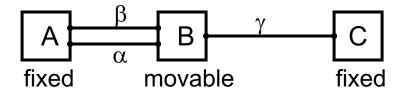
- How to compute wirelength
  - Consider how a net is routed

		Pessin	nistic	Optimistic	
Model	Min. Steiner Tree	Clique Model		HPWL	Star Model
Distance	Manhattan	Manhattan	Euclidean	Manhattan	Euclidean
Accuracy	****	*	*	****	***
Smoothness	*	**	****	**	****

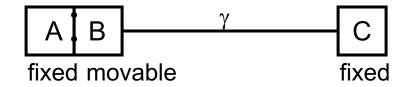


# Another Perspective – Linear v.s. Quadratic Objective Function

Differences between linear and quadratic objective function



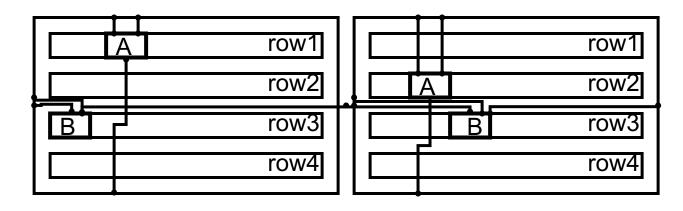
a) Quadratic objective function



b) Linear objective function

# Another Perspective – Linear v.s. Quadratic Objective Function

 Quadratic objective function tends to make very long net shorter than linear objective function does, and let short nets become slightly longer



Linear objective function

Quadratic objective function

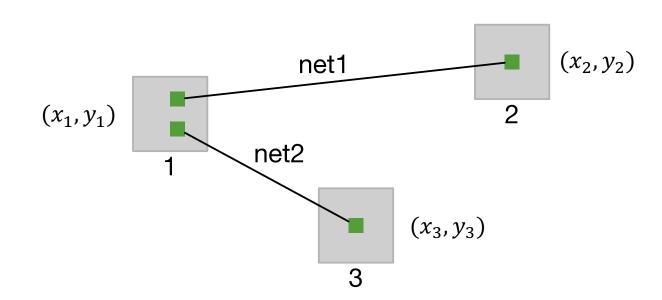
#### Compute wirelength for **net1**

$$WL_1 = (x_1 - x_2)^2 + (y_1 - y_2)^2$$

Compute wirelength for net2

$$WL_2 = (x_1 - x_3)^2 + (y_1 - y_3)^2$$





Compute wirelength for net1

$$WL_1 = (x_1 - x_2)^2 + (y_1 - y_2)^2$$

Compute wirelength for net2

$$WL_2 = (x_1 - x_3)^2 + (y_1 - y_3)^2$$



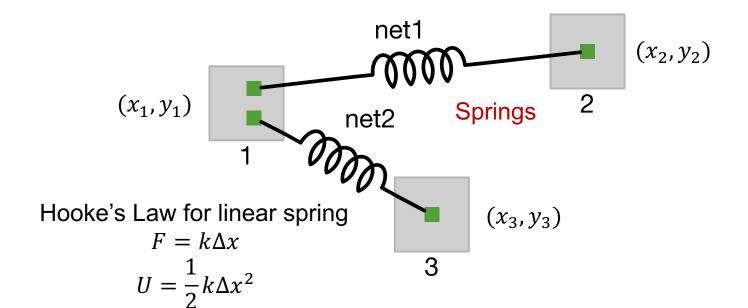
Physical intuition?

How to solve?

### **Quadratic Programming (QP)**

$$\min \frac{1}{2}x^T A x - b^T x$$

Gradient of 
$$x$$
  
 $Ax - b = 0$ 



#### Compute wirelength for net1

$$WL_1 = (x_1 - x_2)^2 + (y_1 - y_2)^2$$

Compute wirelength for net2

$$WL_2 = (x_1 - x_3)^2 + (y_1 - y_3)^2$$



# $(x_1, y_1)$ 1 $(x_2, y_2)$ 2 $(x_3, y_3)$ 3

### Any problem?

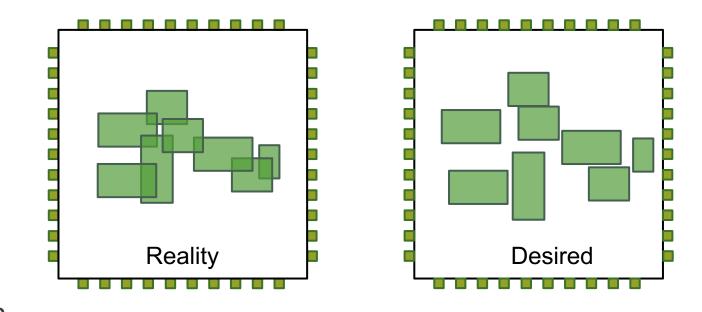
#### Optimal solution

$$x_1 = x_2 = x_3$$

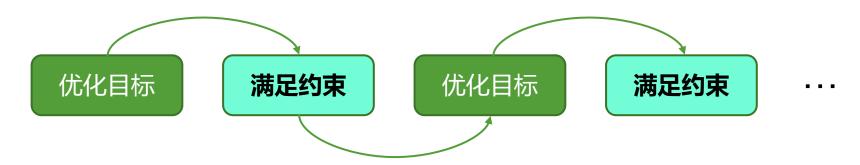
$$y_1 = y_2 = y_3$$

All blocks overlap!

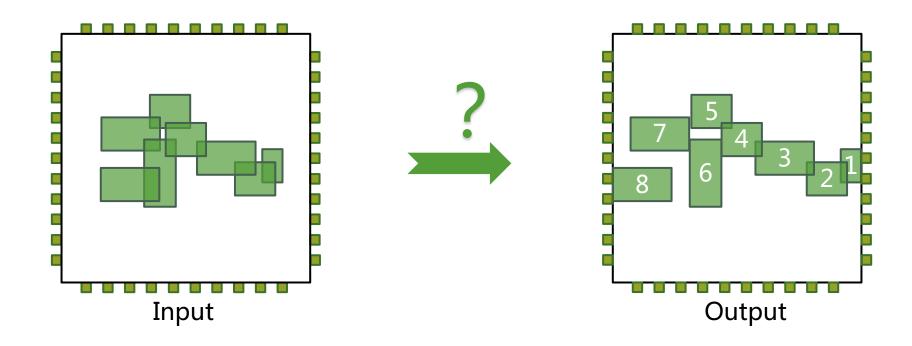
Optimizing the objective results in overlaps



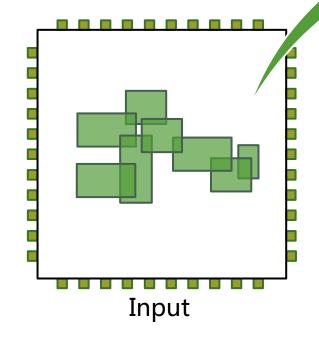
Iterative optimization



- Rough Legalization
  - Consider the horizontal direction
  - Design a mapping/function

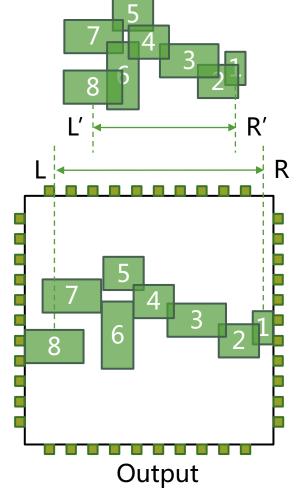


- Rough Legalization
  - Consider the horizontal direction
  - Design a mapping/function

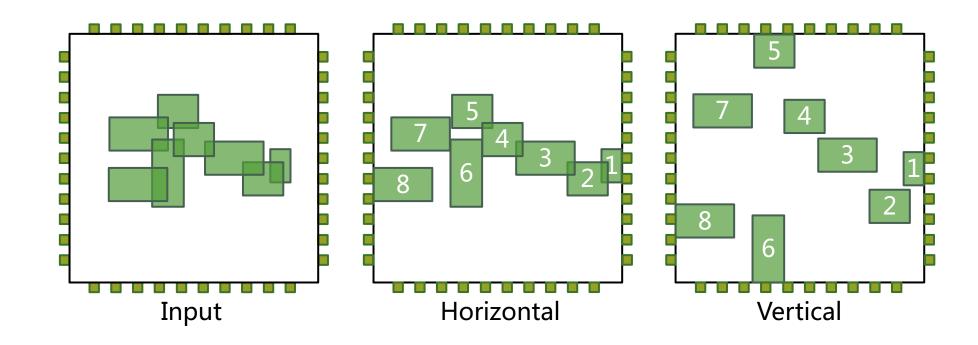


Linear mapping

$$x_i = \frac{R' - x_i'}{R' - L'} \times (R - L)$$

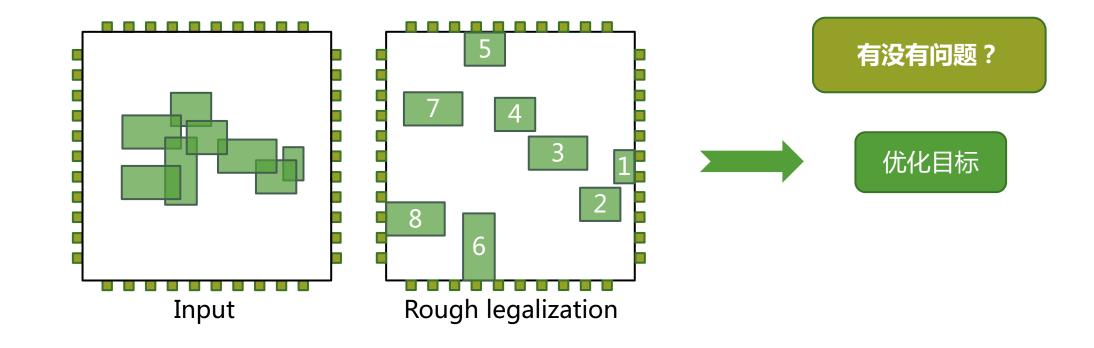


- Rough Legalization
  - Do it for horizontal and vertical directions



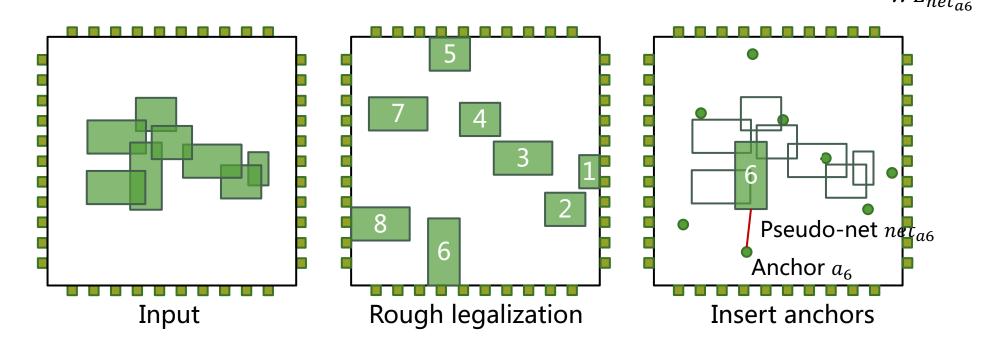
Rough Legalization

Original obj. 
$$min....+\sum (x_6-x_j)^2+...$$

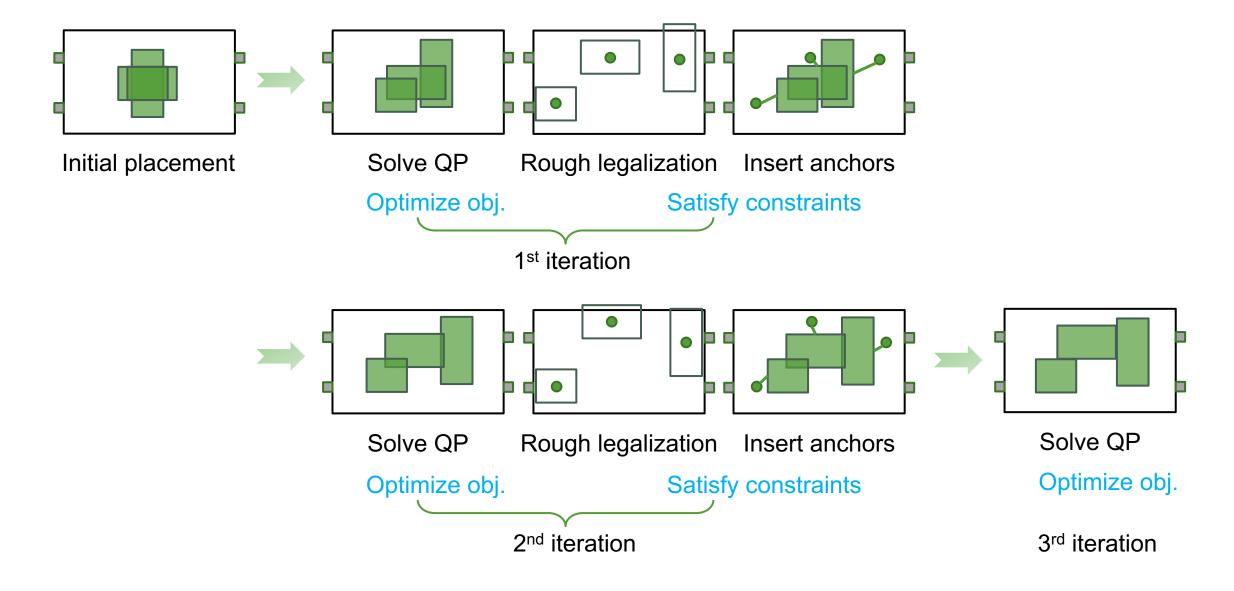


- Rough Legalization
  - Leverage anchors

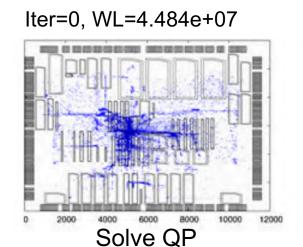
Original obj. 
$$min. \cdots + \sum (x_6 - x_j)^2 + \cdots$$
 Anchor loc. Obj. with anchors  $min. \cdots + \sum (x_6 - x_j)^2 + w_6(x_6 - x_{a_6})^2 + \cdots$   $WL_{net_{a_6}}$ 



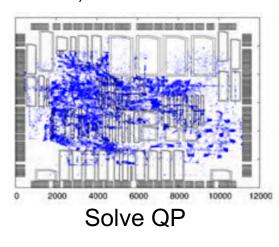
## Quadratic Placement – Overall Optimization Flow



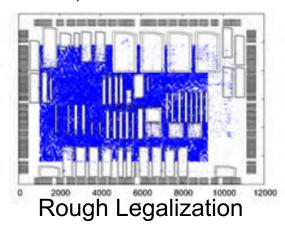
## Quadratic Placement – 211K-Cell Example



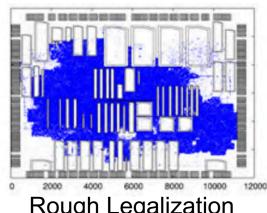
Iter=10, WL=6.496e+07



Iter=1, WL=1.501e+08

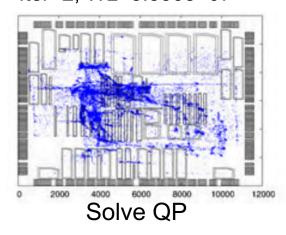


Iter=11, WL=9.208e+07

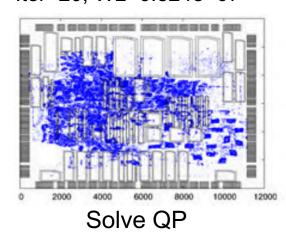


Rough Legalization

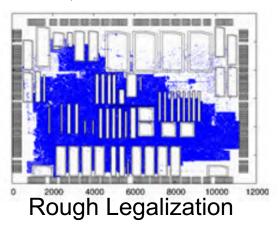
Iter=2, WL=5.556e+07



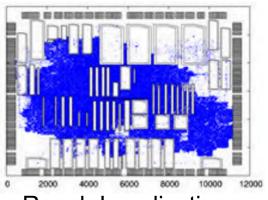
Iter=20, WL=6.824e+07



Iter=3, WL=1.173e+08



Iter=21, WL=8.572e+07

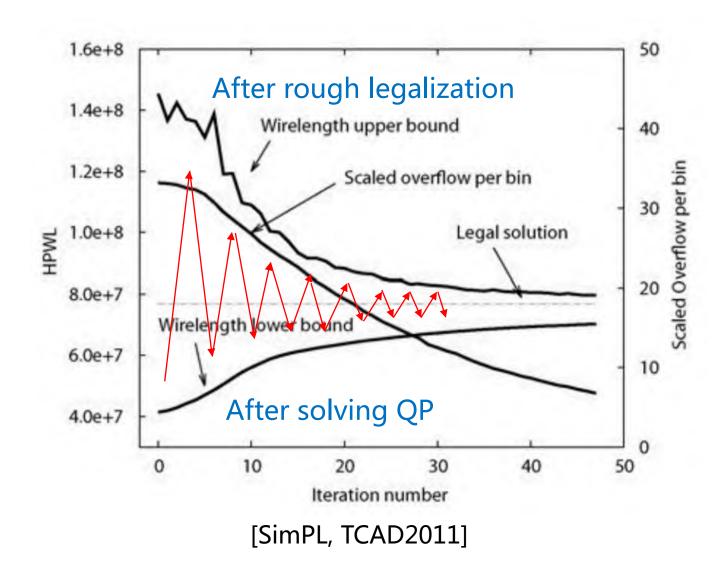


Rough Legalization

## Quadratic Placement – 211K-Cell Example

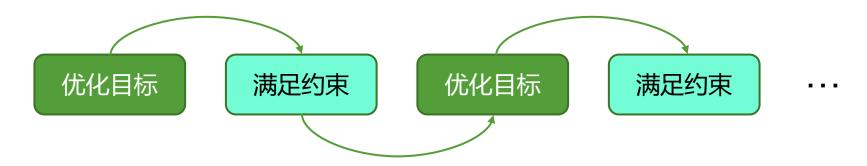
Measuring the density distribution

$$overflow = \sum_{i \in all \ bins} \max(D_i - 1, 0)$$



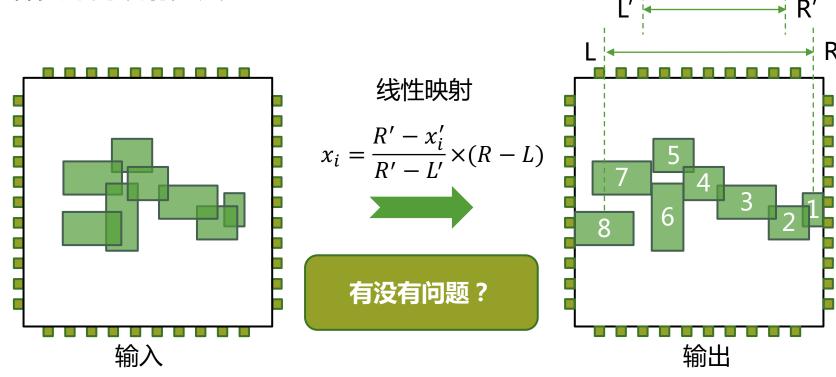
## Quadratic Placement – Summary

- Iterative optimization
- Wirelength models : HPWL, clique model, star model
- Rough legalization



## 课后思考

- 去除重叠 (Rough Legalization)
  - 在什么情况下线性映射效果会差
  - 设计一种更好的映射方法



## Quadratic Placement – Gordian

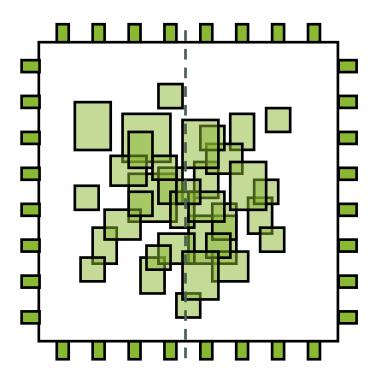
- Global optimization
  - Solves a sequence of quadratic programming problems

$$-\min_{x,y} \sum w_i \left( (x_i - x_j)^2 + (y_i - y_j)^2 \right)$$

- Partitioning
  - Enforces the non-overlap constraints

## Partitioning

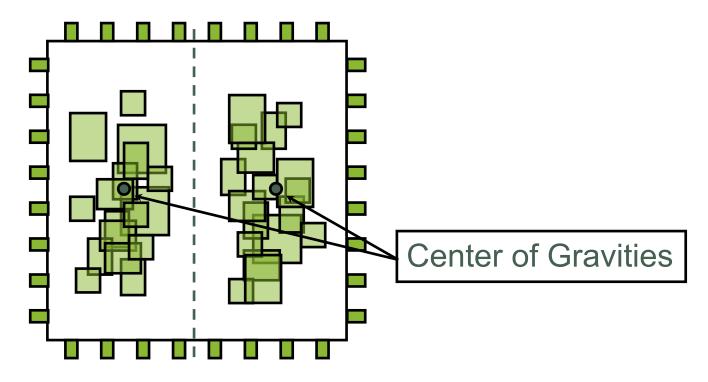
Find a good cut direction and position.



Improve the cut value using FM.

## Applying the Idea Recursively

■ Before every level of partitioning, do the Global Optimization again with additional constraints that the center of gravities should be in the center of regions.



Always solve a single QP (i.e., global).

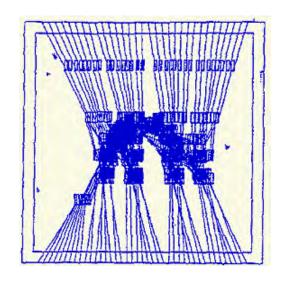
## Center of Gravity Constraints

## The center of gravity constraints

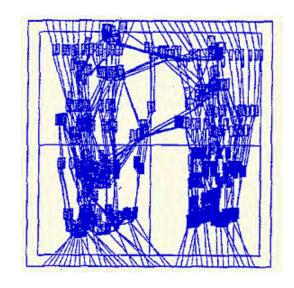
- At level *l*, chip is divided into  $q \leq 2^{l}$  regions
- For region p, the center coordinates:  $(u_p, v_p)$
- $M_p$ : set of modules in region p
- Matrix from for all regions

constraint: 
$$\sum_{u \in M_p} F_u x_u = u_p \sum_{u \in M_p} F_u$$
$$A^l X = u^l, a_{iu} = \begin{cases} F_i / \sum_{i \in M_p} F_i & \text{if } i \in M_p \\ 0 & \text{otherwise} \end{cases}$$

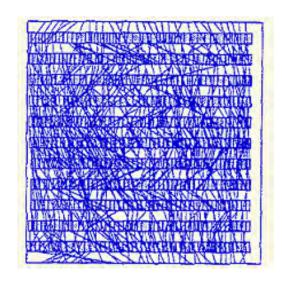
## **Process of Gordian**



(a) Global placement with 1 region



(b) Global placement with 4 region



(c) Final placements

## Force-Directed Placement – Kraftwerk

Iteratively solve the quadratic formulation:

Min 
$$f(p) = \frac{1}{2} p^T C p + d^T p + const$$
  
 $\Rightarrow C p + d = 0$  // equivalent to spring force // equilibrium

Spread cells by additional forces:

$$Cp + d + f = 0$$

## Requirements to the Additional Force

- ► For a given placement, the additional force working on a cell depends only on the coordinates of the cells
- Regions with higher density are the sources of the forces. Regions with lower density are the sinks
- The forces do not form circles
- In infinity, the force should be zero
- Density-based force proposed
  - Push cells away from dense region to sparse region

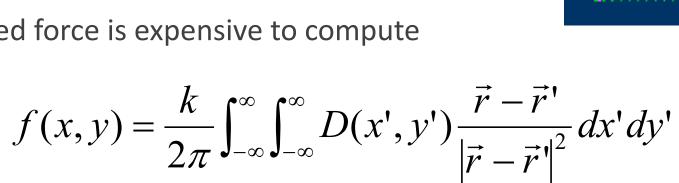
$$f(x,y) = \frac{k}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} D(x',y') \frac{\vec{r} - \vec{r}'}{|\vec{r} - \vec{r}'|^2} dx' dy'$$
where  $\vec{r} = (x,y)$  and  $\vec{r}' = (x',y')$ 

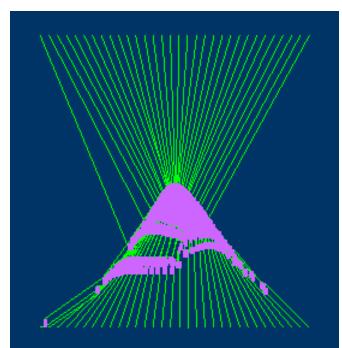
## Some Potential Problems of Kraftwerk

- Convergence is difficult to control
  - Large K → oscillation
  - Small K → slow convergence

Example: Layout of a multiplier







## The History of Placement Algorithms

<1970-1980s	1980s-1990s	1990s-2010s			>2010s	
Partitioning	Simulated	Min-Cut	Analytic		Analytic	
Farmoning	Annealing	(Multi-level)	Quadratic	Nonlinear	Quadratic	Nonlinear
Breuer	Timberwolf VPR	FengShui	GORDIAN	APlace	POLAR	ePlace RePlAce
Dunlop & Kernighan	Dragon	Capo	BonnPlace	Naylor Synopsis	SimPL ComPLx	DREAMPlace
Quadratic Assignment		Capo +Rooster	mFar	NTUplace	MAPLE	
Cadence QPlace			Kraftwerk	mPL6		
Low quality Low efficiency		FastPlace				
			Warp3			

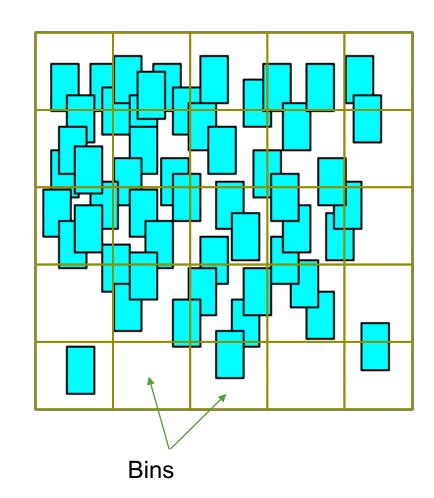
## Nonlinear Placement

- Mathematical formulation
  - $-d_i$  denotes the density of bin i

$$\min_{x,y} WL(x,y),$$
s.t.  $d_b(x,y) \le t_d, \forall b \in Bins$ 

- Nonlinear placement objective
  - Lagrangian relaxation

$$\min_{x,y} WL(x,y) + \lambda D(x,y)$$
Wirelength Density

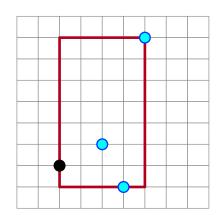


## Wirelength Smoothing

- $\blacktriangleright$   $WL(x,y) = \sum_{e \in E} WL_e(x,y)$
- - Equivalently  $\left(\max_{i} x_{i} \min_{i} x_{i}\right) + \left(\max_{i} y_{i} \min_{i} y_{i}\right)$
- Log-sum-exp (LSE)

$$-LSE(\mathbf{x}; \gamma) = \gamma \ln \sum_{i} e^{\frac{x_{i}}{\gamma}}$$

- $-\max\{x_1,\cdots,x_n\} < LSE(x;\gamma) \le \max\{x_1,\cdots,x_n\} + \gamma \ln(n)$
- $-LSE(\mathbf{x}; \gamma) \approx \max\{x_1, \cdots, x_n\}$
- $-LSE(x; -\gamma) \approx \min\{x_1, \dots, x_n\}$
- $-WL_e(\mathbf{x}, \mathbf{y}; \gamma) = \gamma \left(\ln \sum_{v_i \in e} e^{\frac{x_i}{\gamma}} + \ln \sum_{v_i \in e} e^{-\frac{x_i}{\gamma}} + \ln \sum_{v_i \in e} e^{\frac{y_i}{\gamma}} + \ln \sum_{v_i \in e} e^{-\frac{y_i}{\gamma}}\right)$



## Wirelength Smoothing

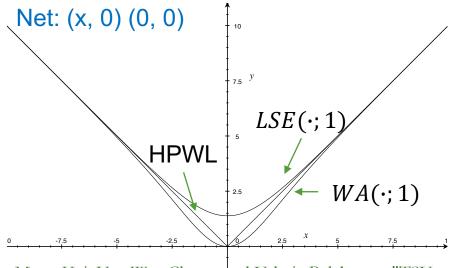
Weighted average (WA)

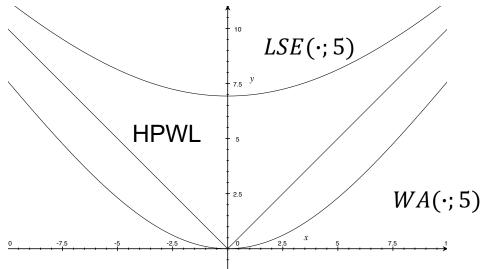
$$-WL_{e}(\mathbf{x},\mathbf{y};\gamma) = \left(\frac{\sum_{v_{i} \in e} x_{i} e^{x_{i}/\gamma}}{\sum_{v_{i} \in e} e^{x_{i}/\gamma}} - \frac{\sum_{v_{i} \in e} x_{i} e^{-x_{i}/\gamma}}{\sum_{v_{i} \in e} e^{-x_{i}/\gamma}}\right) + \left(\frac{\sum_{v_{i} \in e} y_{i} e^{y_{i}/\gamma}}{\sum_{v_{i} \in e} e^{y_{i}/\gamma}} - \frac{\sum_{v_{i} \in e} y_{i} e^{-y_{i}/\gamma}}{\sum_{v_{i} \in e} e^{-y_{i}/\gamma}}\right)$$

 $\blacksquare$  Larger  $\gamma \rightarrow$  smoother, but less accurate

More recent work DAC2019

**BiG: Bivariant smoothing** 





Hsu, Meng-Kai, Yao-Wen Chang, and Valeriy Balabanov. "TSV-aware analytical placement for 3D IC designs." Proceedings of DAC 2011.

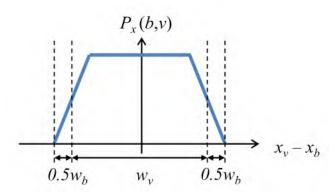
Sun, Fan-Keng, and Yao-Wen Chang. "BiG: A bivariate gradient-based wirelength model for analytical circuit placement." Proceedings of DAC 2019.

## Nonlinear Placement – NTUplace

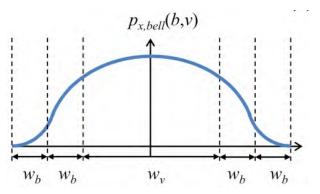
- Chen, Tung-Chieh, et al. "NTUplace: A ratio partitioning based placement algorithm for large-scale mixed-size designs." ISPD 2005
- Chen, Tung-Chieh, et al. "NTUplace3: An analytical placer for large-scale mixed-size designs with preplaced blocks and density constraints." IEEE TCAD 2008.
- ► Hsu, Meng-Kai, et al. "NTUplace4h: A novel routability-driven placement algorithm for hierarchical mixed-size circuit designs." IEEE TCAD 2014
- Huang, Chau-Chin, et al. "NTUplace4dr: a detailed-routing-driven placer for mixed-size circuit designs with technology and region constraints." IEEE TCAD 2017

## **Density Penalty**

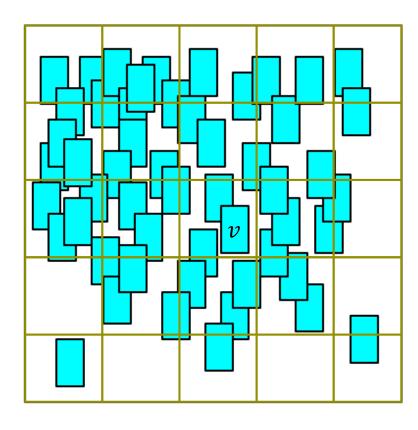
- Potential function for standard cells
  - $-P_{x}(b,v)$  and  $P_{y}(b,v)$  are the overlap functions between bin b and cell v
  - $-D_b(\mathbf{x},\mathbf{y}) = \sum_{v \in V} P_{x}(b,v) P_{y}(b,v)$



Non-smooth Non-convex



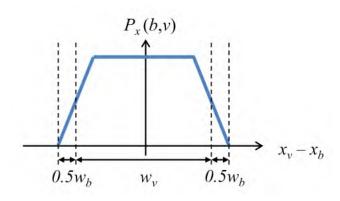
Bell-shape smoothing



### **Density Penalty**

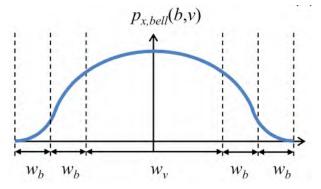
- Potential function for standard cells
  - $-P_{x}(b,v)$  and  $P_{y}(b,v)$  are the overlap functions between bin b and cell v

$$-D_b(\mathbf{x},\mathbf{y}) = \sum_{v \in V} P_{x}(b,v) P_{y}(b,v)$$

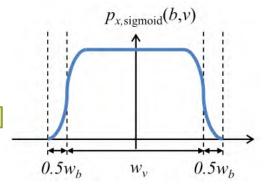


Non-smooth Non-convex

Sigmoid smoothing [NTUplace4h, TCAD2014]



Bell-shape smoothing



If 
$$d_x \leq \frac{w_v}{2} + w_b$$
, 
$$\widehat{P_x}(b,v) = 1 - ad_x^2$$
 If  $\frac{w_v}{2} + w_b \leq d_x \leq \frac{w_v}{2} + 2w_b$ , 
$$\widehat{P_x}(b,v) = b\left(d_x - \frac{w_v}{2} - 2w_b\right)^2$$
 Otherwise, 
$$\widehat{P_x}(b,v) = 0$$

### **Density Penalty**

- Potential function for standard cells
  - Smoothed potential function

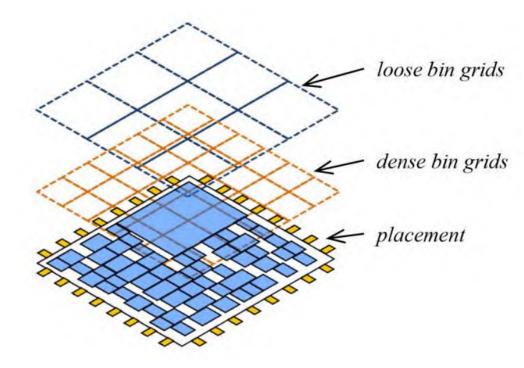
$$-\widehat{D_b}(\mathbf{x},\mathbf{y}) = \sum_{v \in V} \widehat{P_x}(b,v)\widehat{P_y}(b,v)$$

 $= \min_{x,y} WL(x,y) + \lambda D(x,y)$ 



$$\lambda \sum_{b} \left(\widehat{D_b}(\boldsymbol{x}, \boldsymbol{y}) - t_d\right)^2$$

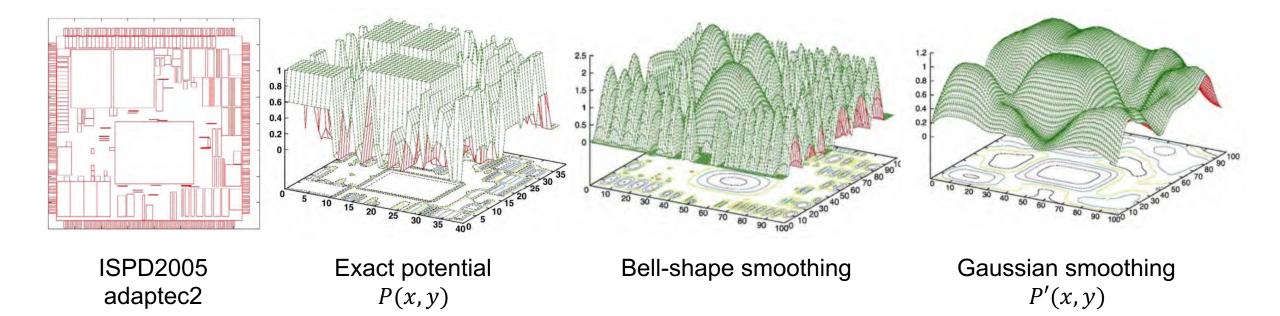
- Challenges
  - Gradient only has local view
  - Need multi-level bins



Multi-level bins

### Density Penalty – Fixed Macros are Different

- Potential function for fixed macros
  - Bell-shape smoothing works well for standard cells
  - For fixed macros, P'(x, y) = G(x, y) \* P(x, y)

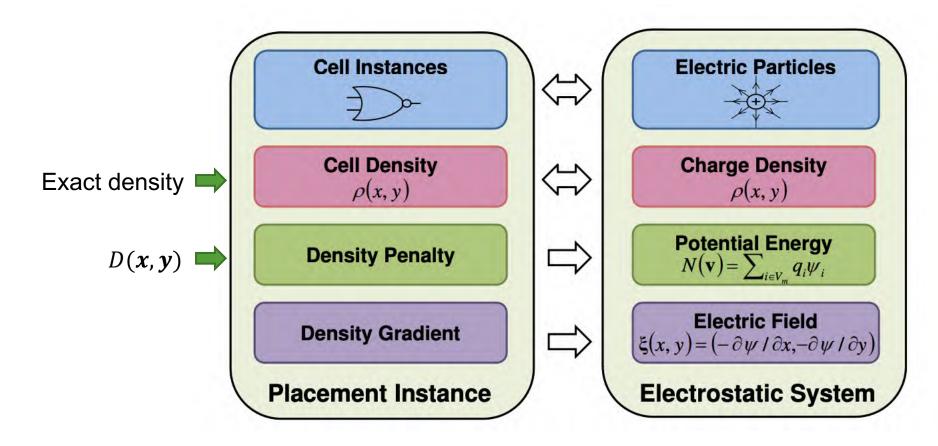


#### Nonlinear Placement – ePlace

- http://vlsi-cuda.ucsd.edu/~ljw/ePlace/
- Lu, Jingwei, et al. "<u>ePlace: Electrostatics-based placement using fast fourier transform and Nesterov's method.</u>" ACM TODAES 2015.
- Cheng, Chung-Kuan, et al. "<u>RePlAce: Advancing solution quality and routability validation in global placement.</u>" IEEE TCAD 2018.
- Lin, Yibo, et al. "<u>DREAMPlace: Deep learning toolkit-enabled gpu acceleration for modern vlsi placement.</u>" IEEE TCAD 2020. (DAC 2019 Best Paper Award)

#### **Electric Potential**

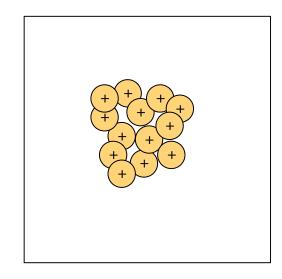
 $= \min_{x,y} WL(x,y) + \lambda D(x,y)$ 

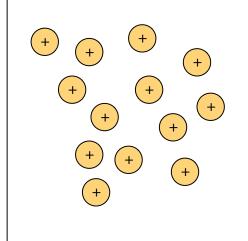


### Electrostatic System

- Isolated electrostatic system
  - Balanced distribution ⇔ minimum potential energy
- If we can minimize the potential energy, then cells are spread out

- lacktriangle To consider  $t_d < 1$ 
  - -s.t.  $d_b(x,y) \le t_d, \forall b \in Bins$
  - Insert fillers: dummy cells filling the area
  - $-area_{fillers} + area_{cells} = area_{placeable} \times t_d$
  - Fillers have no connections





## Poisson's Equation for Electrostatic System

$$\begin{cases} \nabla \cdot \nabla \psi(x,y) = -\rho(x,y), \\ \hat{\mathbf{n}} \cdot \nabla \psi(x,y) = \mathbf{0}, (x,y) \in \partial R, \\ \iint_{R} \rho(x,y) = \iint_{R} \psi(x,y) = 0. \end{cases}$$

Total charge Total energy

To remove DC component  $a_{0,0}=0$  Zero-frequency component



$$a_{u,v} = \frac{1}{m^2} \sum_{x=0}^{m-1} \sum_{y=0}^{m-1} \rho(x,y) \cos(w_u x) \cos(w_v y).$$

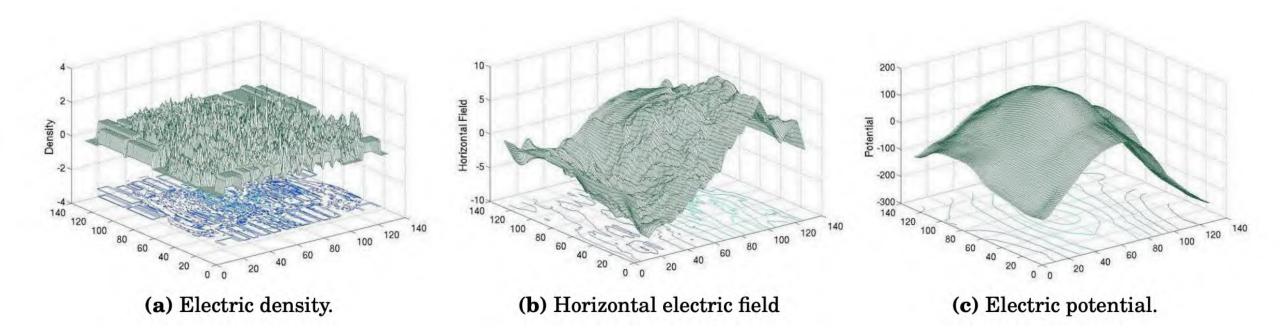
$$\rho_{DCT}(x,y) = \sum_{u=0}^{m-1} \sum_{v=0}^{m-1} a_{u,v} \cos(w_u x) \cos(w_v y),$$

$$\psi_{DCT}(x,y) = \sum_{u=0}^{m-1} \sum_{v=0}^{m-1} \frac{a_{u,v}}{w_u^2 + w_v^2} \cos(w_u x) \cos(w_v y),$$

$$\begin{cases} \xi_{X_{DSCT}} = \sum_{u} \sum_{v} \frac{a_{u,v} w_{u}}{w_{u}^{2} + w_{v}^{2}} \sin(w_{u} x) \cos(w_{v} y), \\ \xi_{Y_{DCST}} = \sum_{u} \sum_{v} \frac{a_{u,v} w_{v}}{w_{u}^{2} + w_{v}^{2}} \cos(w_{u} x) \sin(w_{v} y). \end{cases}$$

In forms of DCT and DST

### **Electric Potential**



## 无约束可微优化问题

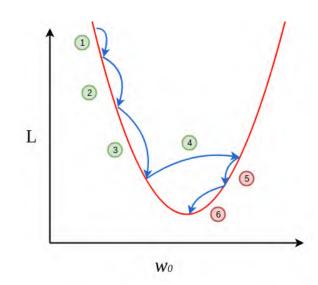
■ 优化目标

$$\min_{x \in R^n} f(x) = WL(x, y) + \lambda D(x, y)$$

- 梯度下降
  - -线搜索: $x^{k+1} = x^k + \alpha_k d^k$
  - 先确定下降方向: 负梯度、牛顿方向、拟牛顿方向等
  - 按某种准则搜索步长

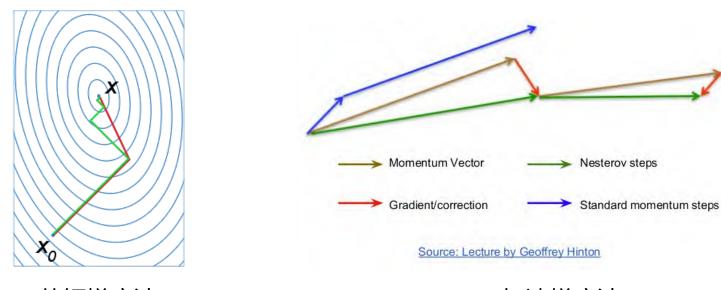
#### ■盲人下山

- 求解f(x)的最小值点如同盲人下山,无法一眼望知谷底,而是
- 首先确定下一步改往哪个方向行走
- 再确定沿着该方向行走多远后停下以便选取下一个下山方向



## 下降方向选取

- 线搜索类算法的数学表述:  $x^{k+1} = x^k + \alpha_k d^k$
- $d^k$ 为迭代点 $x^k$ 处的搜索方向
- α<sub>k</sub>为相应的步长
- ► 下降方向的要求: $(d^k)^T \nabla f(x^k) < 0$



共轭梯度法

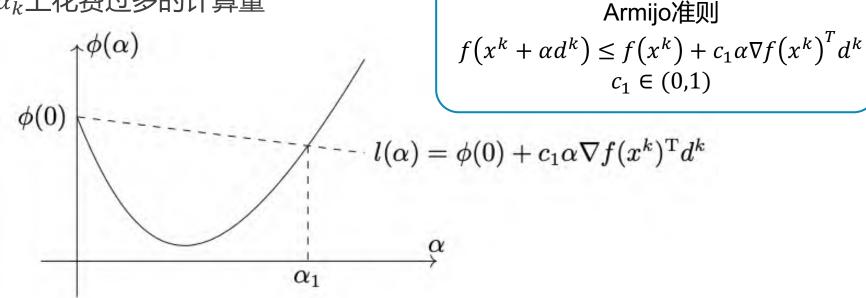
Nesterov加速梯度法

## 步长 $\alpha_k$ 选取

- 精确线搜索算法
  - 首先构造一元辅助函数:  $\phi(\alpha) = f(x^k + \alpha d^k)$
  - 其中,  $\alpha > 0$ 是该辅助函数的自变量
- 线搜索的目标是选取合适的 $\alpha_k$ 使得 $\phi(\alpha_k)$ 尽可能小,这要求
  - $-\alpha_k$ 应该使得f充分下降
  - 不应在寻找 $\alpha_k$ 上花费过多的计算量
- -个自然的想法是寻找 $\alpha_k$ 使得: $\alpha_k = \operatorname{argmin}_{\alpha>0} \phi(\alpha)$ 
  - 即 $\alpha_k$ 为最佳步长;这种线搜索算法称为精确线搜索算法
  - 最佳步长求解计算量大,实际中应用较少

# 步长 $\alpha_k$ 选取

- 精确线搜索算法
  - 首先构造一元辅助函数:  $\phi(\alpha) = f(x^k + \alpha d^k)$
  - 其中,  $\alpha > 0$ 是该辅助函数的自变量
- 线搜索的目标是选取合适的 $\alpha_k$ 使得 $\phi(\alpha_k)$ 尽可能小,这要求
  - $-\alpha_k$ 应该使得f充分下降
  - 不应在寻找 $\alpha_k$ 上花费过多的计算量



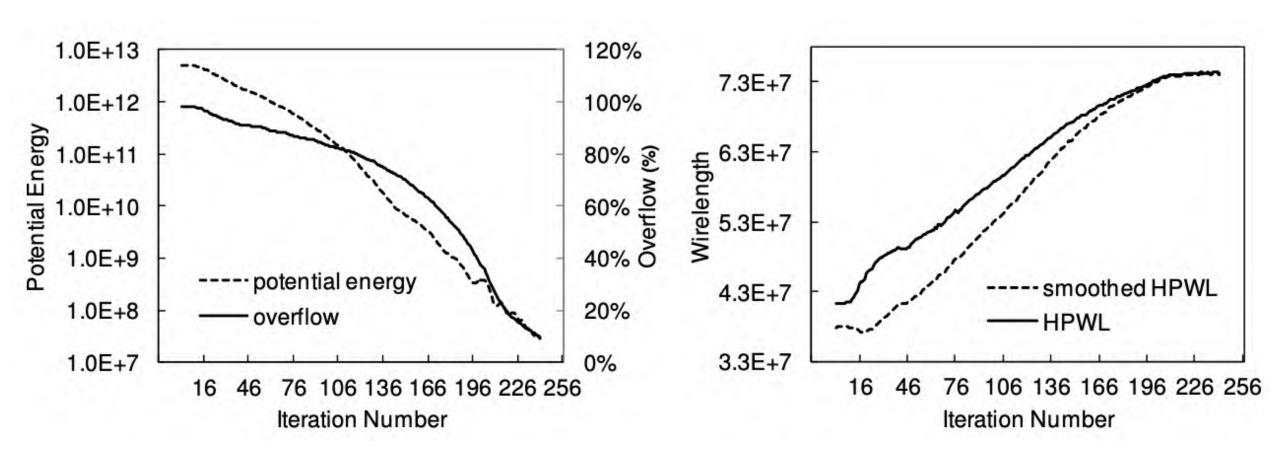
## 步长 $\alpha_k$ 选取

- 精确线搜索算法
  - 首先构造一元辅助函数:  $\phi(\alpha) = f(x^k + \alpha d^k)$
  - 其中,  $\alpha > 0$ 是该辅助函数的自变量
- 线搜索的目标是选取合适的 $\alpha_k$ 使得 $\phi(\alpha_k)$ 尽可能小,这要求
  - $-\alpha_k$ 应该使得f充分下降
  - 不应在寻找 $\alpha_k$ 上花费过多的计算量

#### Algorithm 1 线搜索回退法

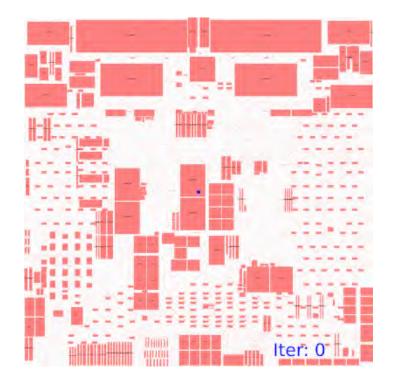
- 1: 选择初始步长 $\hat{\alpha}$ , 参数 $\gamma$ ,  $c \in (0,1)$ . 初始化 $\alpha \leftarrow \hat{\alpha}$ .
- 2: while  $f(x^k + \alpha d^k) > f(x^k) + c\alpha \nabla f(x^k)^T d^k$  do
- 4: end while
- 5: 输出 $\alpha_k = \alpha$ .

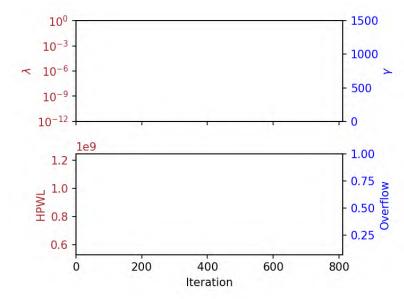
#### **Gradient Descent Iterations**



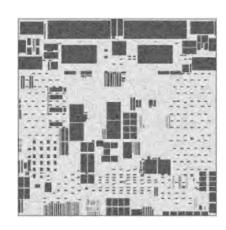
## Bigblue4 (2M-Cell Design)

#### DREAMPlace impl. of the ePlace algorithm

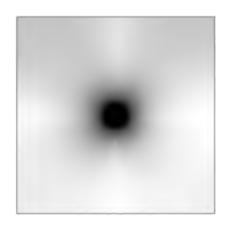




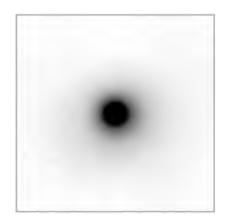
**Placement Metrics** 



**Density Map** 



Potential Map



Field Map

## Nonlinear Placement – Summary

- Nonlinear placement
  - Wirelength smoothing: LSE and WA
  - Density potential (NTUplace)
  - Electric potential (ePlace)
- Open-source tools
  - DREAMPlace
  - <a href="https://github.com/limbo018/DREAMPlace">https://github.com/limbo018/DREAMPlace</a>
  - RePlAce
  - <a href="https://github.com/The-OpenROAD-Project/RePlAce">https://github.com/The-OpenROAD-Project/RePlAce</a>

## 课后思考

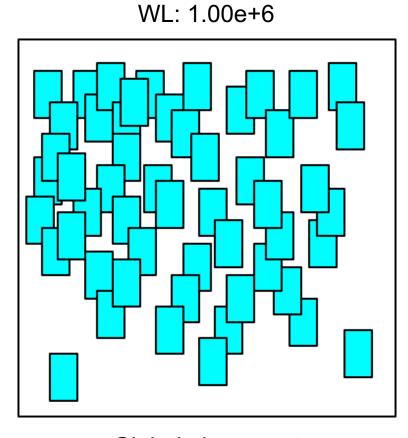
- ▶ 北京大学计划筹建新校区,请你帮忙规划新校区的建筑分布
  - 已知宿舍楼50幢、食堂10个、教学楼10幢、绿地20块
  - 假设各建筑形状为矩形,且已知大小
  - 假设新校区形状如下图
  - 尝试利用Quadratic Placement或Nonlinear Placement框架设计算法流程求解建筑位置
  - 要求1: 宿舍楼、教学楼和食堂尽可能靠近,且不同宿舍楼、教学楼尽量靠近不同的食堂
  - 要求2:不同建筑不能重叠
  - 要求3:写出优化目标、约束条件以及算法流程,并解释设计理由

北京大学新校区范围

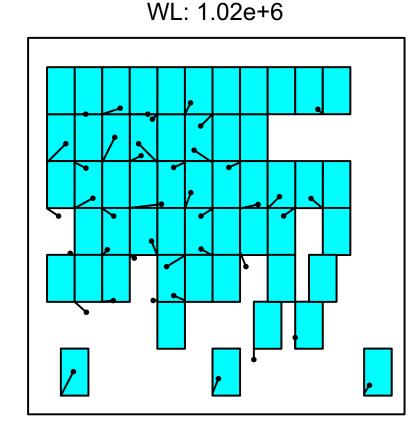
## Summary of Global Placement

<1970-1980s	1980s-1990s	1990s-2010s			>2010s	
Partitioning	Simulated	Min-Cut	Analytic		Analytic	
Partitioning	Annealing	(Multi-level)	Quadratic	Nonlinear	Quadratic	Nonlinear
Breuer	Timberwolf VPR	FengShui	GORDIAN	APlace	POLAR	<b>ePlace</b> RePlAce
Dunlop & Kernighan	Dragon	Саро	BonnPlace	Naylor Synopsis	SimPL ComPLx	DREAMPlace
Quadratic Assignment		Capo +Rooster	mFar	NTUplace	MAPLE	
Cadence QPlace			Kraftwerk	mPL6		
			FastPlace			
			Warp3			

## Typical Placement Flow



WL: 1.05e+6



Global placement

Legalization

**Detailed Placement**