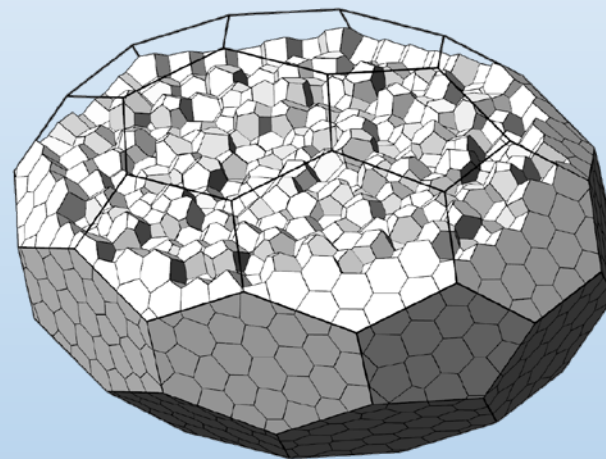
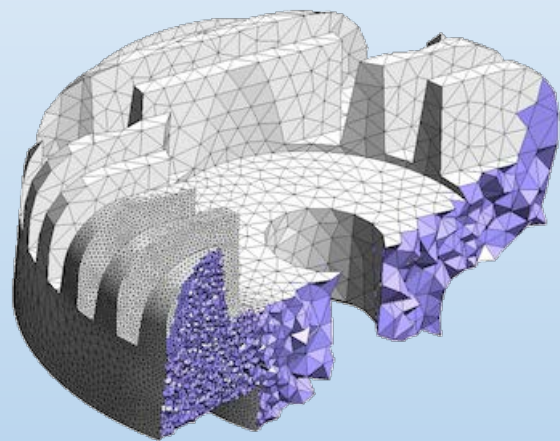




中国科学技术大学2024暑期课程

# Delaunay网格与Voronoi图



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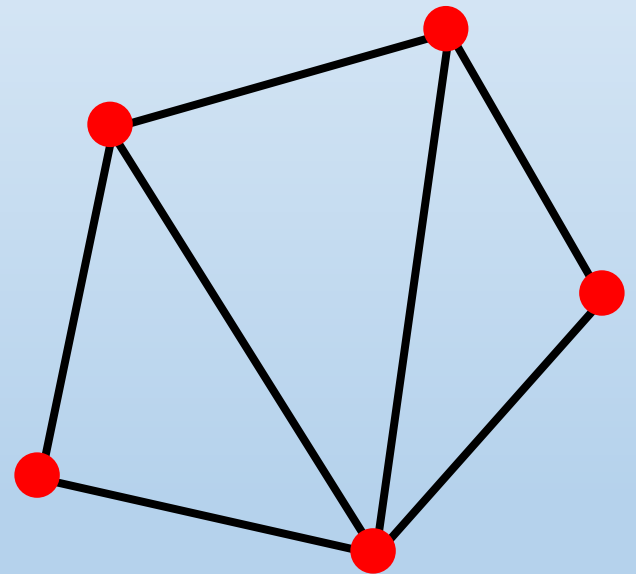
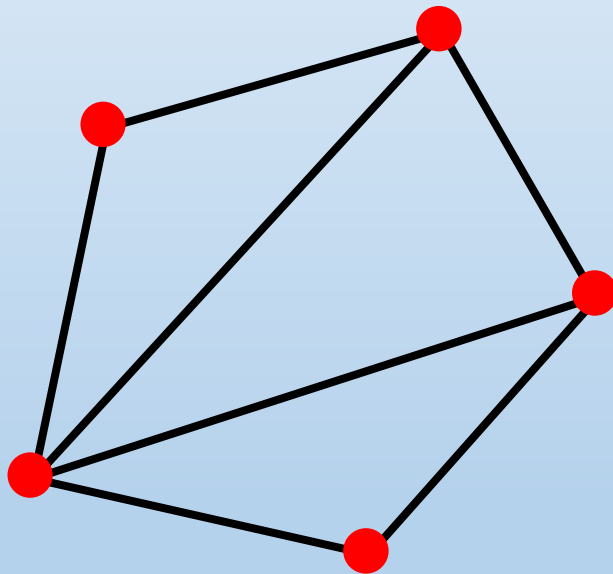
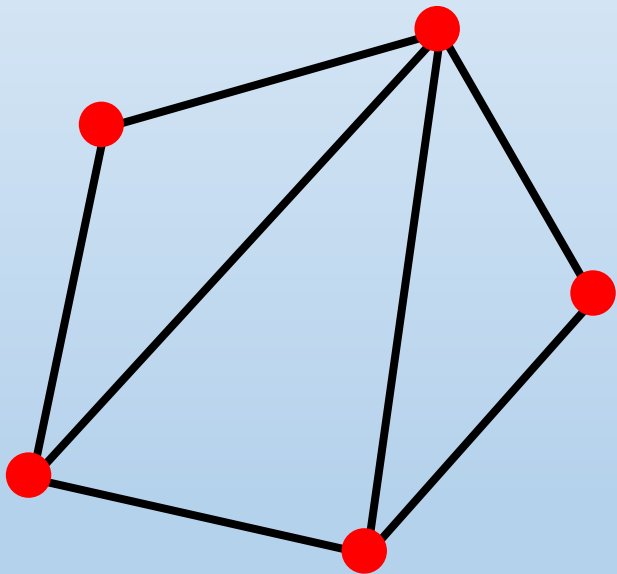
[yanyangxiao.github.io](https://yanyangxiao.github.io)

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  - 并行构造方法

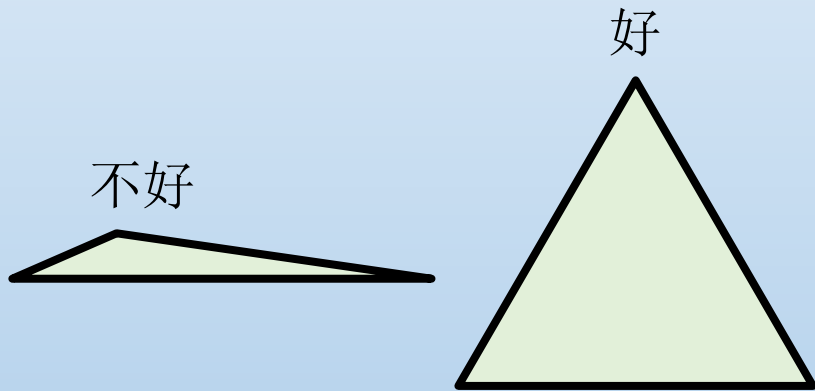
# 点集 $\rightarrow$ 三角网格

- 同一组点有多种不同的连接关系

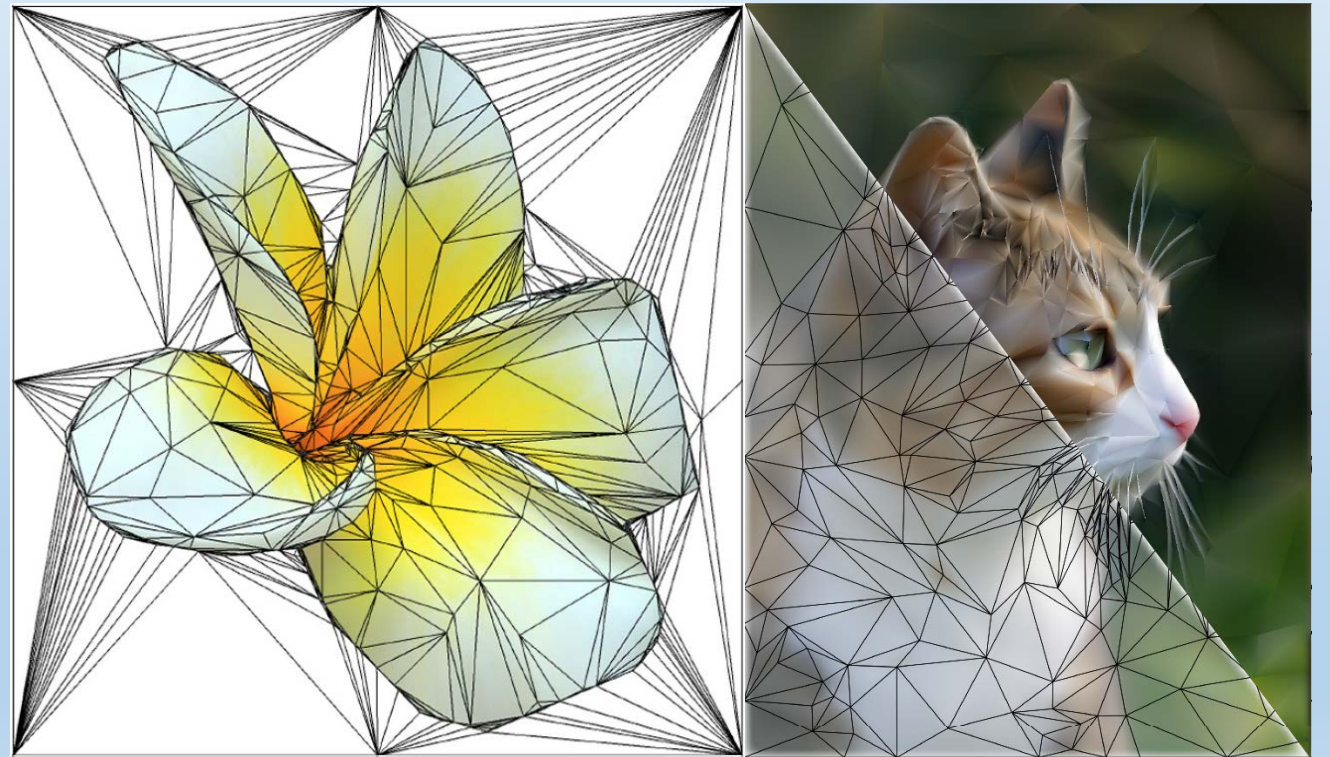


# 点集 $\rightarrow$ 三角网格

- 哪种连接关系“最好”？根据应用需求确定
- 希望获得角度尽可能大的网格  $\rightarrow$  构造Delaunay triangulation



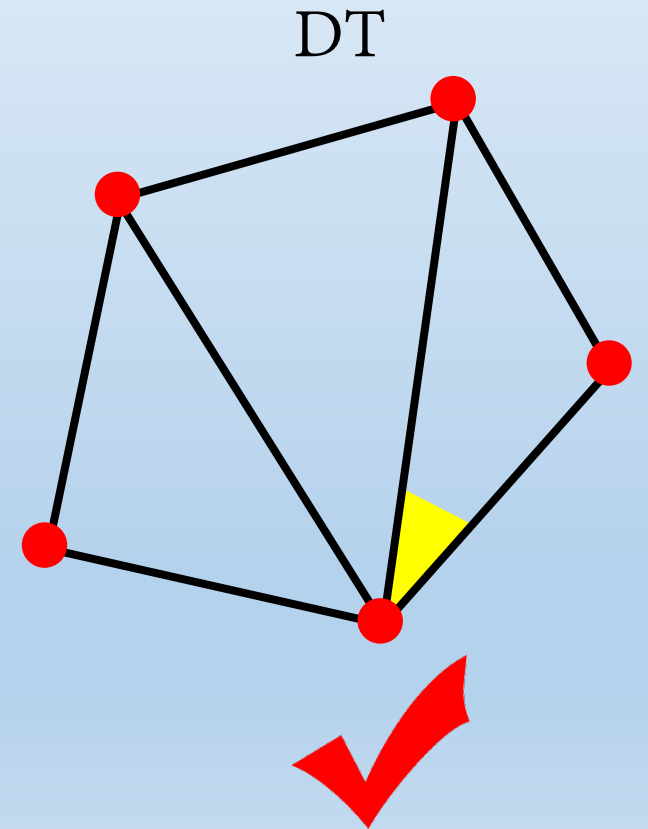
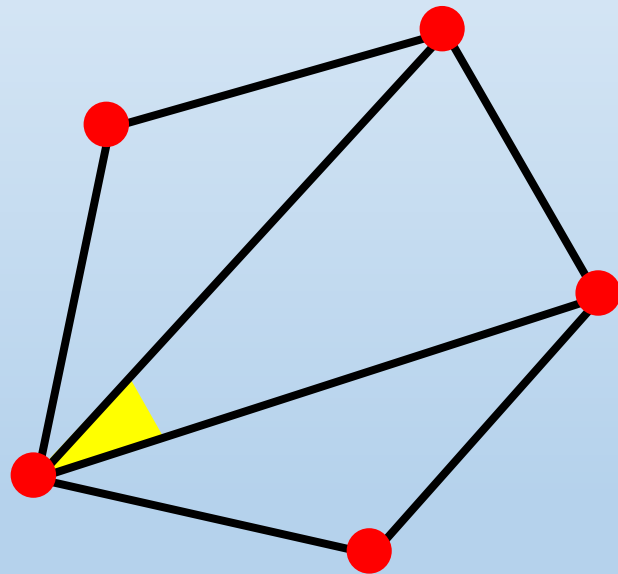
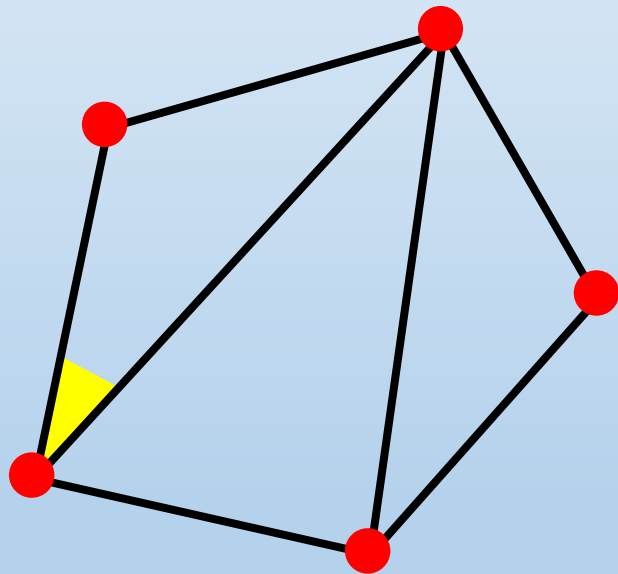
网格生成：不喜欢狭长三角形



图像矢量化/逼近：重建图像与原图误差最低

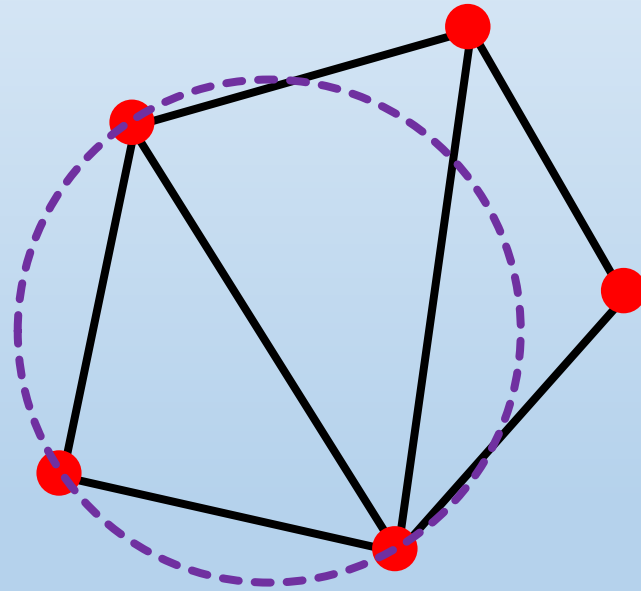
# Delaunay Triangulation (DT)

- 性质1: 在点集所有可能的三角网格中, DT的最小角度最大



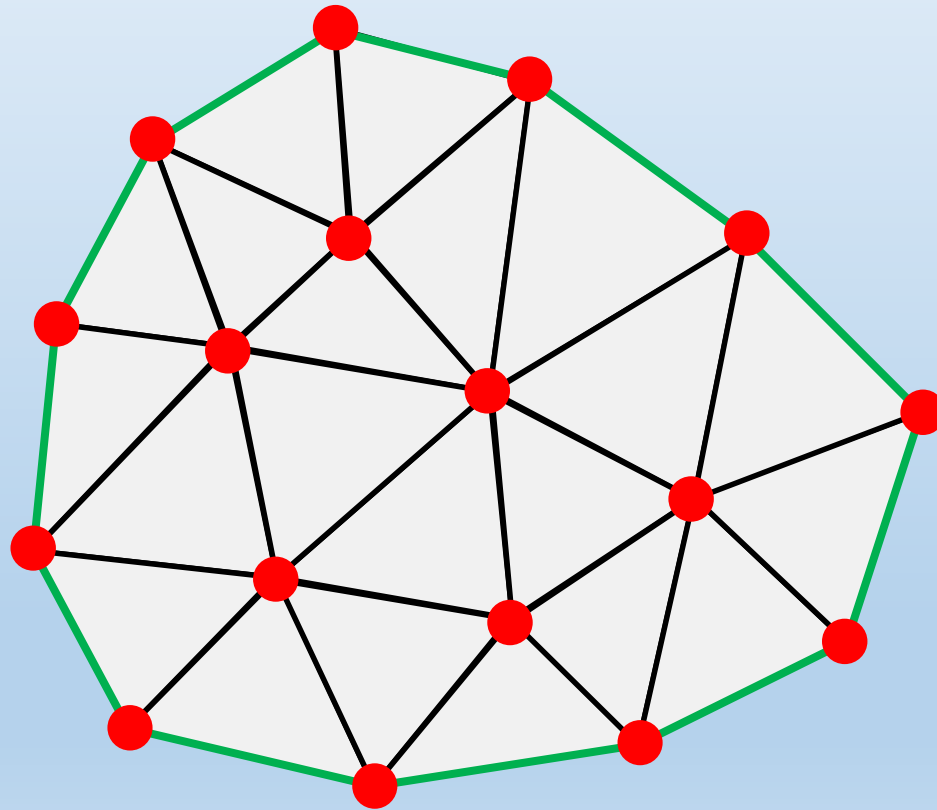
# Delaunay Triangulation (DT)

- 性质2: DT每个三角形的外接圆内都不含点集中的点



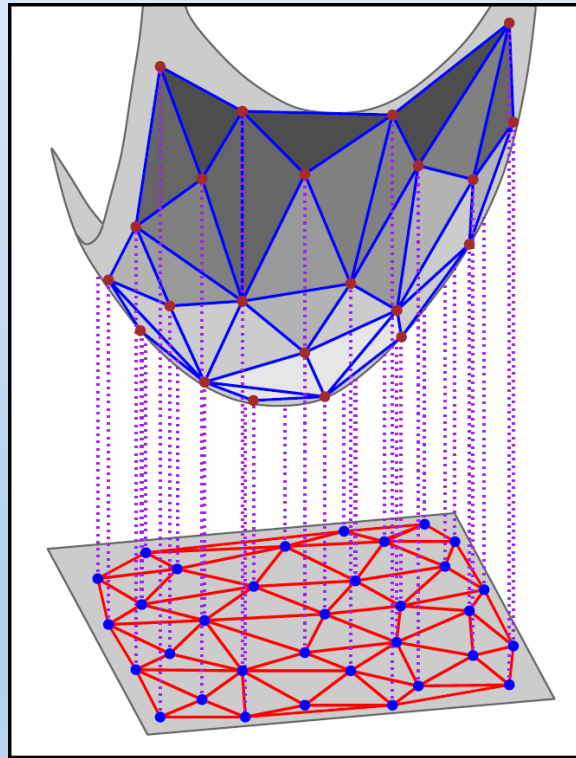
# Delaunay Triangulation (DT)

- 性质3: DT网络的边界是该点集的凸包



# Delaunay Triangulation (DT)

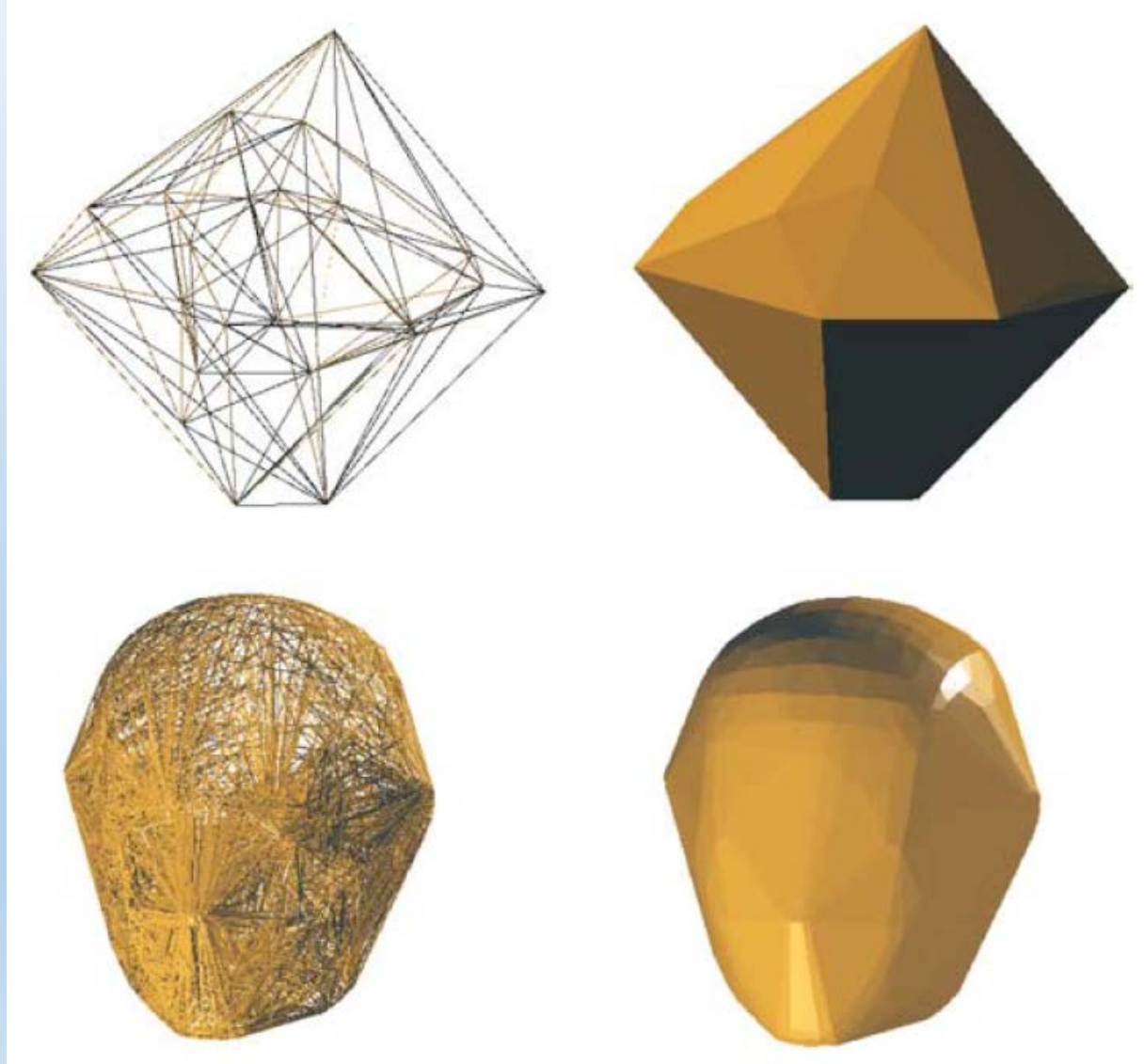
- 性质4: 点集每个点提升到高一维抛物面函数上, 提升点的凸包是一个多面体, 将朝下的面片投影回原空间 = 原点集的DT





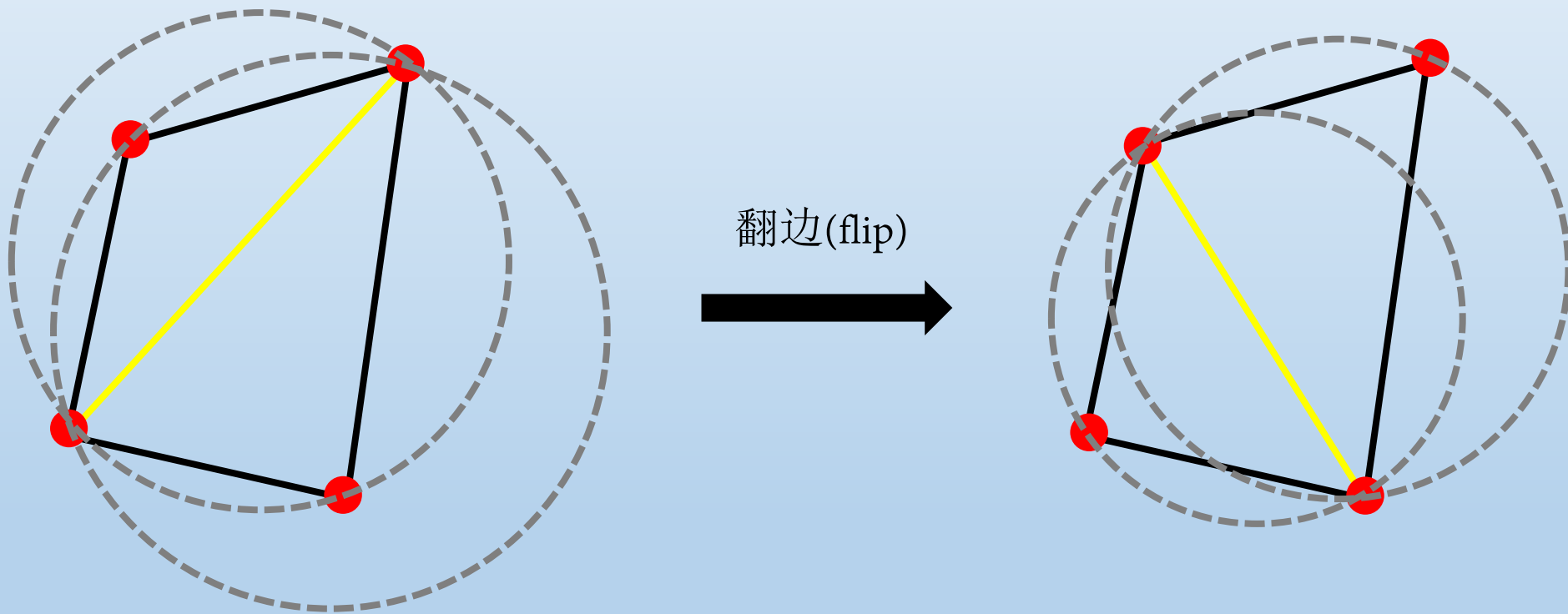
# Delaunay Triangulation (DT)

- 高维DT



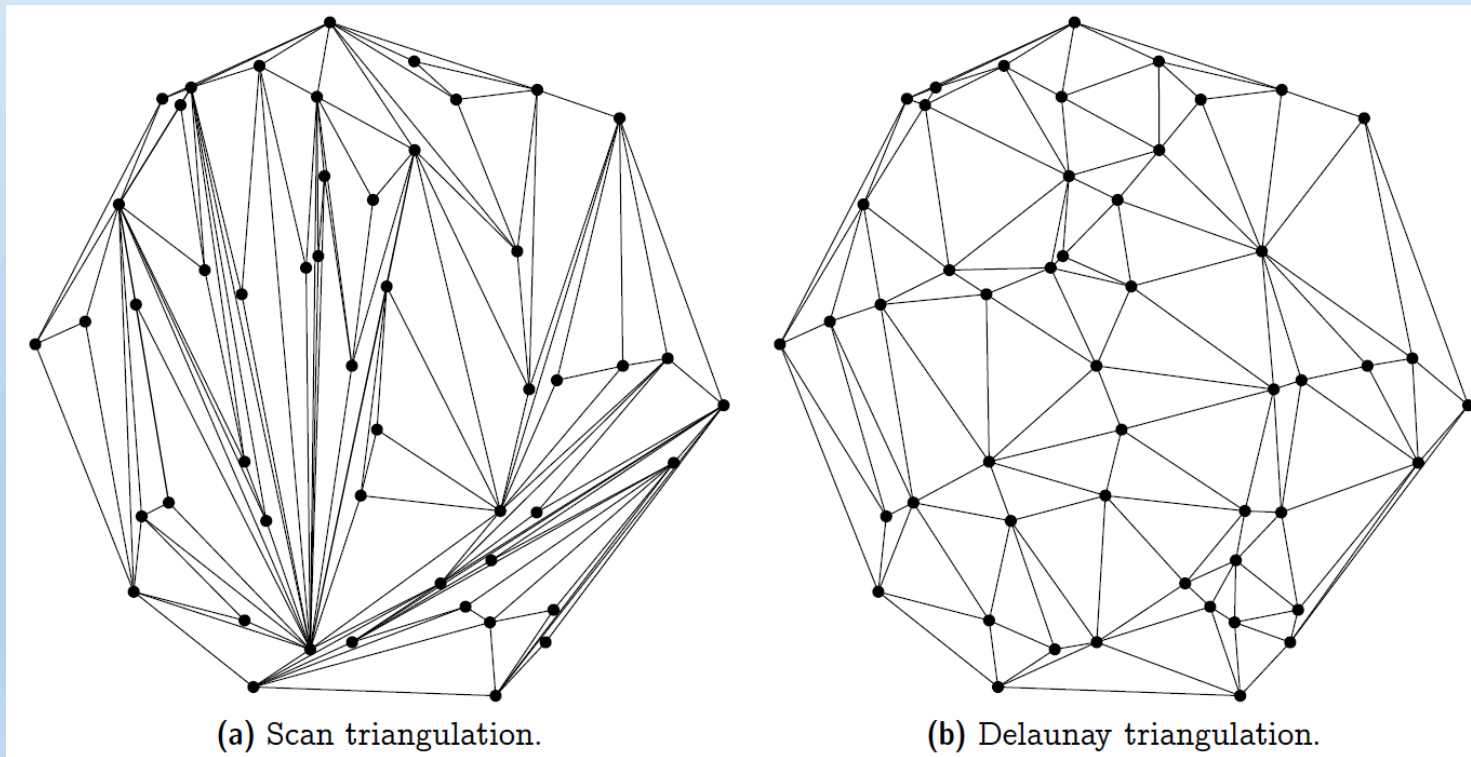
# 构造DT: 1-翻边算法 (Lawson/flipping/local improvement)

- 2D翻转操作



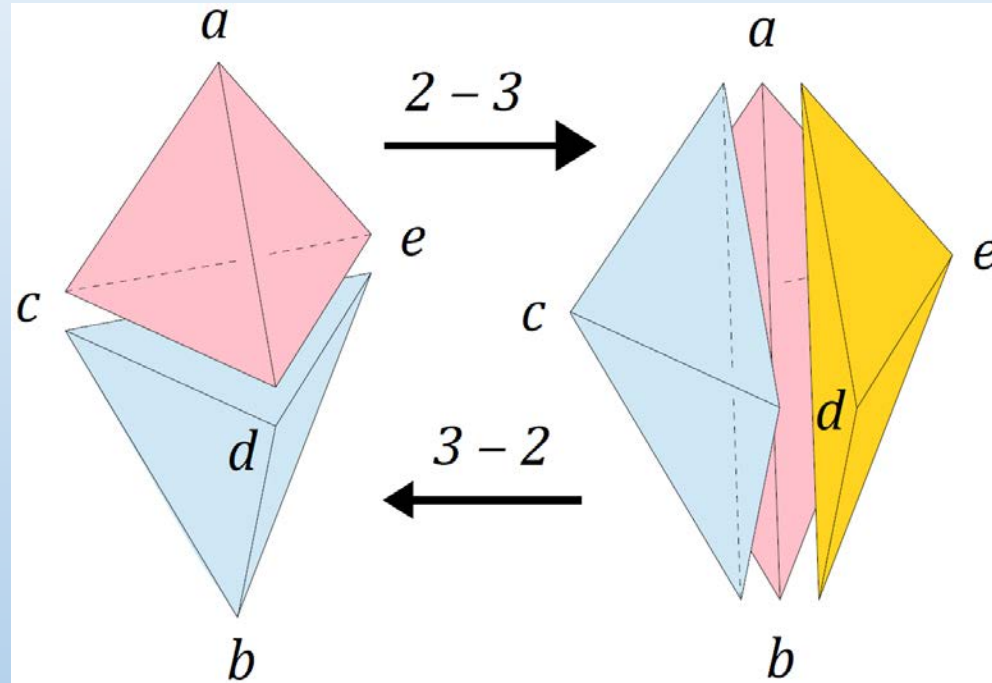
# 构造DT: 1-翻边算法 (Lawson/flipping/local improvement)

- [Lawson1972]: 2D, 任意三角网格可经有限次翻边到达DT
  - Step1: 构造一个初始三角网格
  - Step2: 若存在边不满足Delaunay性质, 则对其翻转



# 构造DT: 1-翻边算法 (Lawson/flipping/local improvement)

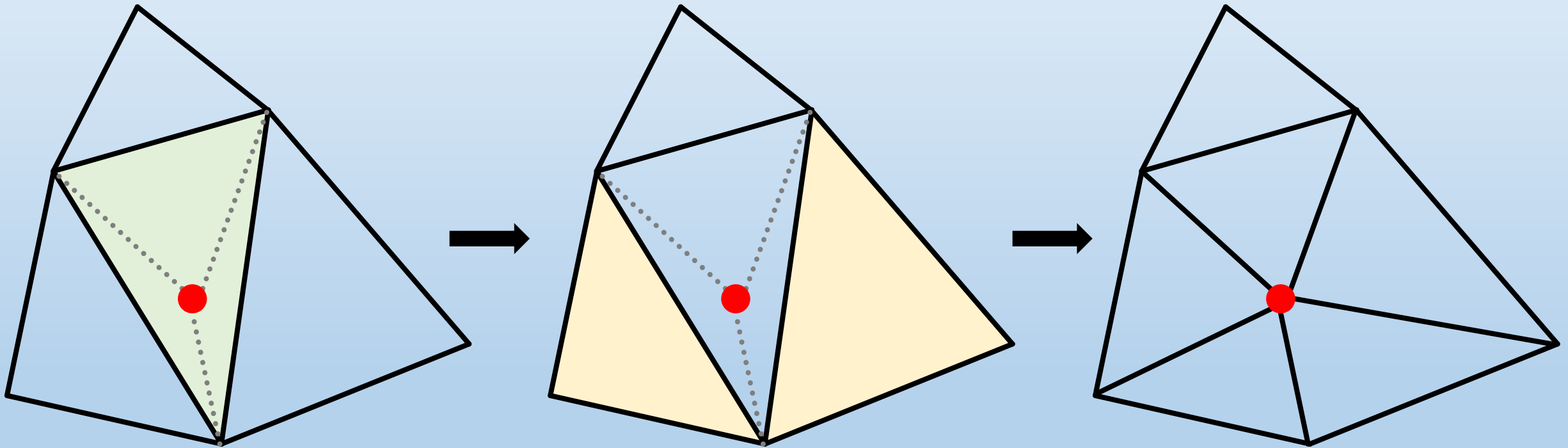
- 3D翻转操作 (bilateral flips)



- [Joe1989]: 3D, 该算法可能在到达DT前卡住

# 构造DT: 2-增长类算法 (incremental insertion)

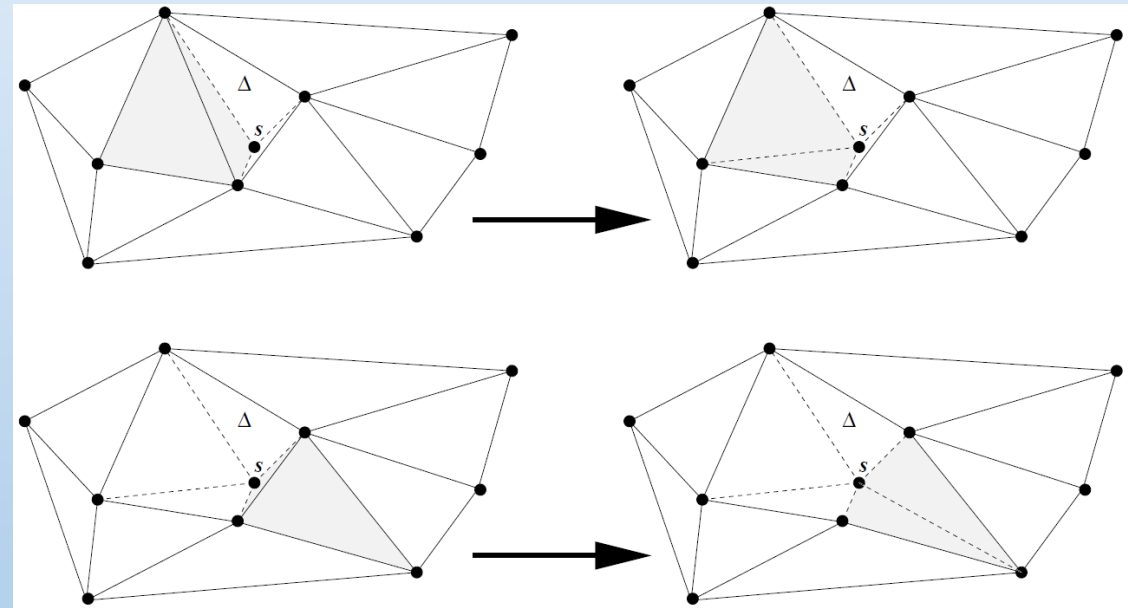
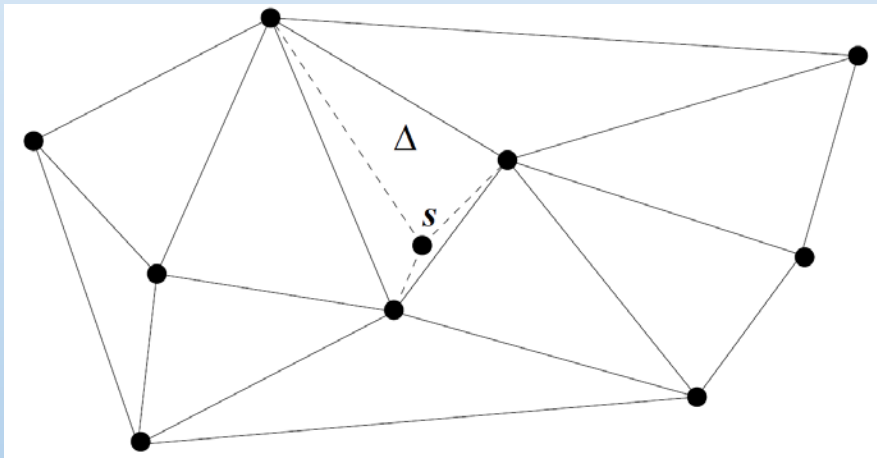
- 逐点插入到网格，并局部更新使其保持为DT



# 构造DT: 2-增长类算法 (incremental insertion)

- 局部更新策略: (1) flip

-点插入到网格后, 不断翻转非Delaunay边



需向外扩散测试

# 构造DT: 2-增长类算法 (incremental insertion)

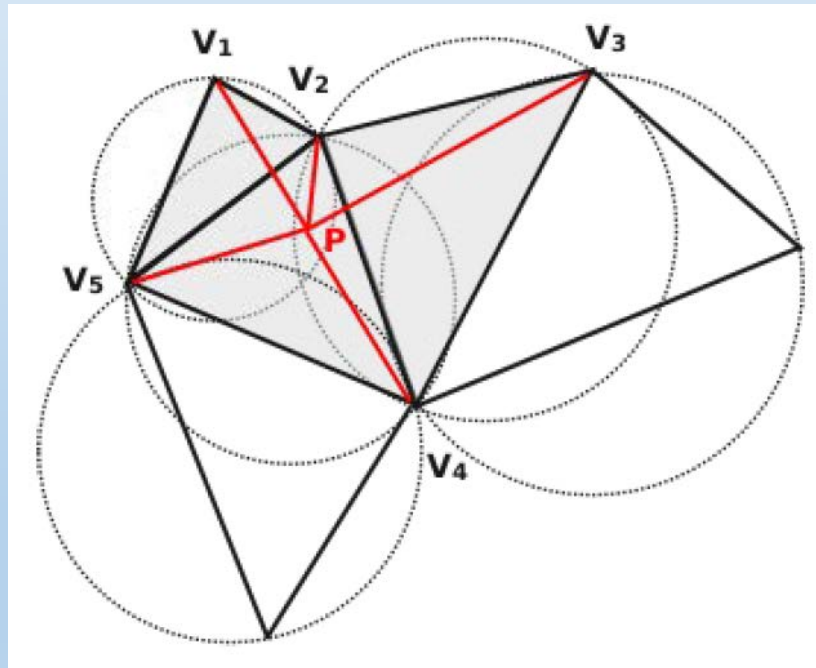
- 局部更新策略: (2) Bowyer-Watson

-Step1: 找出外接圆包含新点的所有三角形, 并删除



空腔 cavity

-Step2: 对新点与空腔多边形顶点三角化

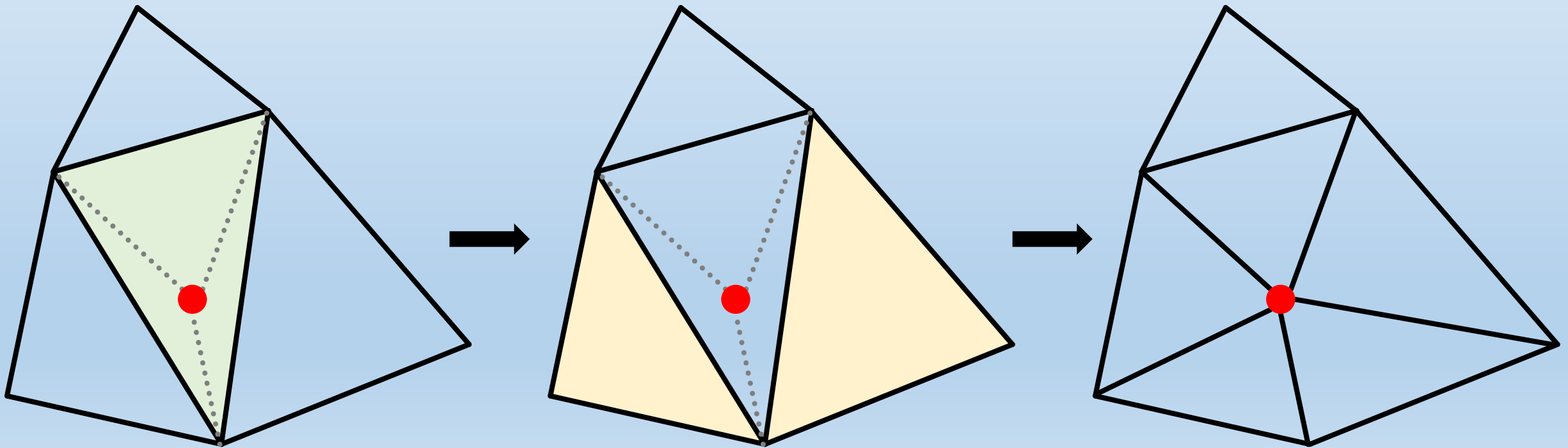


A. Bowyer. Computing Dirichlet tessellations. The computer journal, 1981, 24(2): 162-166.

D. F. Watson. Computing the n-dimensional Delaunay triangulation with application to Voronoi polytopes. The computer journal, 1981, 24(2): 167-172.

# 构造DT: 2-增长类算法 (incremental insertion)

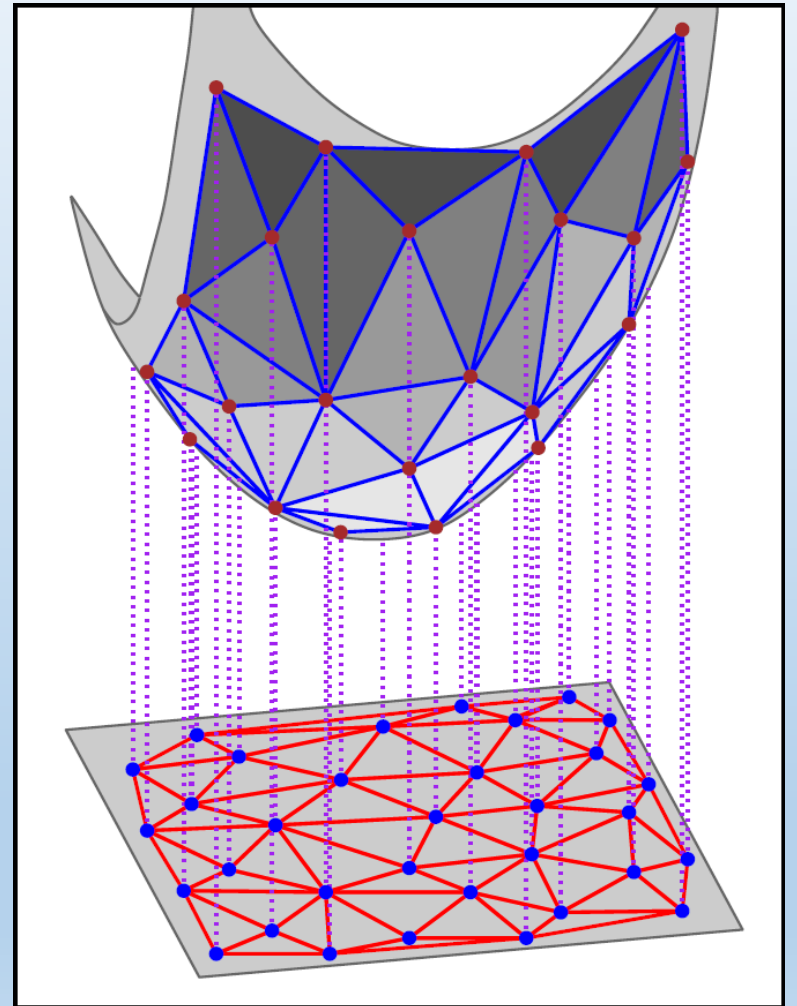
- 逐点插入到网格，并局部更新使其保持为DT
- [Guibas et al.1992]: 插入顺序随机时，翻边次数与点数呈线性，而与点的分布无关
- 适用于构造任意维度的DT





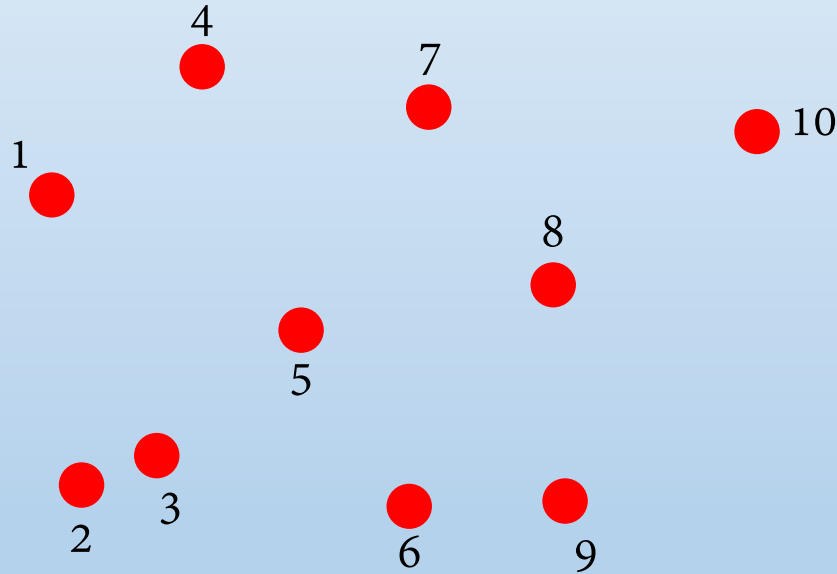
# 构造DT: 3-高维嵌入算法 (higher dimensional embedding)

- 构建高一维凸包来获得原点集的DT:
  - Step1: 每个点提升到高一维抛物面函数上
  - Step2: 计算提升点的凸包
  - Step3: 凸包朝下的面片投影回原空间
- 关键: 高维凸包的计算
- 适用于构造任意维度的DT



# 构造DT: 4-分治法

- 划分点集, 独立构造DT, 再合并相邻DT形成更大的DT:
  - Step1: 对所有点按照x坐标升序排序, x相同时按照y坐标升序排序

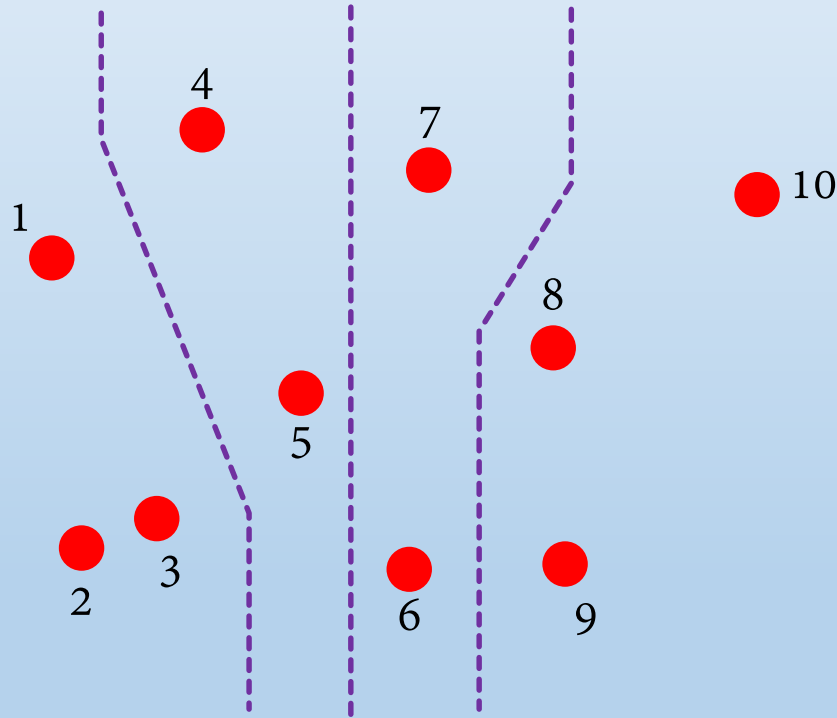


L. Guibas and J. Stolfi. Primitives for the manipulation of general subdivisions and the computation of Voronoi diagrams. ACM Transactions on Graphics, 1985, 4(2): 75-123.

谢增广. 平面点集Delaunay三角剖分的分治算法. 计算机工程与设计, 2012, 33(7): 2562-2568.

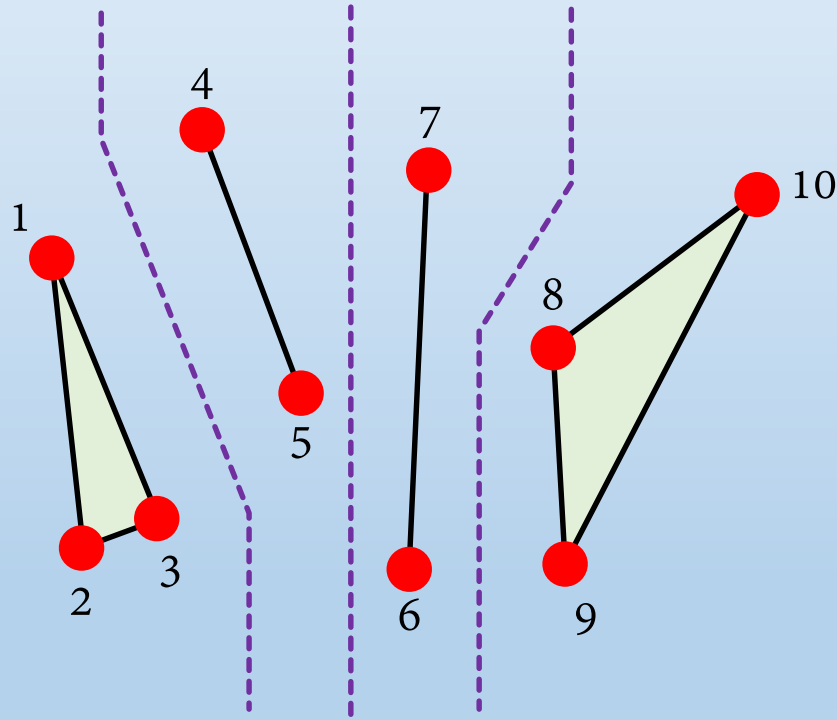
# 构造DT: 4-分治法

- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step2: 划分点集，直至每个子集点的数量不多于3



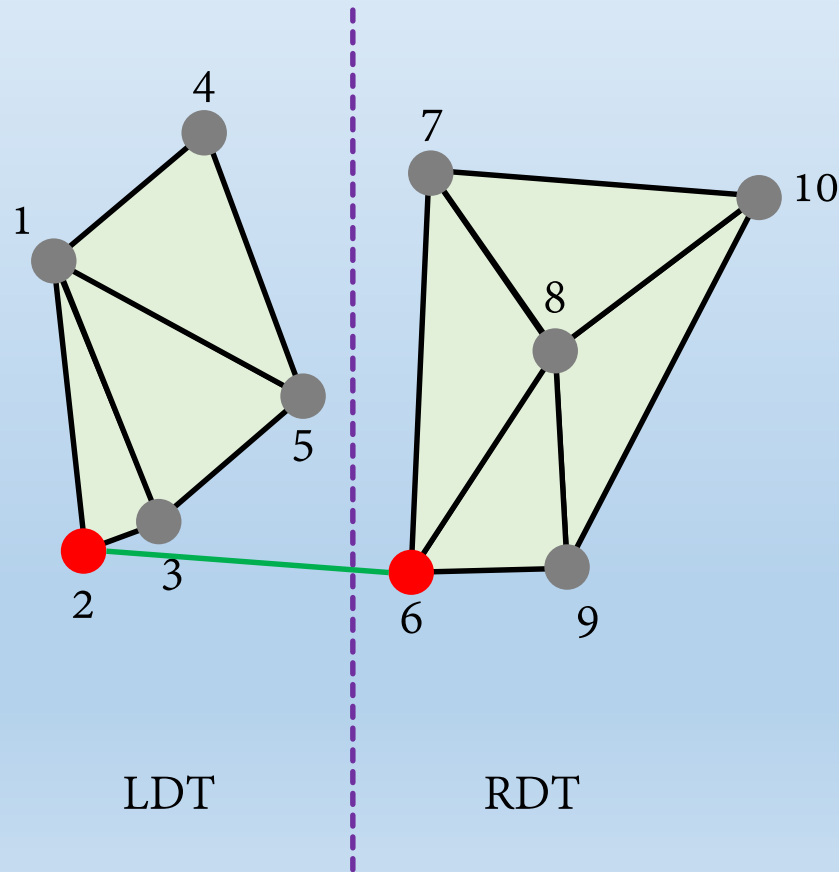
# 构造DT: 4-分治法

- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step3: 每个子集独立构造DT (必为三角形或线段)



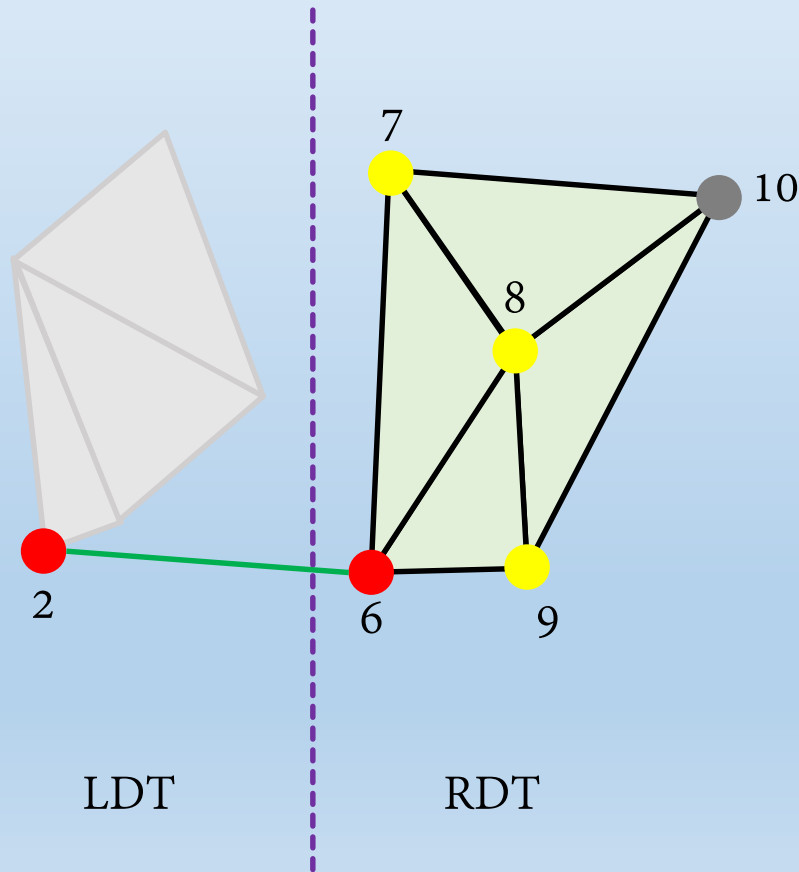
# 构造DT: 4-分治法

- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step4: 不断合并相邻的DT，直至剩余1个DT结果



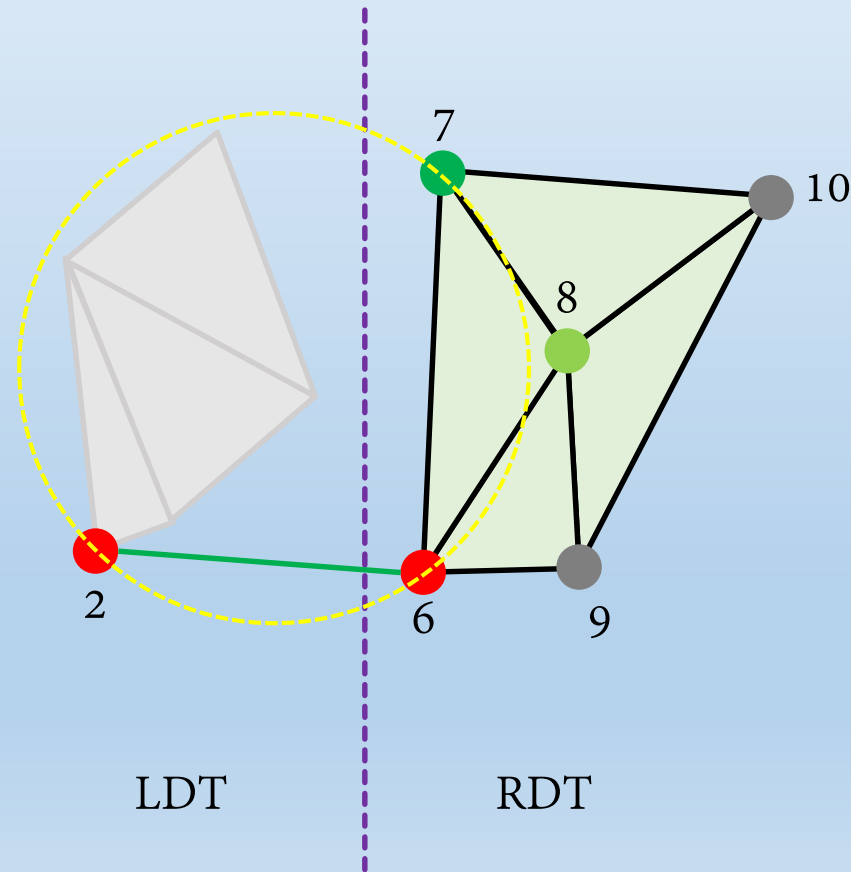
# 构造DT: 4-分治法

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-Step4: 不断合并相邻的DT，直至剩余1个DT结果



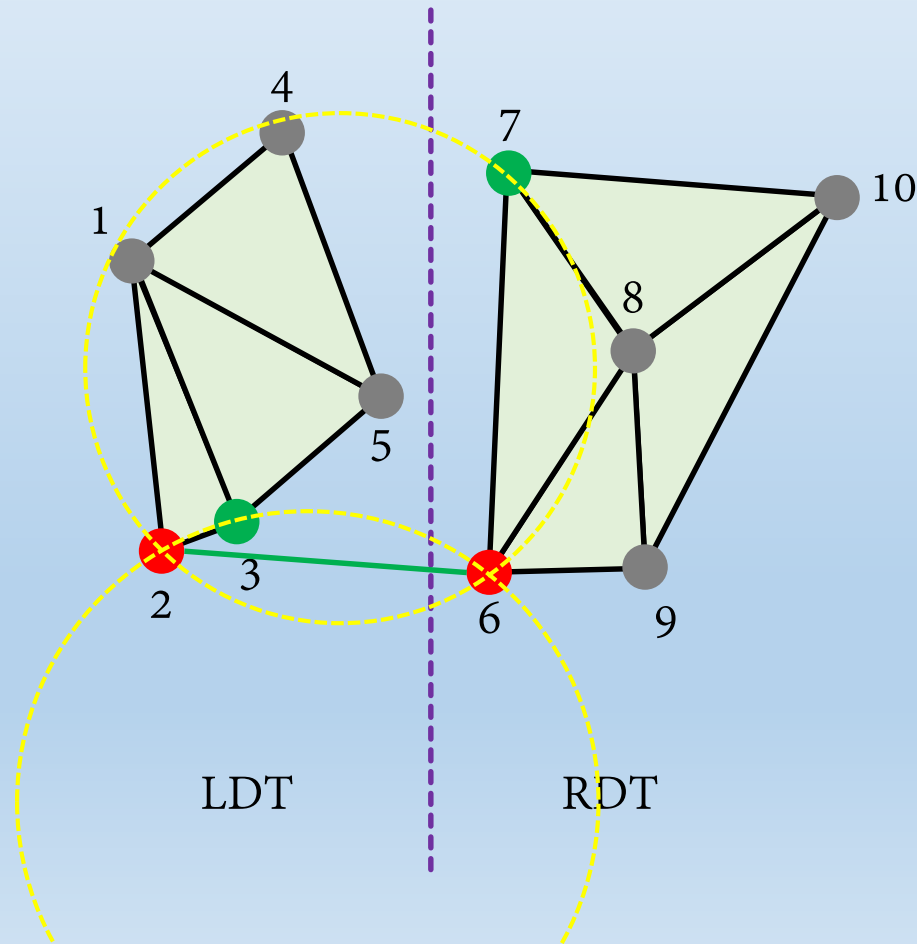
# 构造DT: 4-分治法

- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step4: 不断合并相邻的DT，直至剩余1个DT结果



# 构造DT: 4-分治法

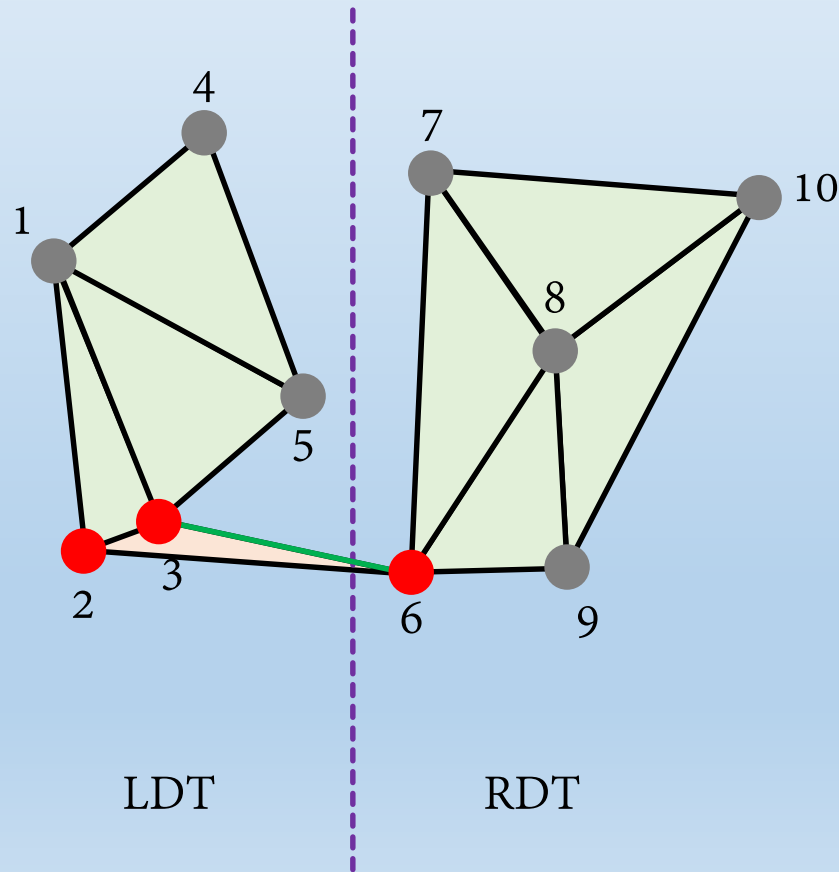
- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step4: 不断合并相邻的DT，直至剩余1个DT结果





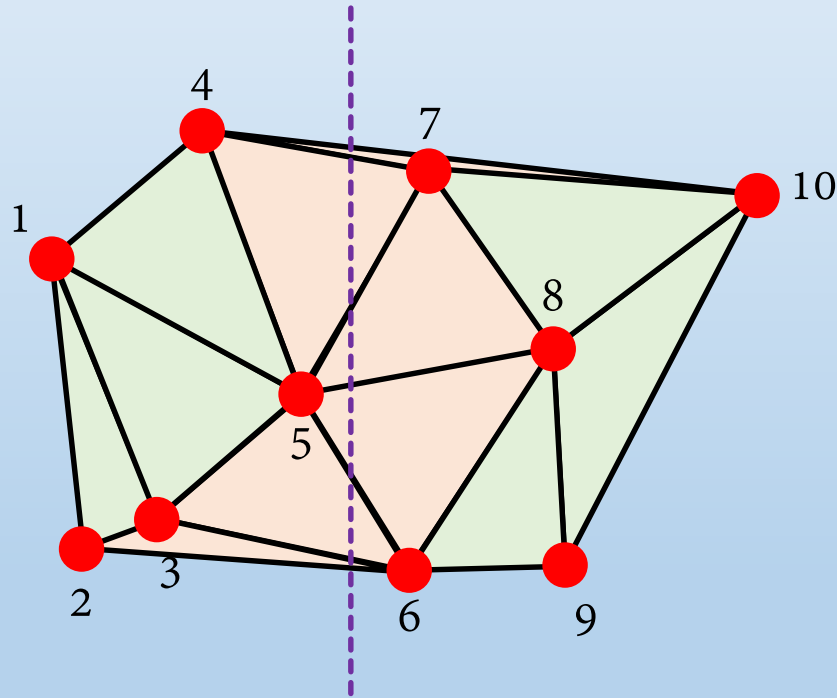
# 构造DT: 4-分治法

- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step4: 不断合并相邻的DT，直至剩余1个DT结果



# 构造DT: 4-分治法

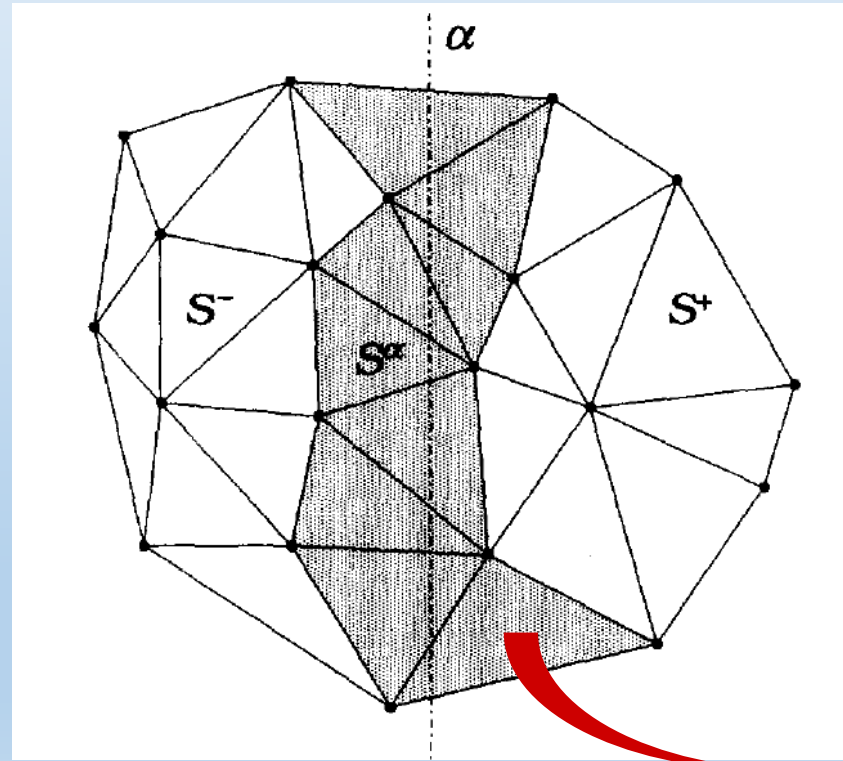
- 划分点集，独立构造DT，再合并相邻DT形成更大的DT:  
-Step4: 不断合并相邻的DT，直至剩余1个DT结果



- 高维DT的合并较复杂: 无显式的顶点邻接顺序

# 构造DT: 5-DeWall算法

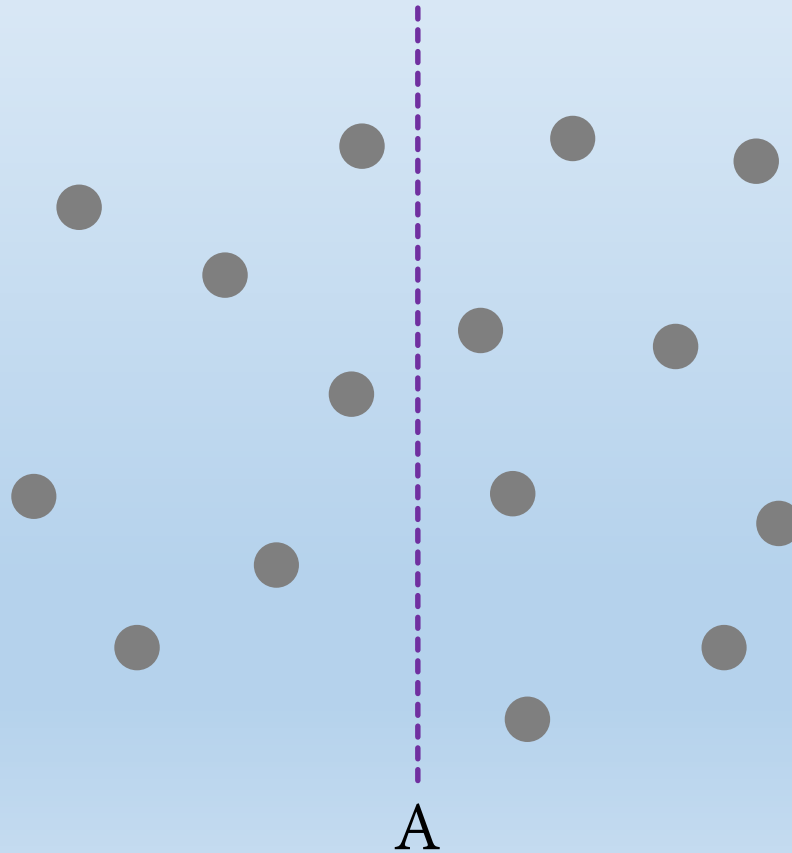
- 复杂的划分过程，无合并，适用于构造任意维度的DT
- 与一般分治法的过程相反



Delaunay Wall

# 构造DT: 5-DeWall算法

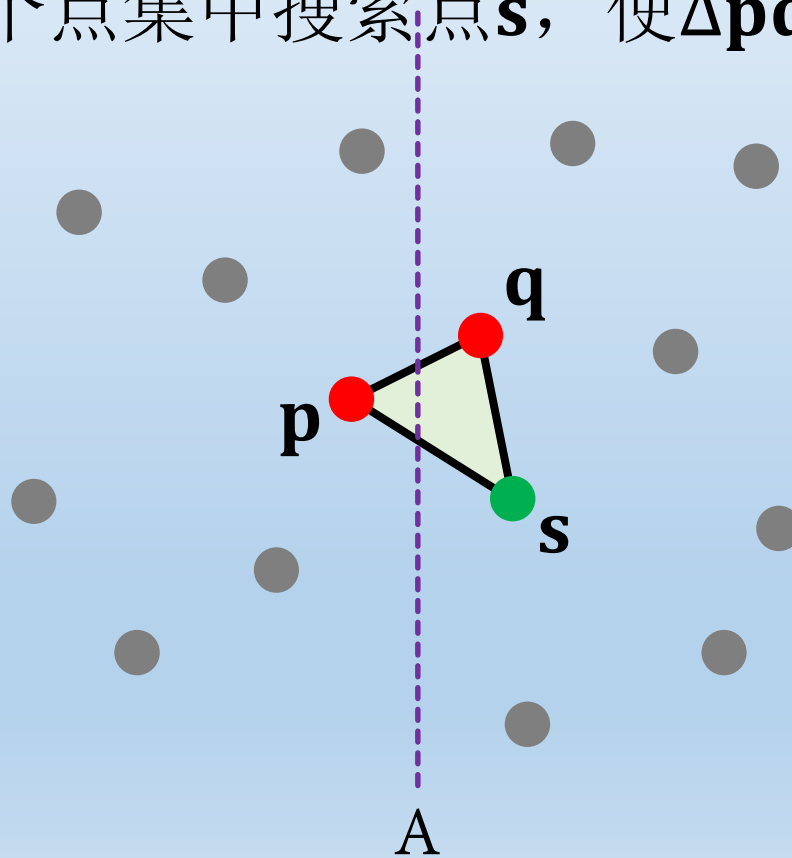
-Step1: 确定分割平面, 划分点集



# 构造DT: 5-DeWall算法

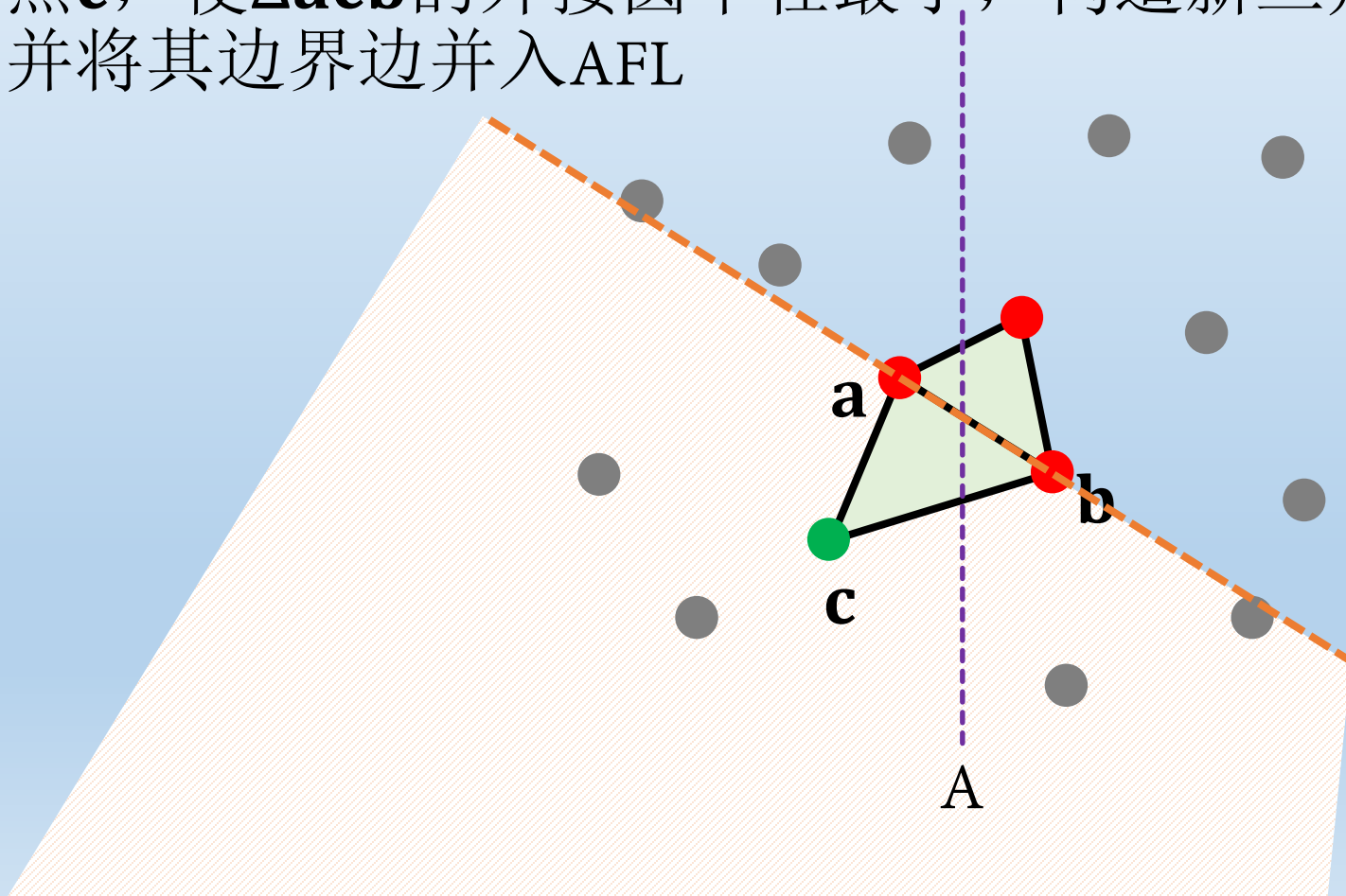
-Step2: 构造第一个三角形并入DeWall:

从左子集中找到离分割平面最近的点 $p$ , 再从右子集中找到离 $p$ 最近的点 $q$ , 再从整个点集中搜索点 $s$ , 使 $\Delta pqs$ 的外接圆半径最小



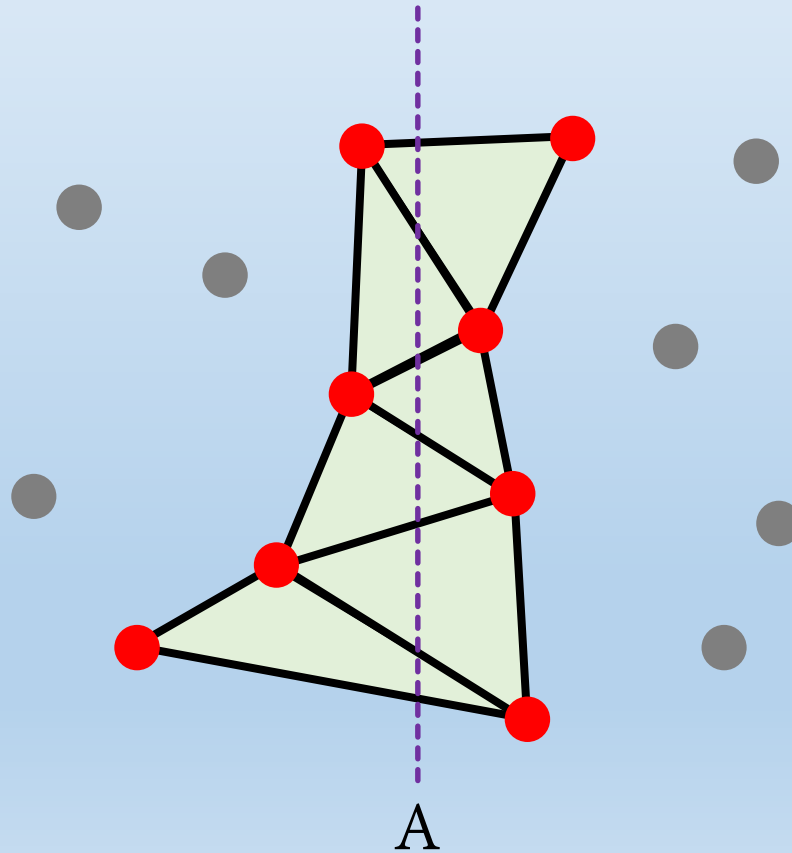
# 构造DT: 5-DeWall算法

-Step3: 维护一个列表AFL, 初值为第一个三角形的三条边, 每次从中取出一条边**ab**, 若它与分割平面相交, 则从**ab**外半空间中搜索点**c**, 使 $\Delta acb$ 的外接圆半径最小, 构造新三角形**acb**并入DeWall, 并将其边界边并入AFL



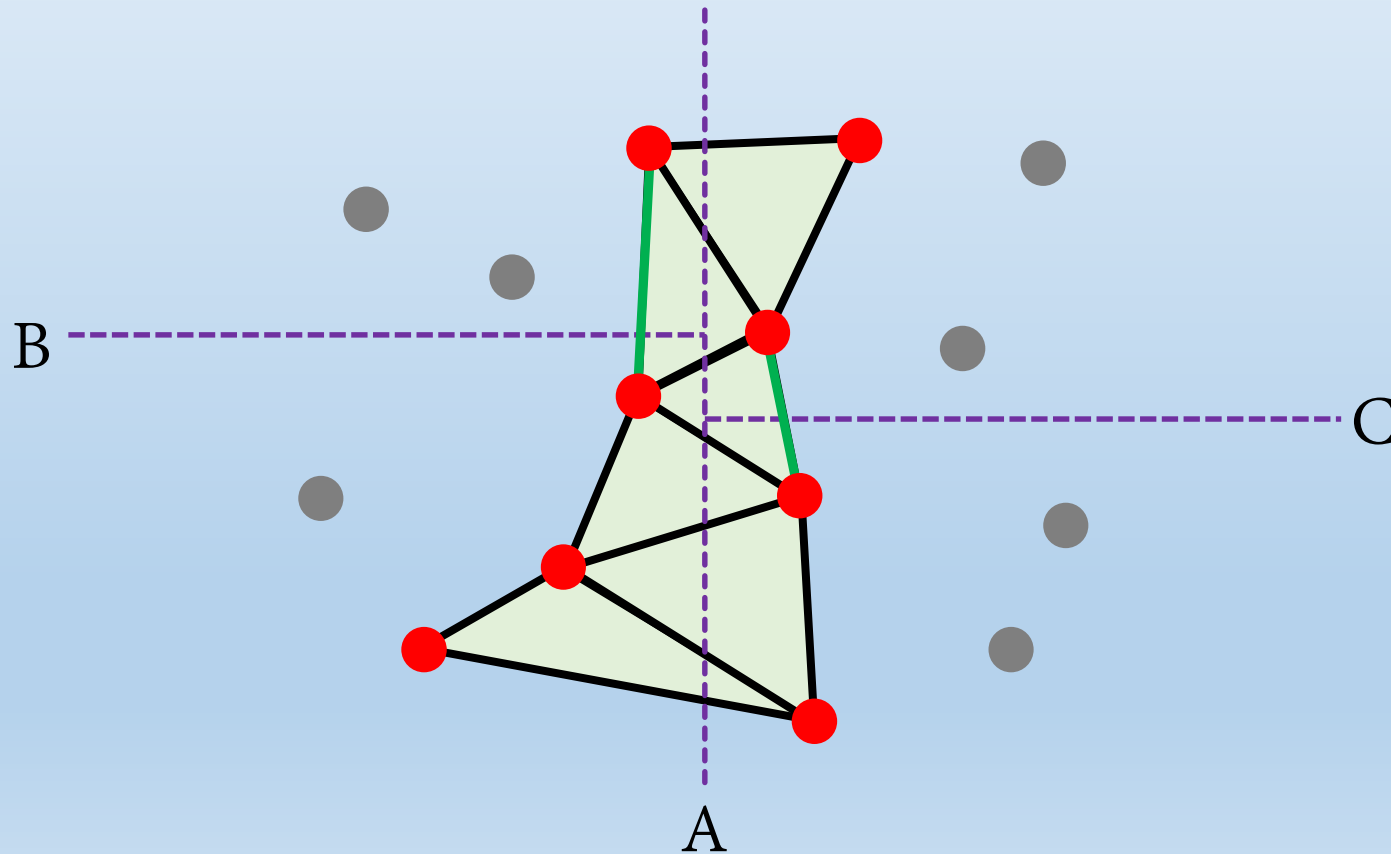
# 构造DT: 5-DeWall算法

-Step4: 迭代Step3直至AFL为空, 可获得该分割平面对应的DeWall, 并入结果DT



# 构造DT: 5-DeWall算法

-Step5: 对两个子集分别应用新分割平面并计算各自的DeWall  
上一层DeWall结果的边界可用于AFL的初始化





# 构造DT： 其他算法

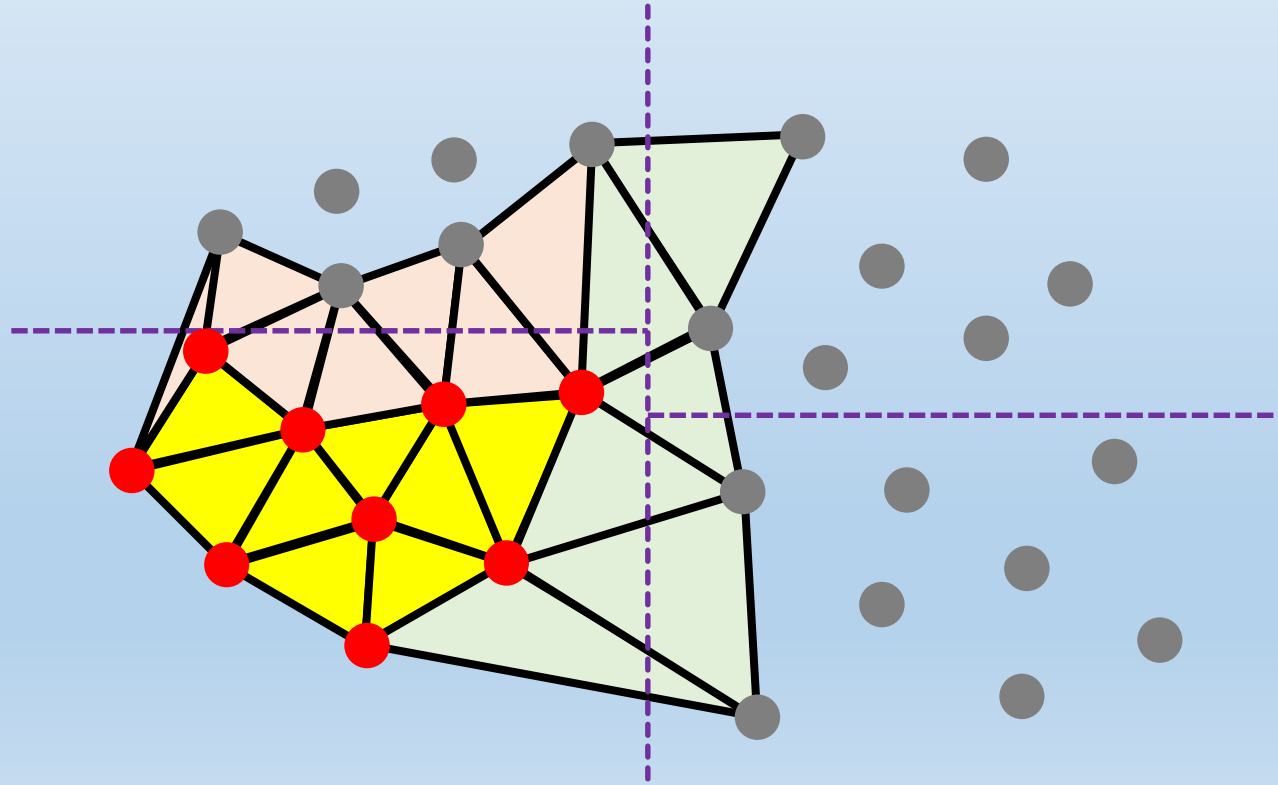
- 扫描线算法 sweepline algorithm
- 卷包裹算法 gift wrapping algorithm

# 构造DT: 主流代码库

- CGAL <https://www.cgal.org/>  
2D/3D DT, randomized incremental insertion using Bowyer-Watson
- TetGen <https://www.wias-berlin.de/software/tetgen/1.5/index.html>  
3D DT, randomized incremental insertion using flipping
- Qhull <http://www.qhull.org/>  
2D/3D DT, higher dimensional embedding

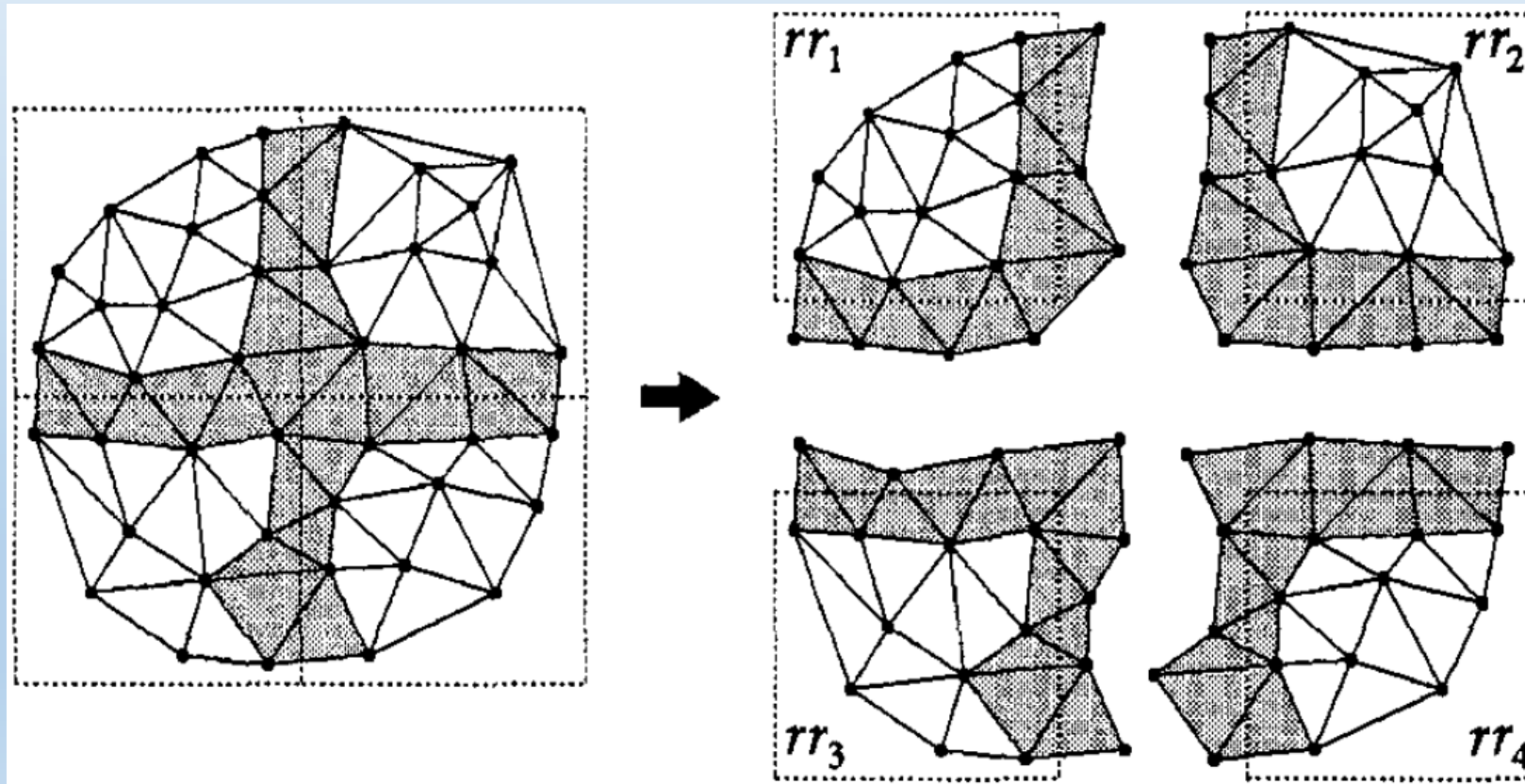
# 并行构造3D DT: 1-并行DeWall算法

- 划分点集，记与某个子集相关的所有分割平面的集合 $P_k$
- 每个线程需构造： $P_k$ 中每个平面的DeWall+子集内部的DT四面体
- 分割平面上的DeWall会被多个线程重复计算



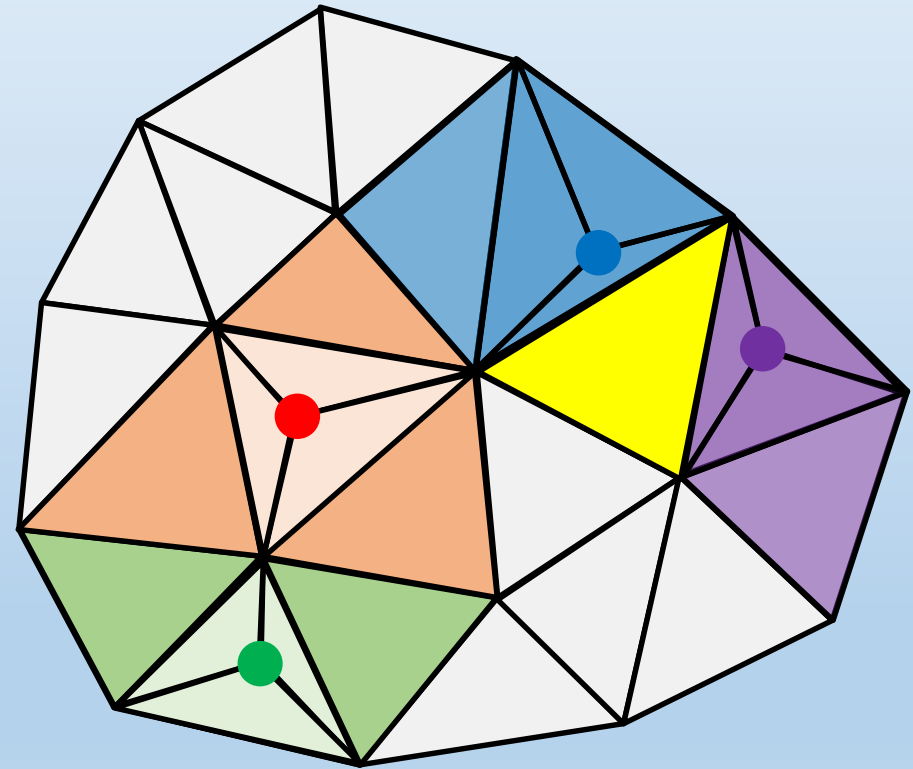
# 并行构造3D DT: 2-并行构造算法

- 划分点集，在每个格子里分别用扩散构造的方式获得DT四面体
- 格子边界的四面体会被重复计算



# 并行构造3D DT: 3-并行增长算法

- 并行向多个四面体中同时插入新点，并通过局部更新保持DT
- 受影响四面体/顶点需要加锁、解锁以防冲突
- 局部更新策略：
  - [Kohout2003]: 翻面
  - [Foteinos2012]: Bowyer-Watson

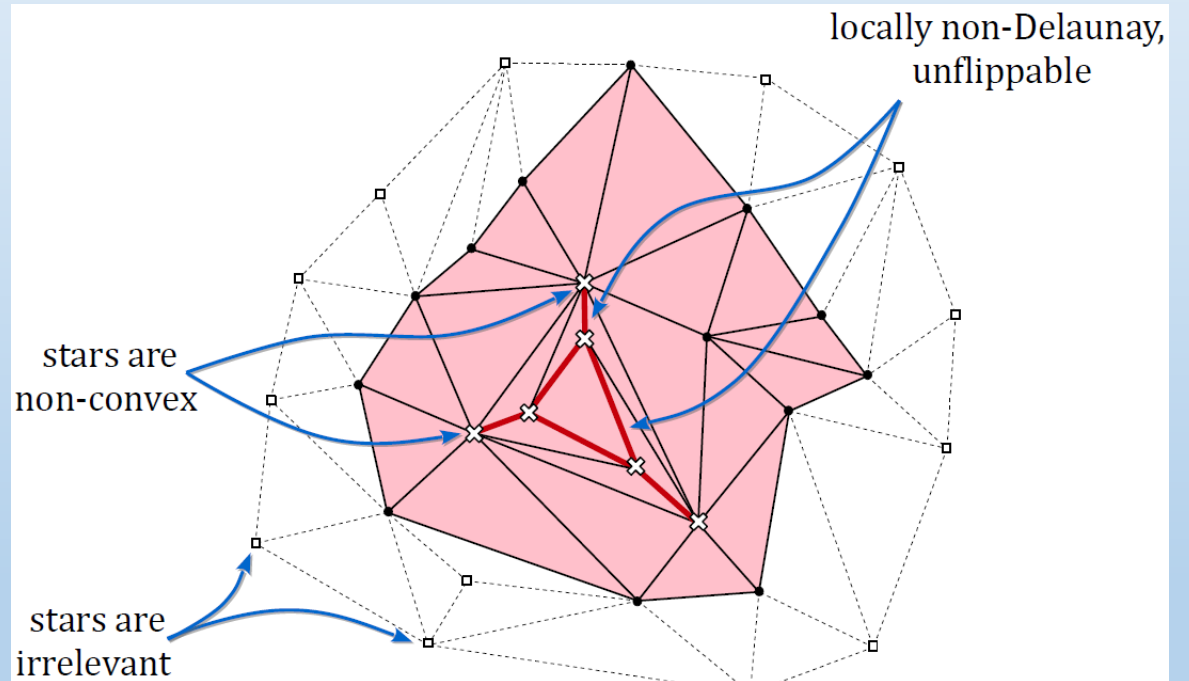
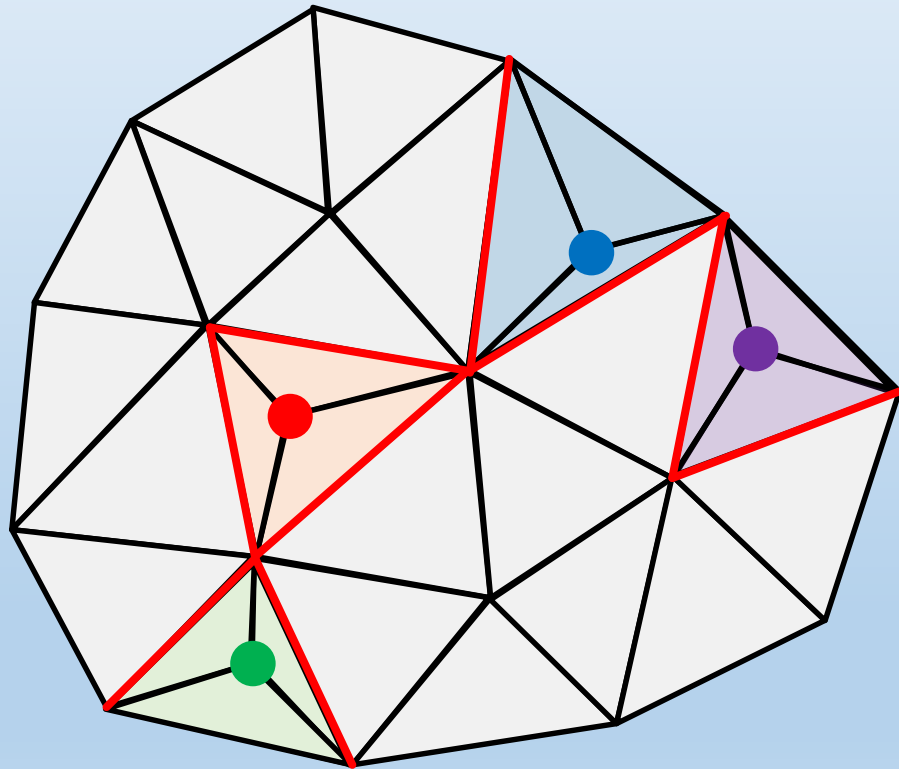


J. Kohout, I. Kolingerova. Parallel Delaunay triangulation in  $E^3$ : Make it simple. The Visual Computer, 2003, 19: 532-548.

P. Foteinos, N. Chrisochoides. Dynamic Parallel 3D Delaunay Triangulation. In Proceedings of the 20th International Meshing Roundtable, W. Quadros Ed., Berlin, 2012: 3-20.

# 并行构造3D DT: 4-GPU增长+CPU矫正

- 并行插入新点, 迭代标记需要翻转的面, 并行翻转 (未加锁)
- GPU端结果存在非Delaunay的面  $\rightarrow$  CPU端用[Shewchuck2005]矫正



T. Cao, A. Nanjappa, M. Gao, T. Tan. A GPU accelerated algorithm for 3D Delaunay triangulation. In Proceedings of I3D, 2014: 47-54.

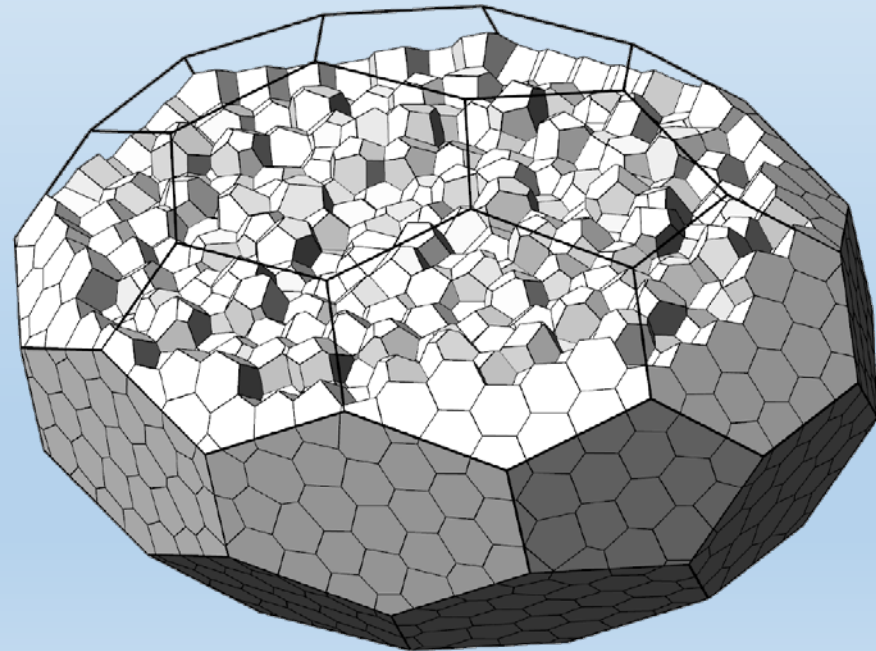
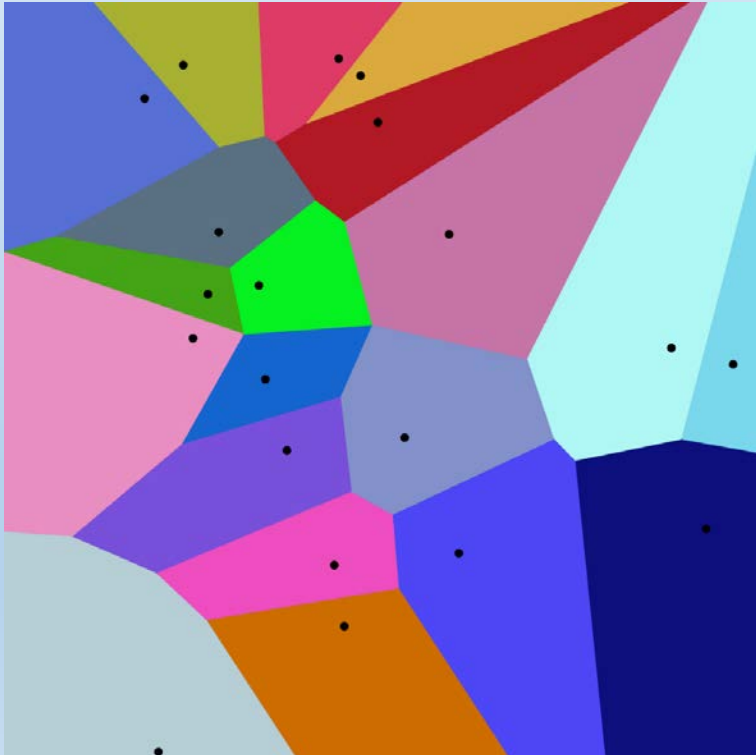
J. Shewchuk. Star Splaying: An Algorithm for Repairing Delaunay Triangulations and Convex Hulls. In Proc. 21st Symp. on Computational Geometry, 2005: 237-246.

# 目录

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  - 并行构造方法
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  - 定义
  - 串行构造方法
  - 并行构造方法

# Voronoi Diagram (VD)

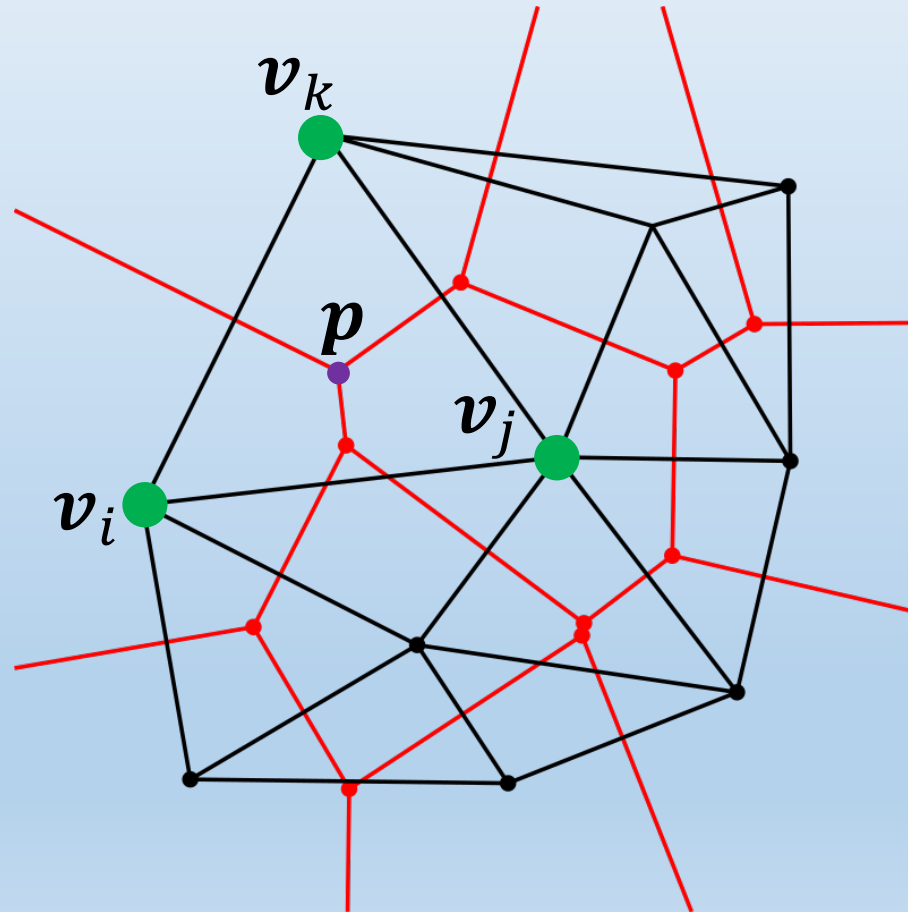
- 种子点集  $\{\mathbf{v}_i \in R^d\}_{i=1}^n$ , Voronoi图将空间划分成 $n$ 个子区域
- $\mathbf{v}_i$ 的子区域  $\Omega_i = \{\mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\| \leq \|\mathbf{x} - \mathbf{v}_j\|, \forall j \neq i\}$  (胞元)
- 高维VD





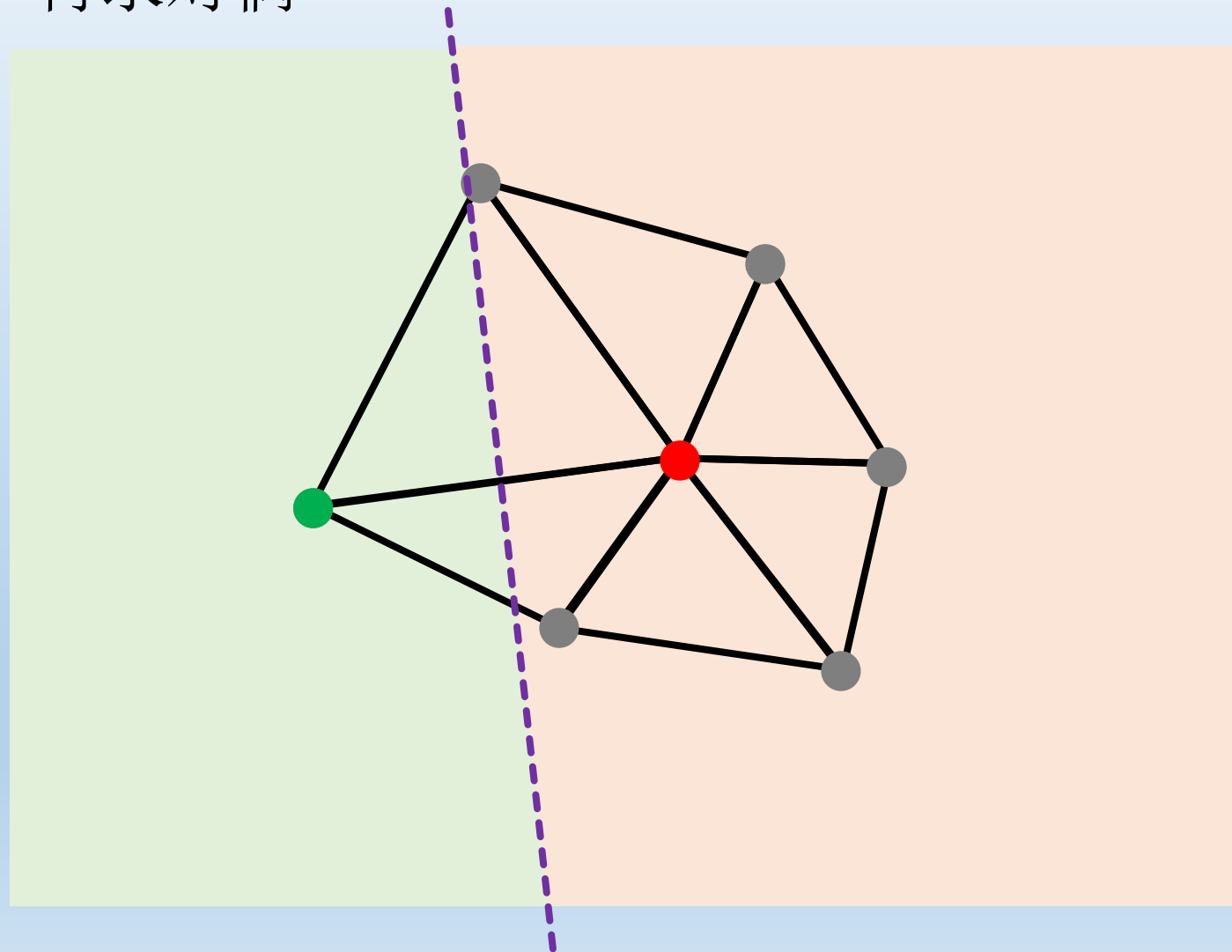
# VD与DT的对偶关系

- 三个相邻Voronoi胞元对应的种子点构成一个DT三角形



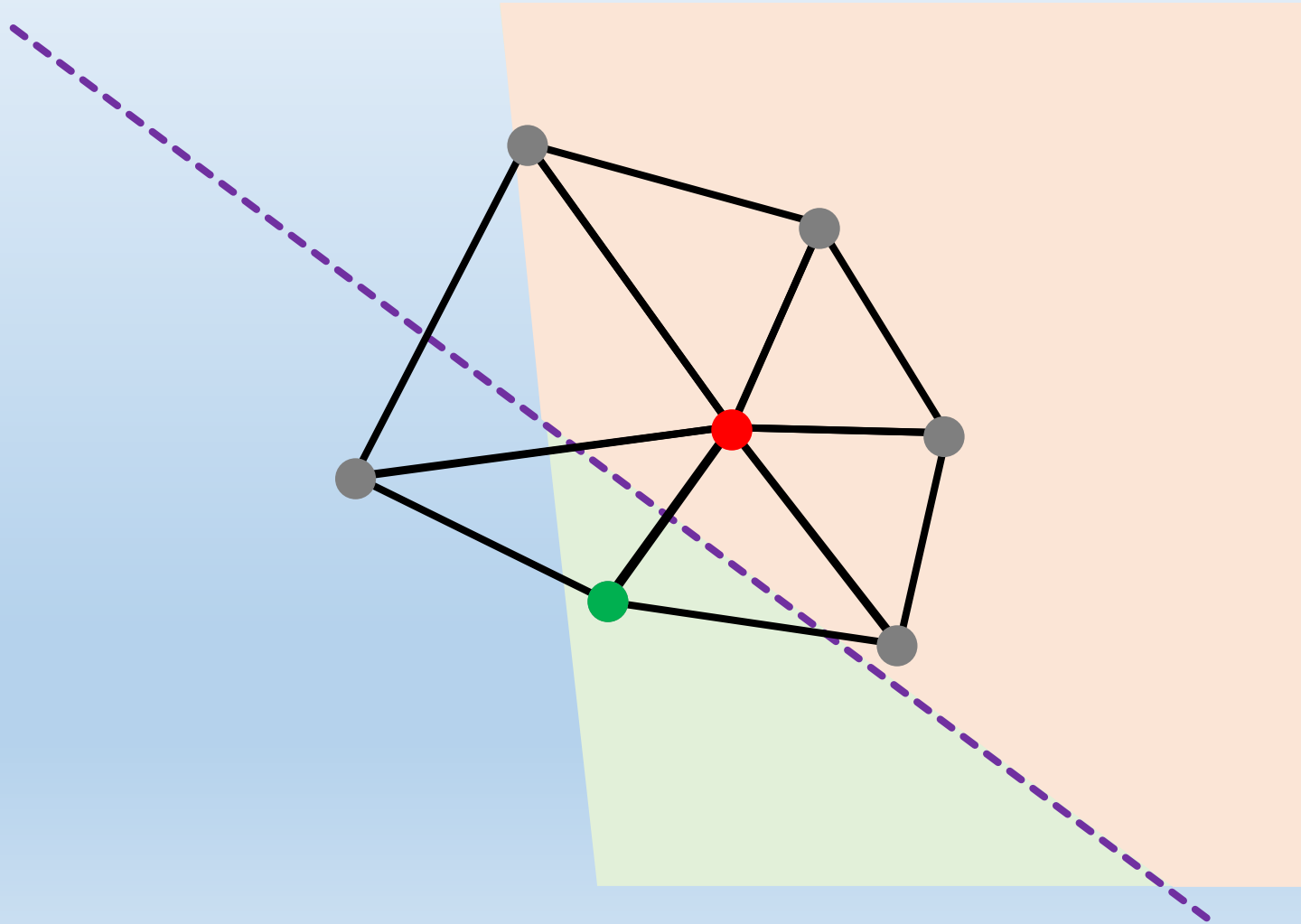
# 构造VD: 1-基于DT的方法

- 先构造DT, 再求对偶



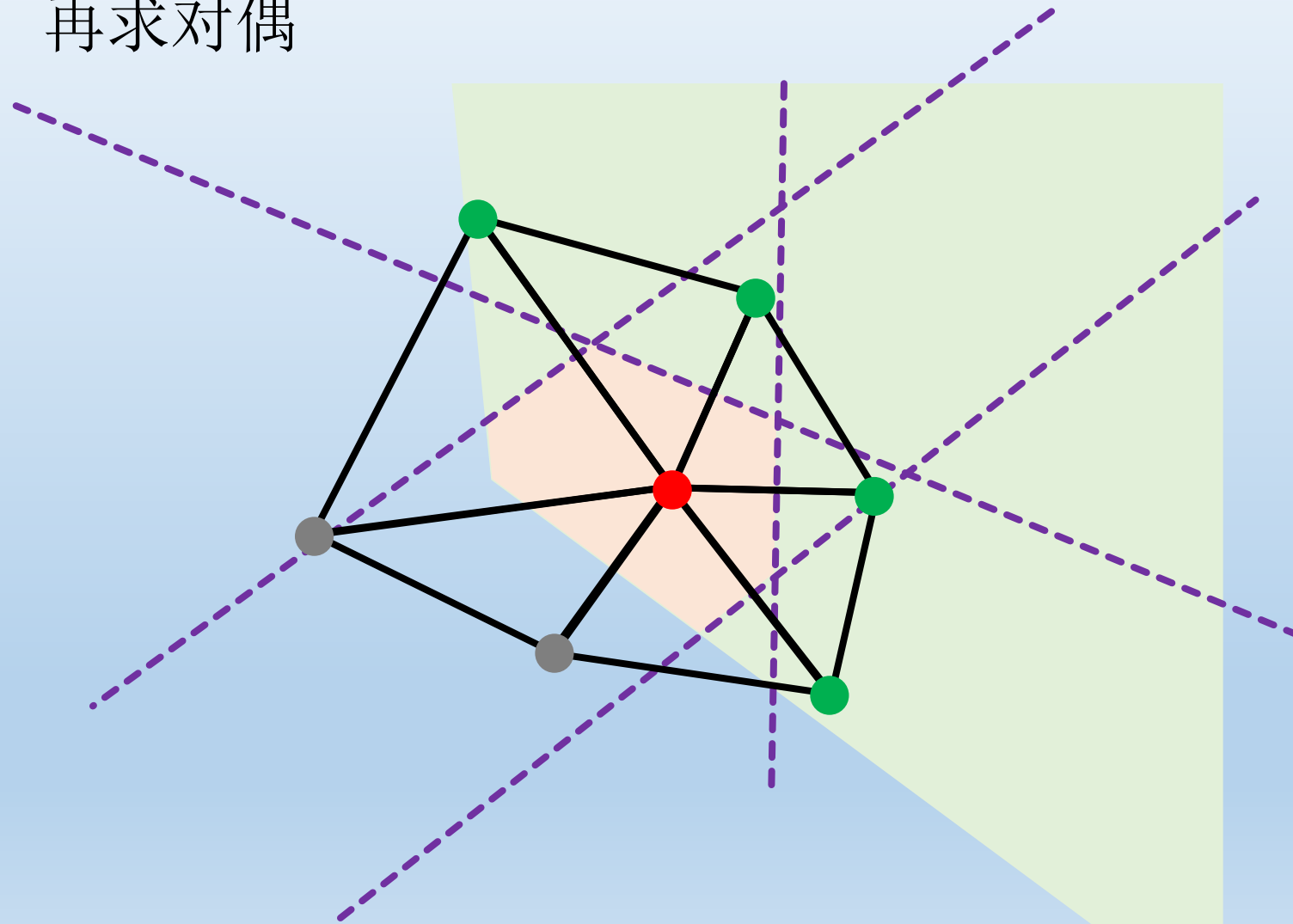
# 构造VD: 1-基于DT的方法

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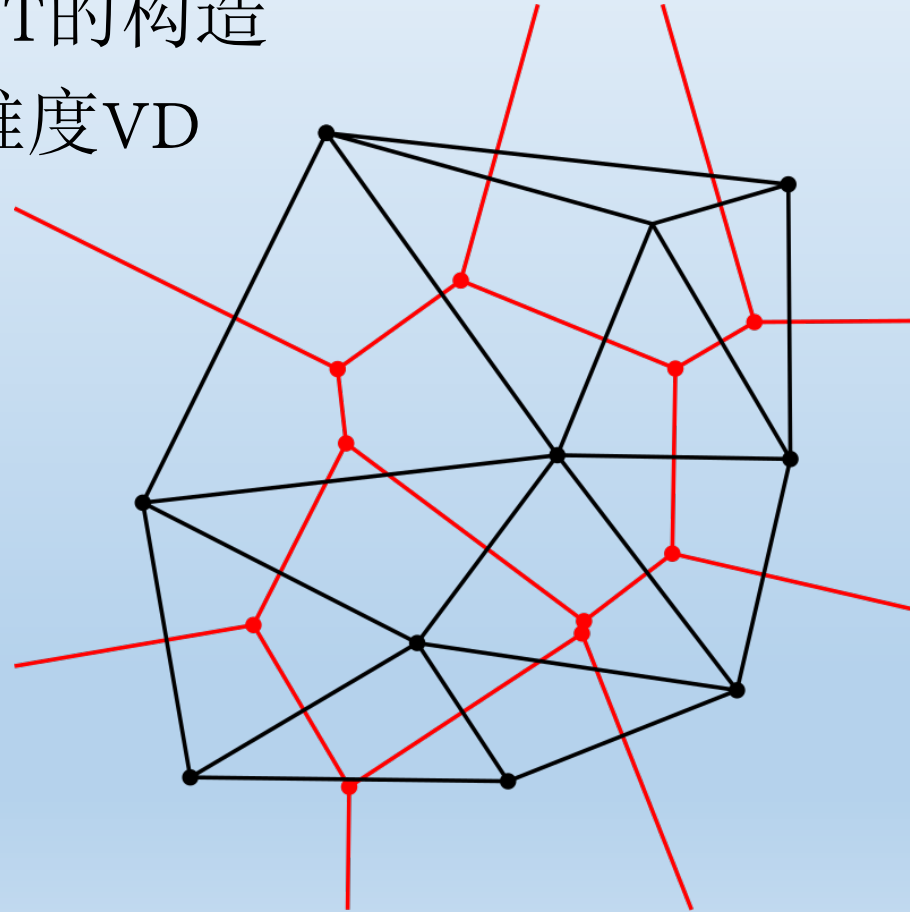
# 构造VD: 1-基于DT的方法

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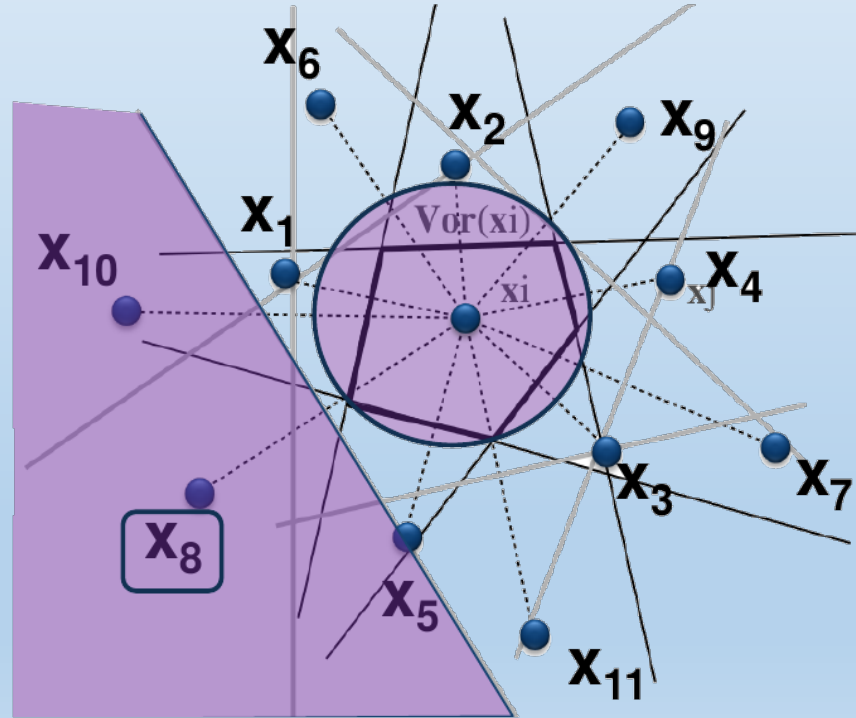
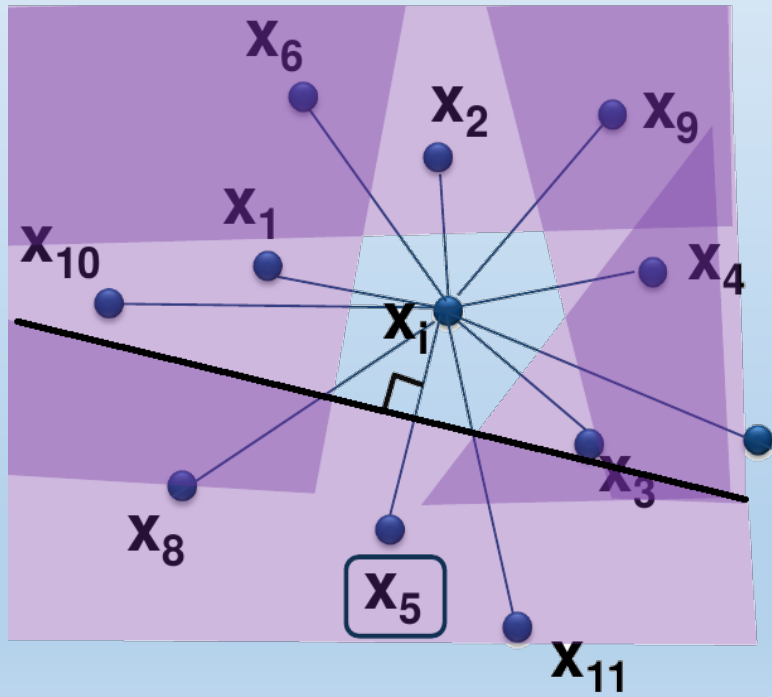
# 构造VD: 1-基于DT的方法

- 先构造DT, 再求对偶
- 效率主要取决于DT的构造
- 适用于构造任意维度VD



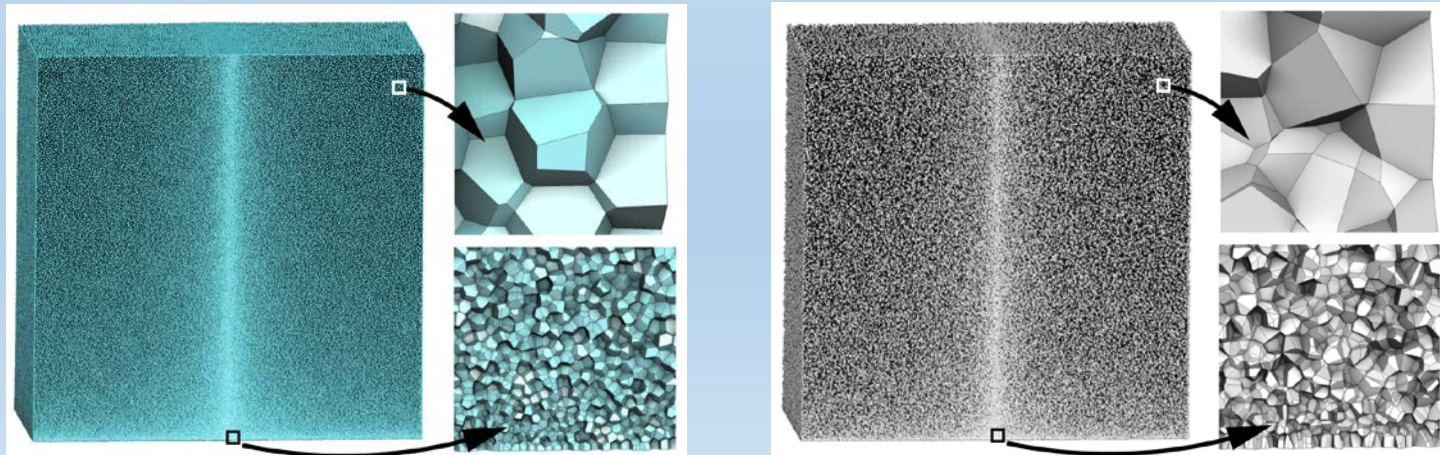
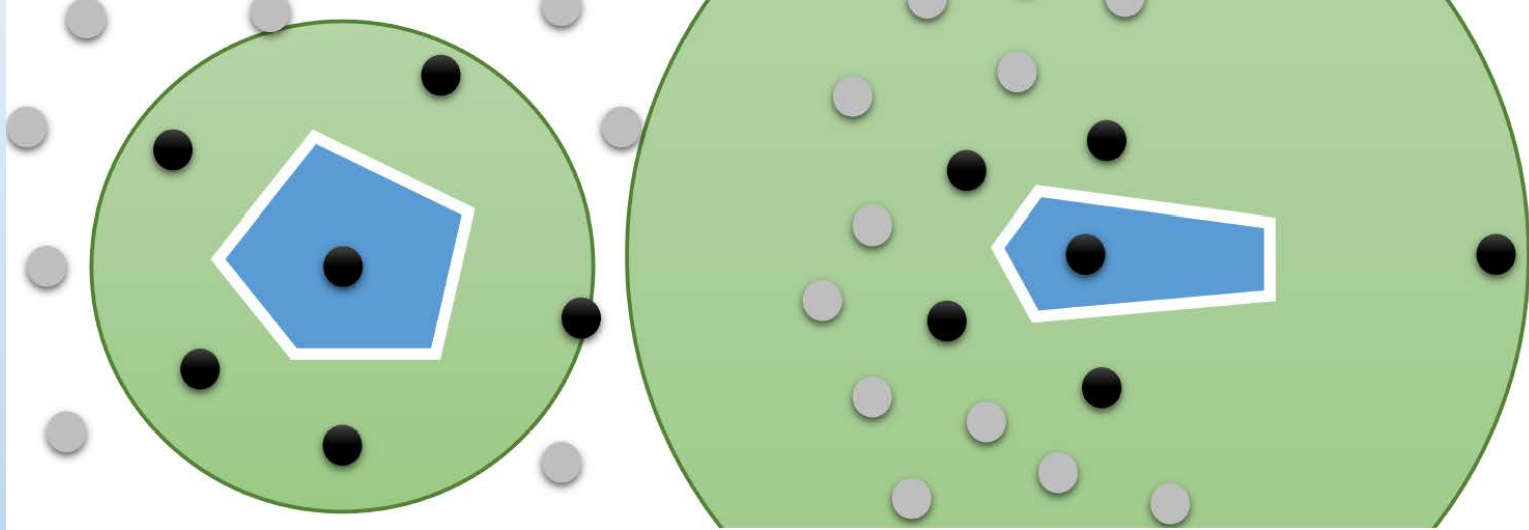
# 构造VD: 2-基于kNN的方法

- [Levy2013]: 每个Voronoi胞元是其种子点与所有其他种子点之间半空间的交集
- 计算 $\Omega_i$ : 对其他种子点排序 $N_i$ , 由近及远裁剪, 至满足结束条件



# 构造VD: 2-基于kNN的方法

- 缺点: 效率受点分布影响 (胞元裁剪结束条件是否快速达到)



# 构造VD：其他算法

- 高维嵌入算法 [Brown1979]
- 扫描线算法 [Fortune1987]
- 分治法 [Shamos1975]

K. Brown. Voronoi diagrams from convex hulls. *Information Processing Letters*, 1979, 9(5): 223–228.

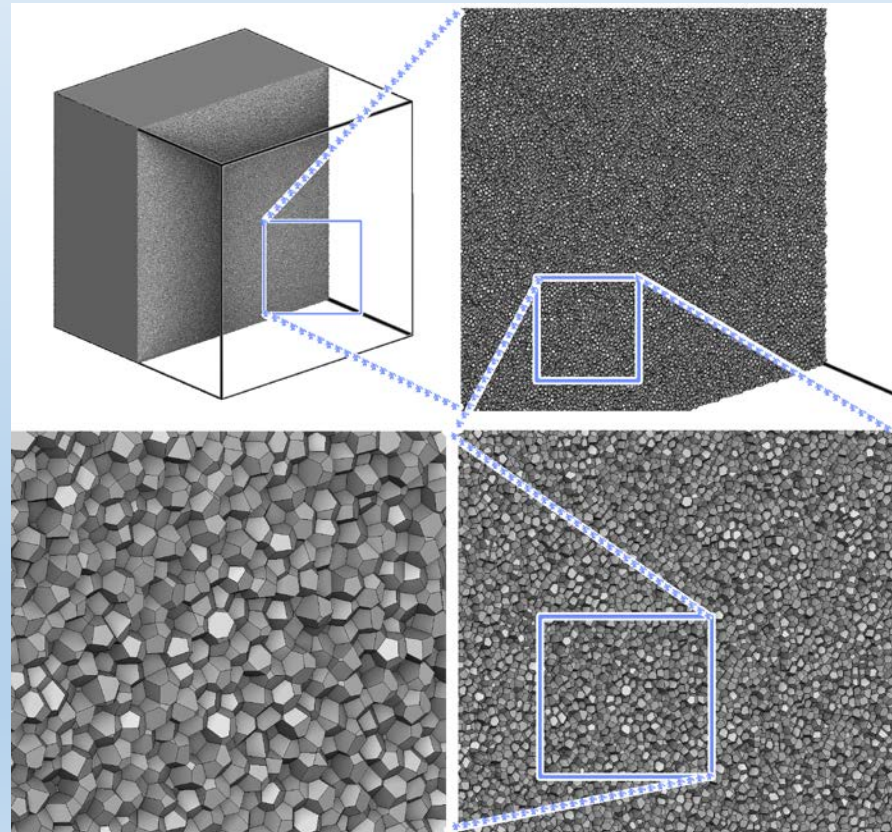
S. Fortune. A sweepline algorithm for Voronoi diagrams. *Algorithmica*, 1987, 2: 153-174.

M. Shamos, D. Hoey. Closest-point problems. In: 16th Annual symposium on foundations of computer science, 1975: 151–62.



# 并行构造VD: 基于kNN的方法

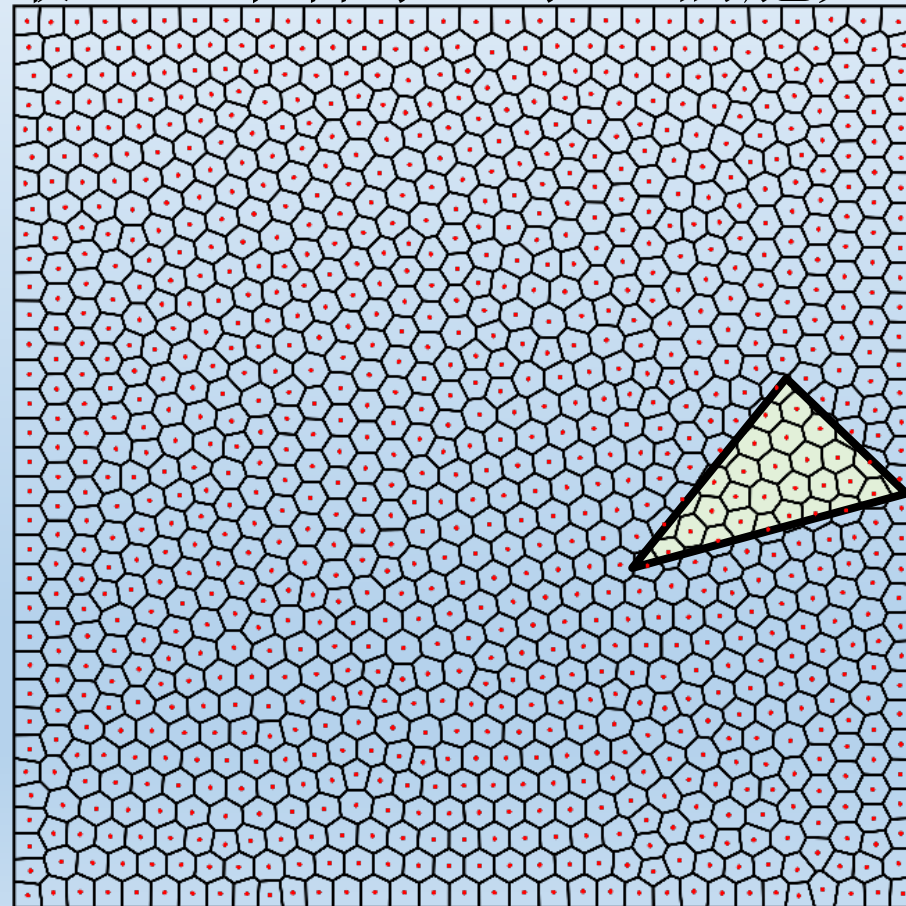
- Step1: 并行搜索每个种子点各自的 $N_i$ ,  $|N_i|$ 由用户给定
- Step2: 并行裁剪每个胞元



NVidia V100, 1千万点, 0.8s

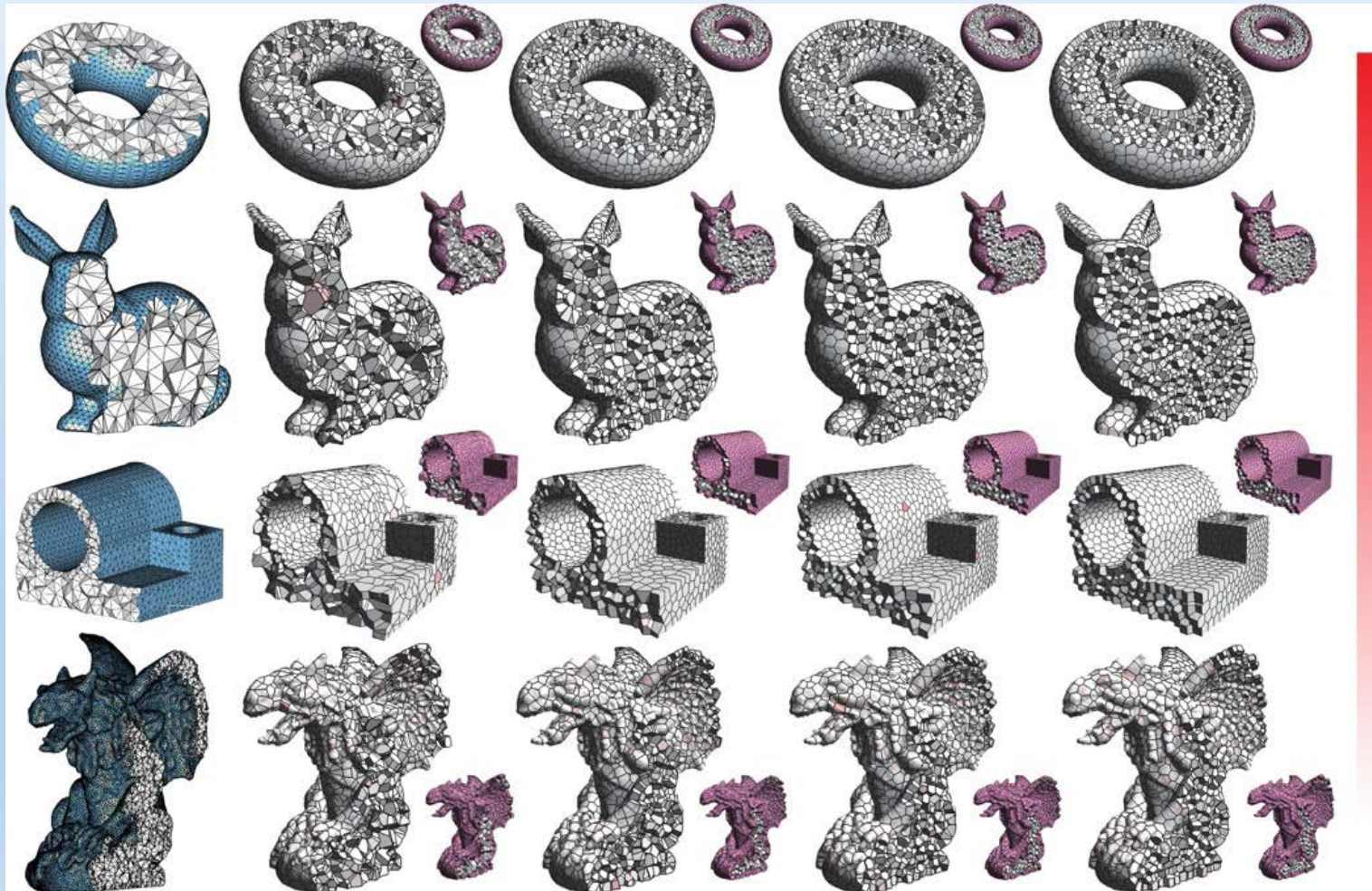
# 并行构造VD：基于kNN的方法

- [Liu2022]: 进一步求3D VD与不规则求解域(多个四面体)的交集  
- 离每个四面体重心最近20个种子, 求它们胞元与该四面体的交集



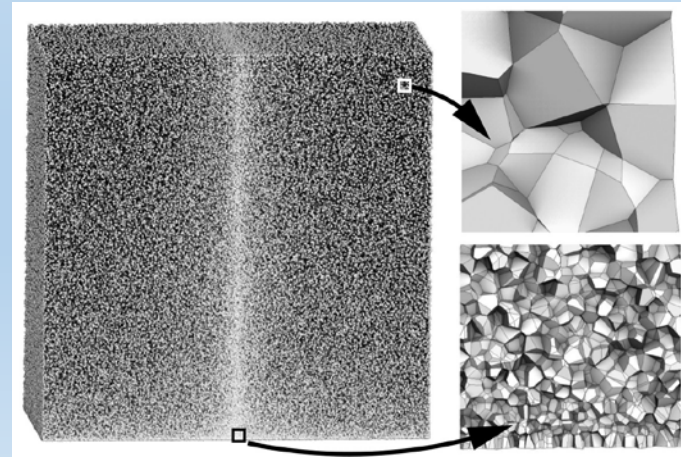
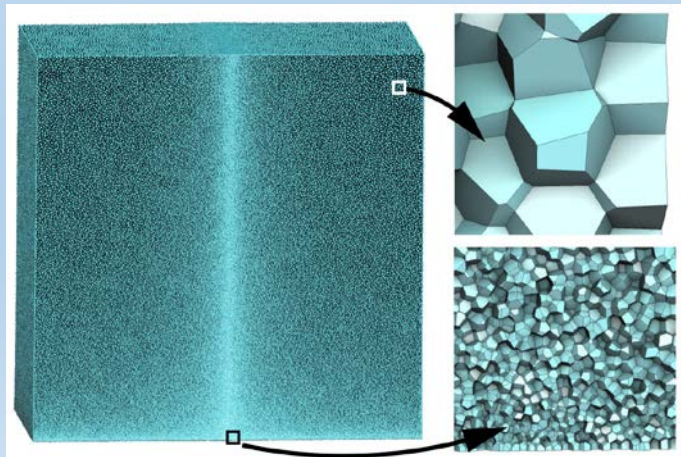
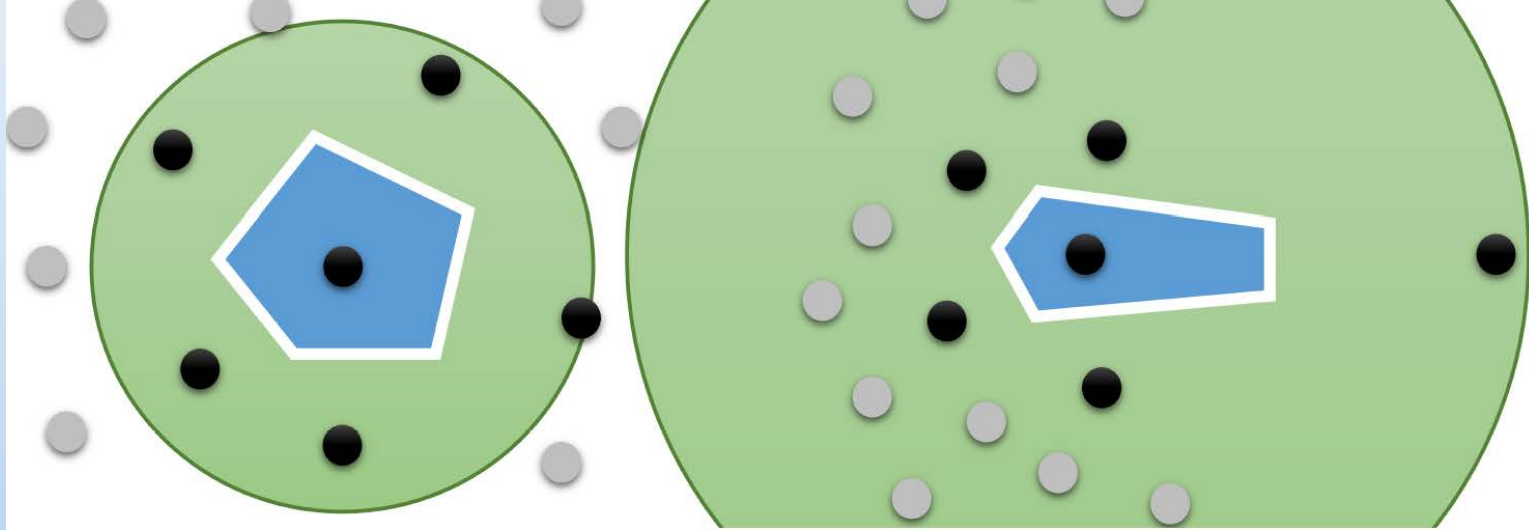
# 并行构造VD: 基于kNN的方法

- [Liu2022]: 进一步求3D VD与不规则求解域(多个四面体)的交集



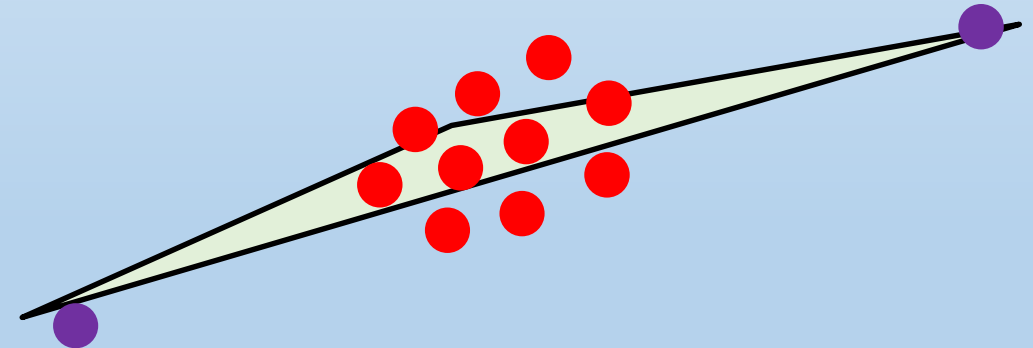
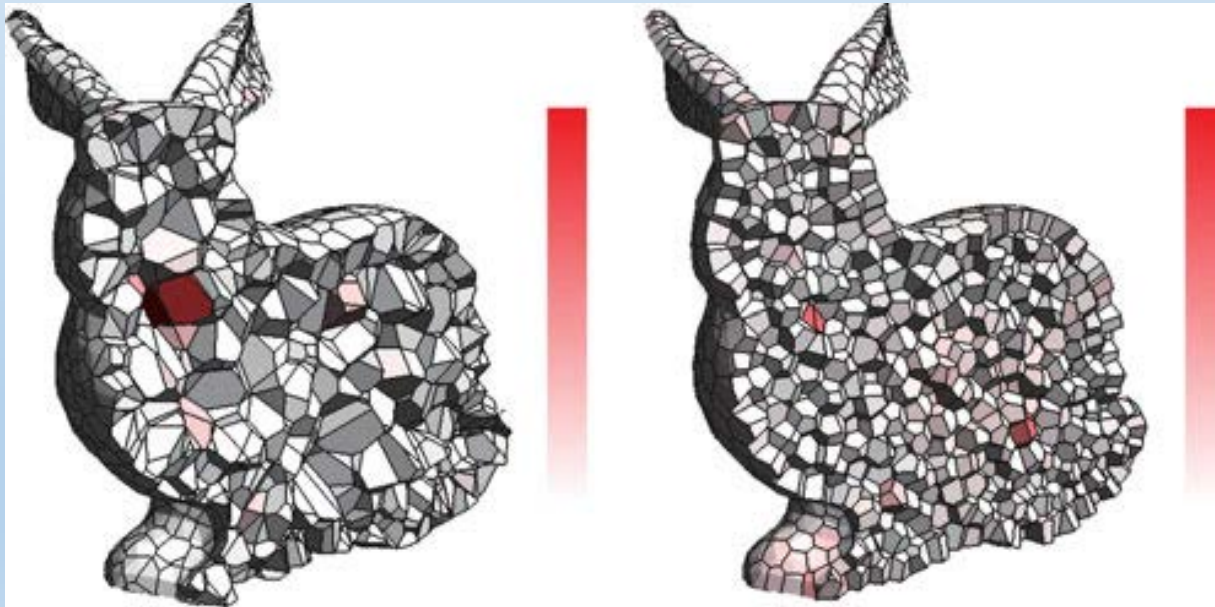
# 并行构造VD: 基于kNN的方法

- 缺点1: 效率受点分布影响 (胞元裁剪结束条件是否快速达到)



# 并行构造VD: 基于kNN的方法

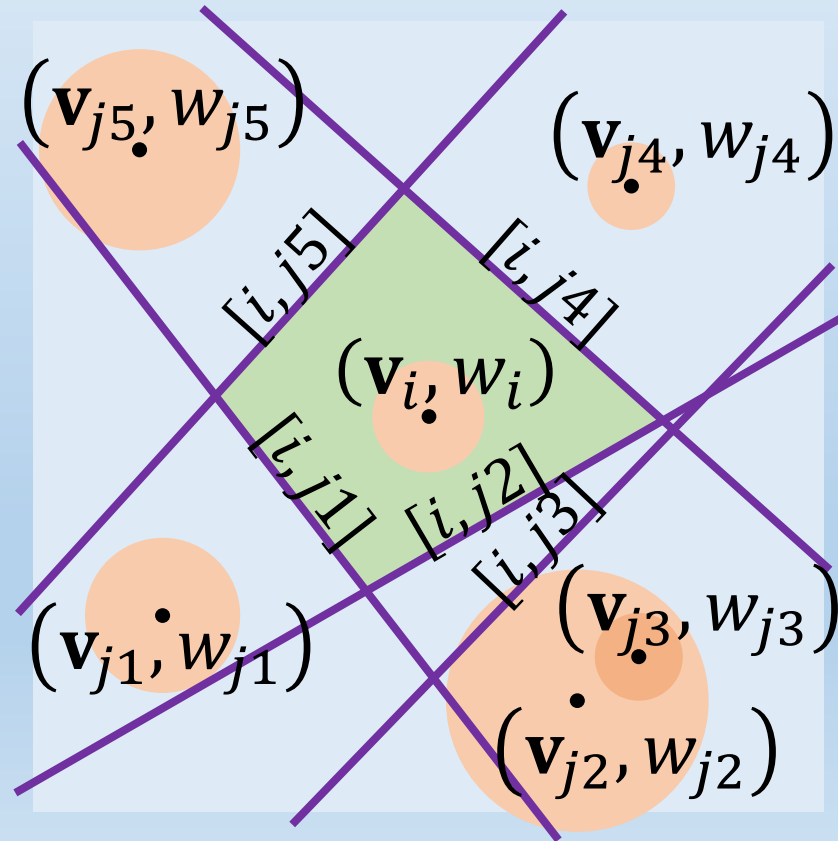
- 缺点2: 部分胞元是近似解
  - 原因1: 未达到裁剪结束条件 (除非 $|N_i|$ 足够大)
  - 原因2: 狭长四面体可能与更多胞元有交集却未被计算到



# Power图的快速构造 基于kNNN的方法

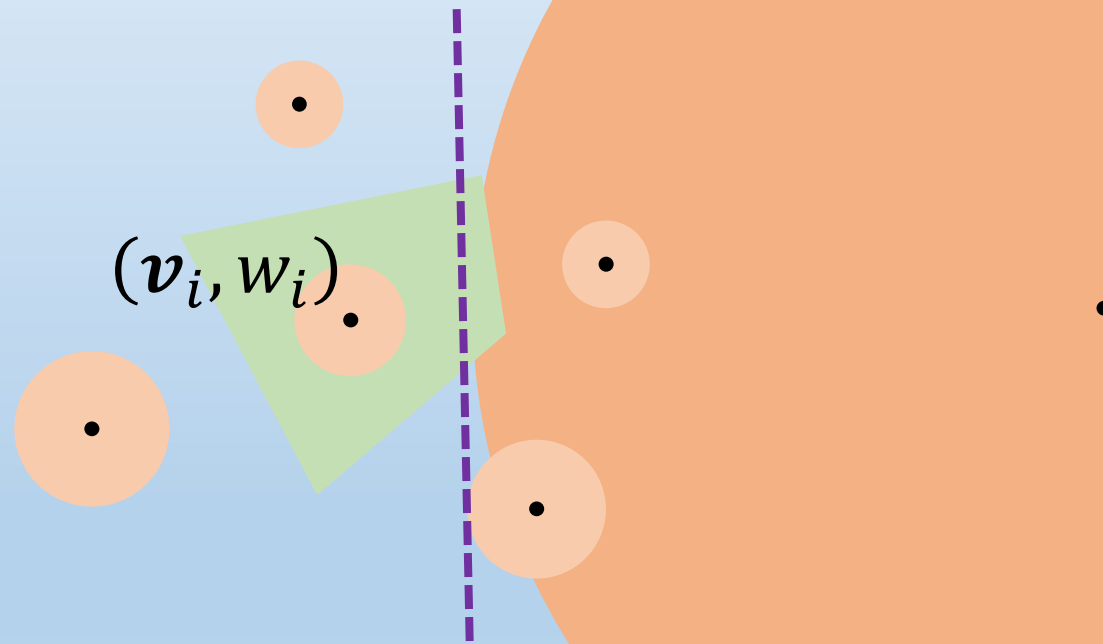
# Power图

- 种子点  $X = \{\mathbf{v}_i\}_{i=1}^n$ , 权重  $W = \{w_i\}_{i=1}^n$
- Power胞元  $\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\|^2 - w_i \leq \|\mathbf{x} - \mathbf{v}_j\|^2 - w_j, \forall j \neq i \right\}$



# 基于kNN的方法不能直接应用于Power图的构造

- 每个胞元的构造都需要遍历所有其他种子才能保证结果的正确性





# Power图 = 高一维受限Voronoi图

- Power胞元

$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\|^2 - w_i \leq \|\mathbf{x} - \mathbf{v}_j\|^2 - w_j, \forall j \neq i \right\}$$

- 引入  $\eta \geq w_{max} = \max\{w_1, \dots, w_n\}$

$$(\Omega_i)_\eta = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\|^2 + \eta - w_i \leq \|\mathbf{x} - \mathbf{v}_j\|^2 + \eta - w_j, \forall j \neq i \right\}$$

$$(\Omega_i)_\eta = \Omega_i$$

# Power图 = 高一维受限Voronoi图

- Power胞元

$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\|^2 + \underbrace{\eta - w_i}_{\geq 0} \leq \|\mathbf{x} - \mathbf{v}_j\|^2 + \underbrace{\eta - w_j}_{\geq 0}, \forall j \neq i \right\}$$



$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{x} - \mathbf{v}_i\|^2 + (0 - \pm\sqrt{\eta - w_i})^2 \leq \|\mathbf{x} - \mathbf{v}_j\|^2 + (0 - \pm\sqrt{\eta - w_j})^2, \forall j \neq i \right\}$$

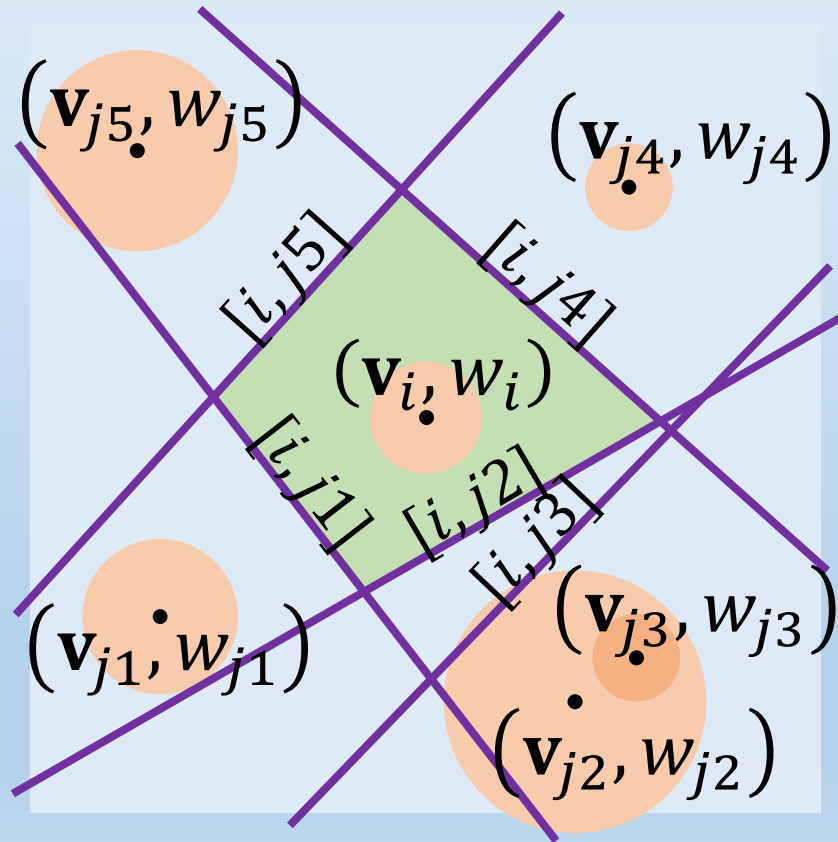
- 令  $\mathbf{y} = (\mathbf{x}, 0) \in R^{d+1}$ ,  $\mathbf{p} = (\mathbf{v}, \pm\sqrt{\eta - w}) \in R^{d+1}$  (提升点)

$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{y} - \mathbf{p}_i\|^2 \leq \|\mathbf{y} - \mathbf{p}_j\|^2, \forall j \neq i \right\}$$

= 提升点 $\mathbf{p}_i$ 的Voronoi胞元约束在 $R^d$ 的部分

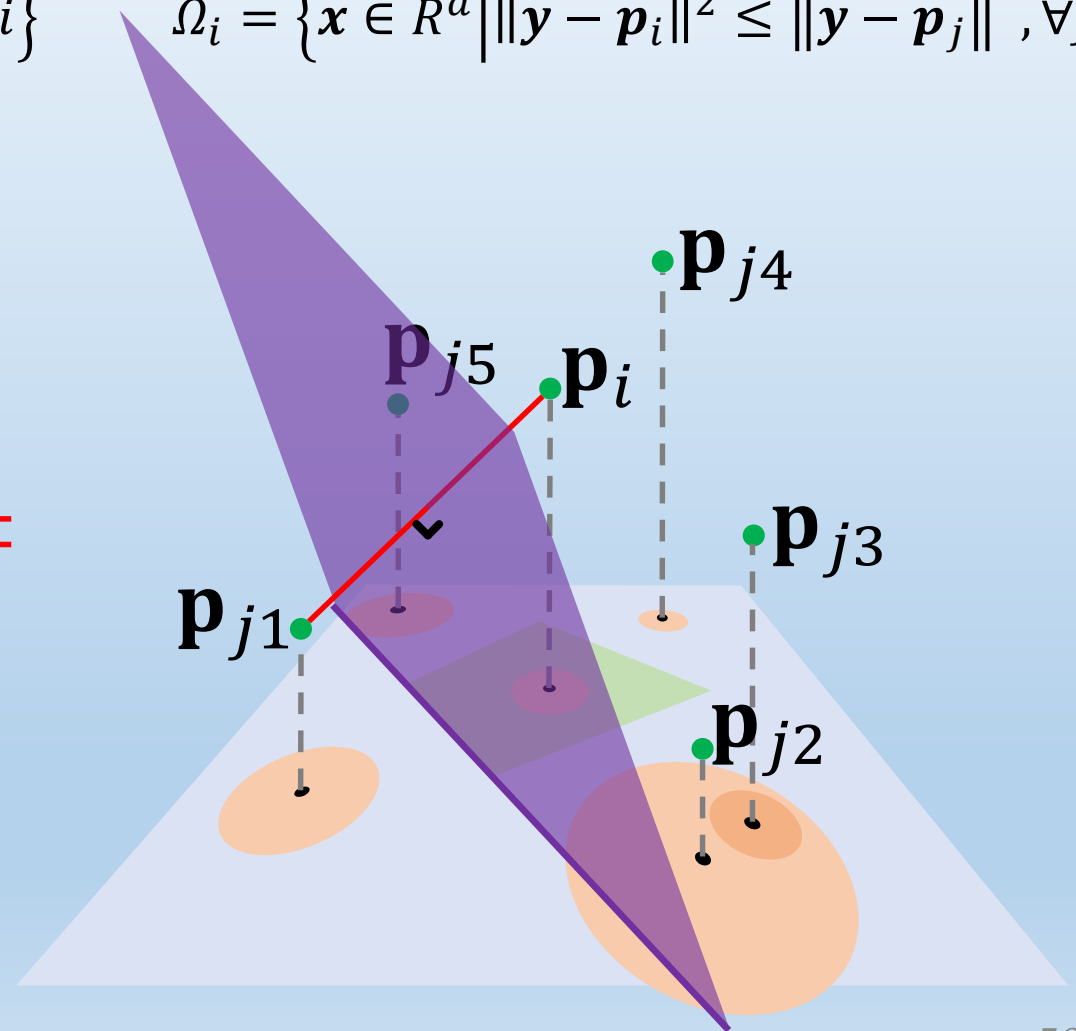
# Power图 = 高一维受限Voronoi图

$$\Omega_i = \{x \in R^d \mid \|x - v_i\|^2 - w_i \leq \|x - v_j\|^2 - w_j, \forall j \neq i\}$$

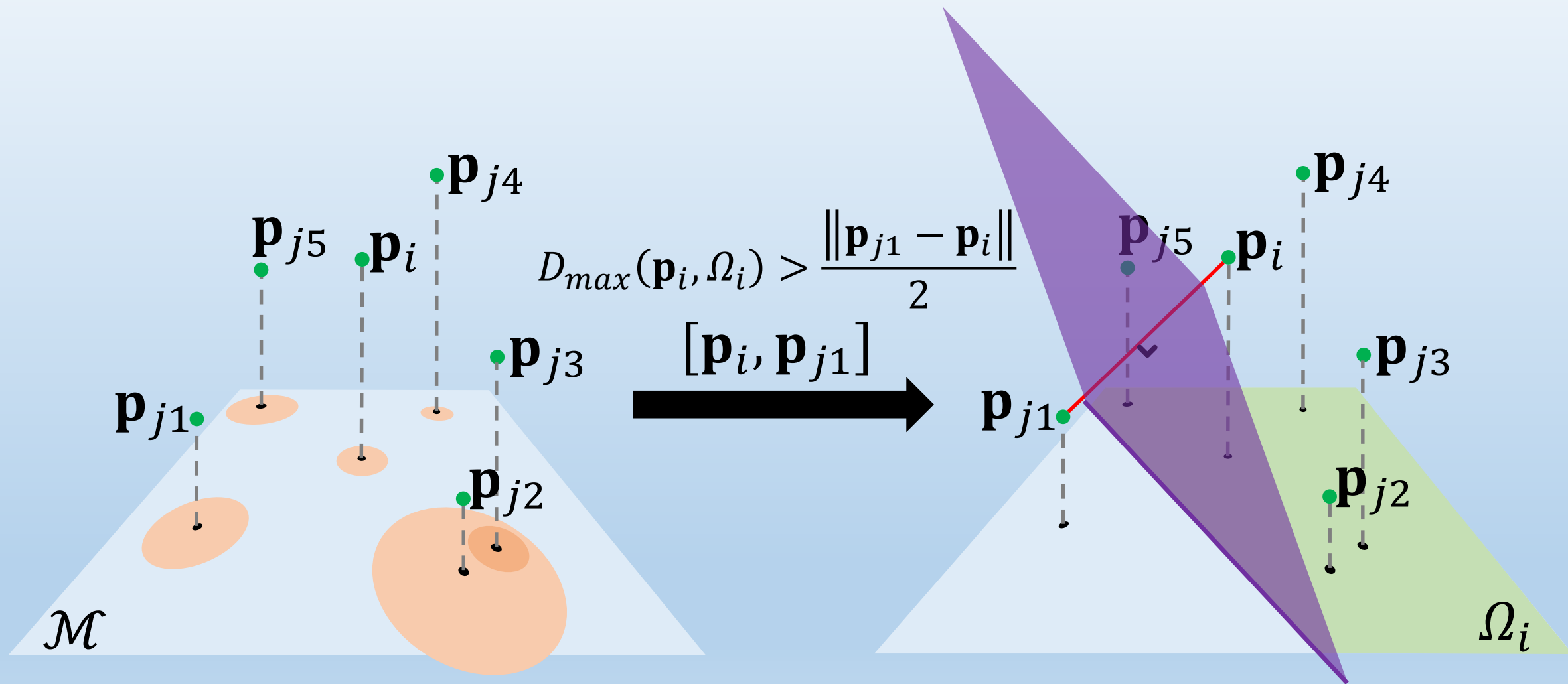


$$\Omega_i = \{x \in R^d \mid \|y - p_i\|^2 \leq \|y - p_j\|^2, \forall j \neq i\}$$

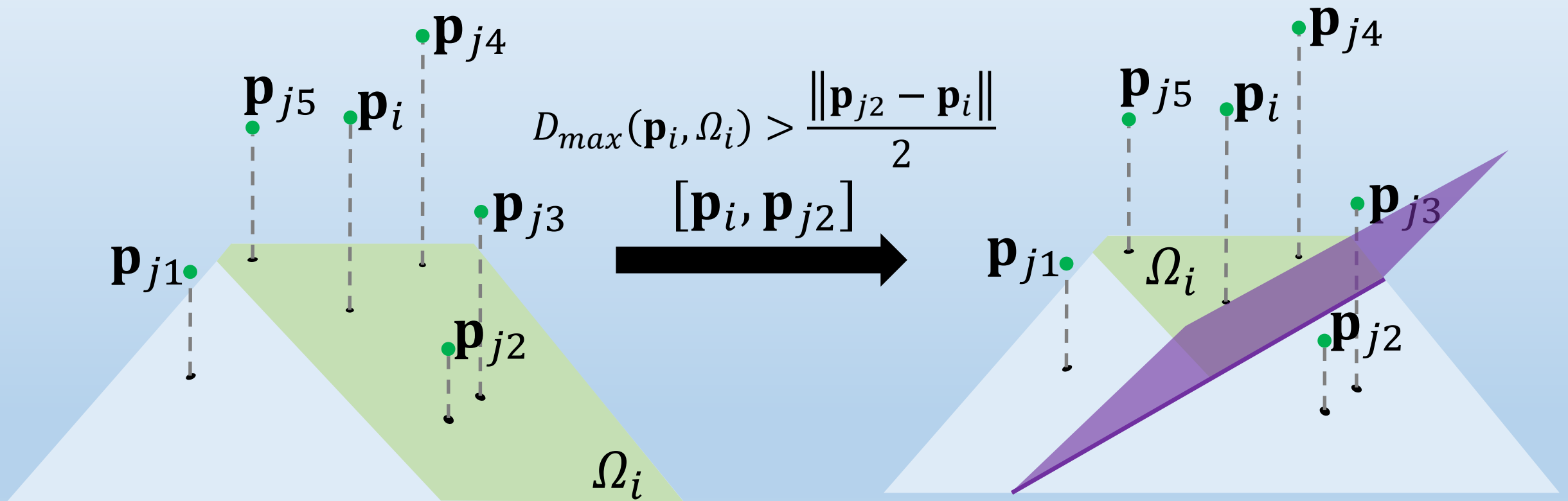
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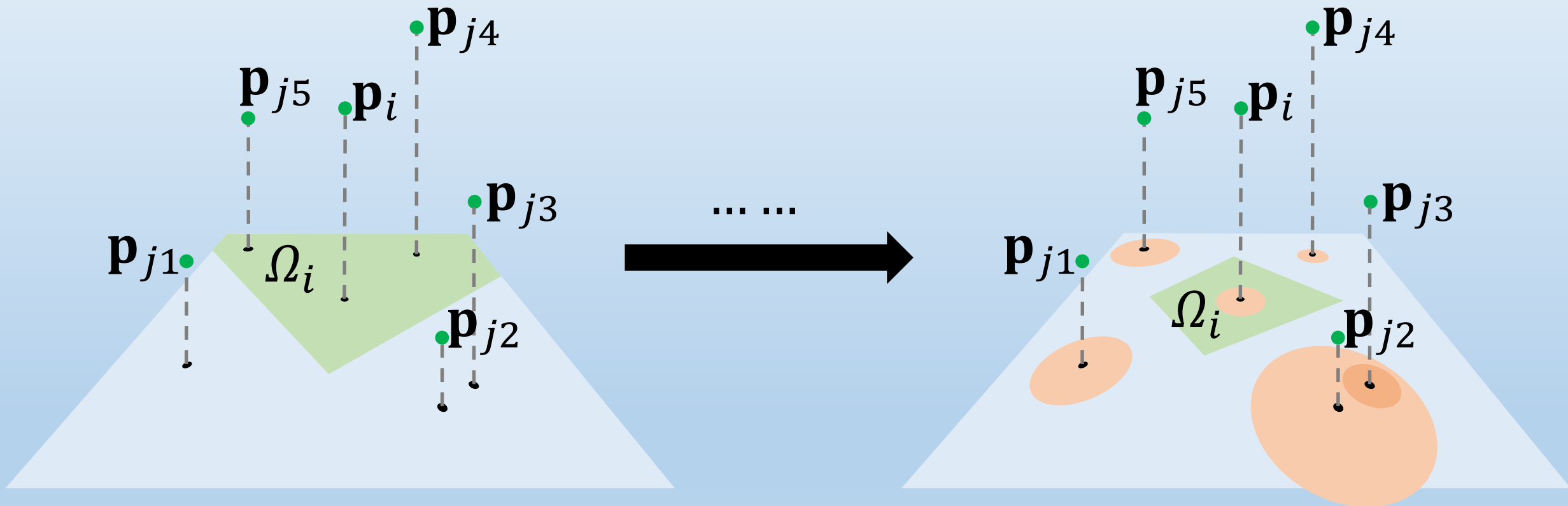
# Power图的快速构造：基于kNN的方法



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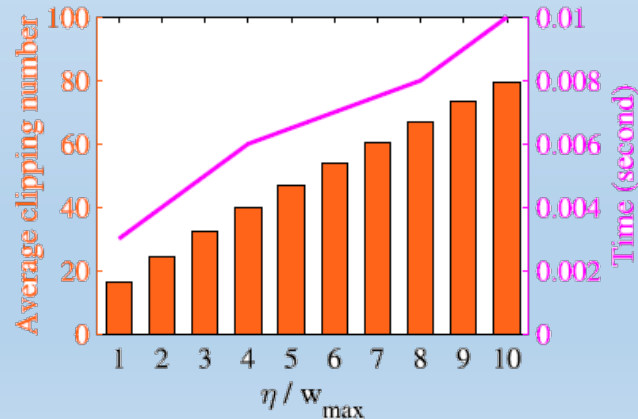
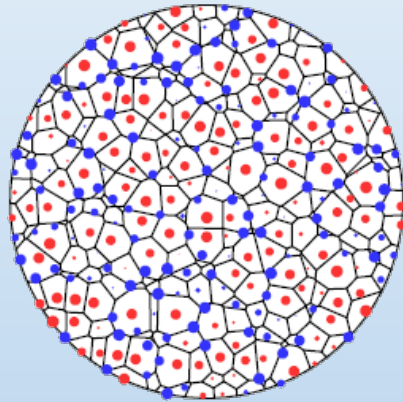


# Power图的快速构造：基于kNN的方法

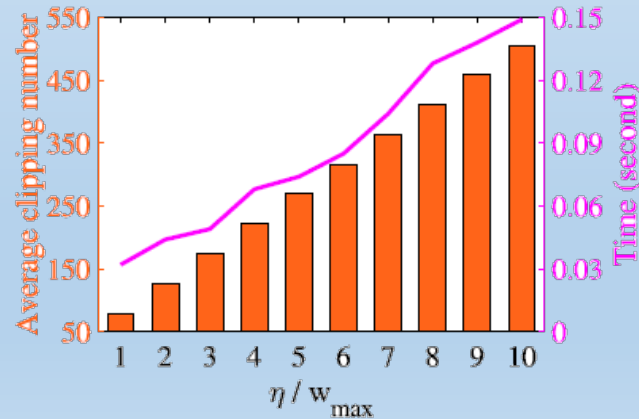
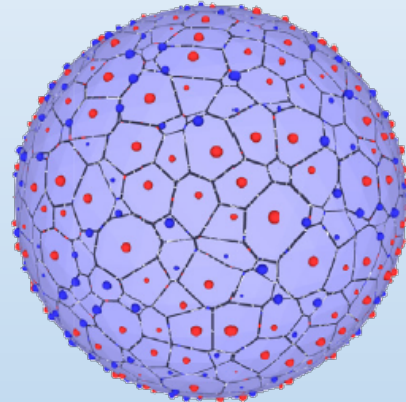


# Power图的快速构造：基于kNN的方法

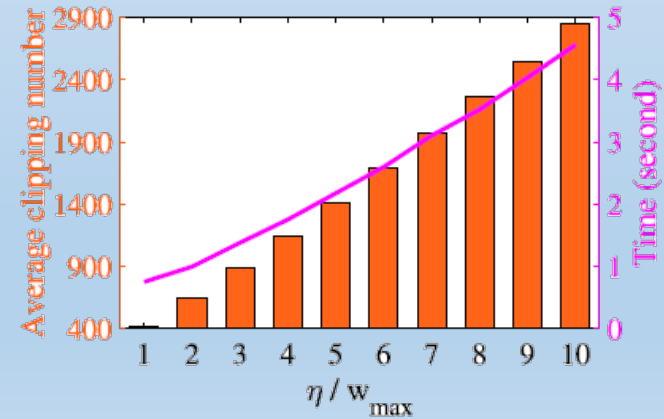
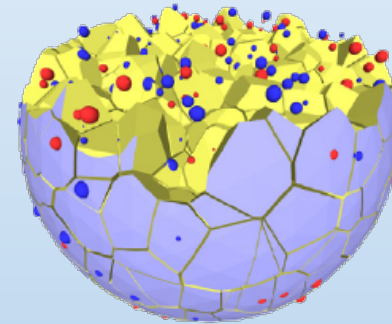
- $\eta$ 控制提升点到 $R^d$ 的高度，其值越小power胞元构造得越快



(a) 2D case, 300 weighted seeds



(b) Surface case, 800 weighted seeds



(c) 3D case, 1500 weighted seeds

# Power图的快速构造：加速技巧

- 每个种子有两个提升点可选，它们的胞元相同

$$\mathbf{p} = (\mathbf{v}, \sqrt{\eta - w}), \mathbf{q} = (\mathbf{v}, -\sqrt{\eta - w})$$

$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{y} - \mathbf{p}_i\|^2 \leq \|\mathbf{y} - \mathbf{p}_j\|^2, \forall j \neq i \right\}$$

$$\Omega_i = \left\{ \mathbf{x} \in R^d \mid \|\mathbf{y} - \mathbf{q}_i\|^2 \leq \|\mathbf{y} - \mathbf{p}_j\|^2, \forall j \neq i \right\}$$



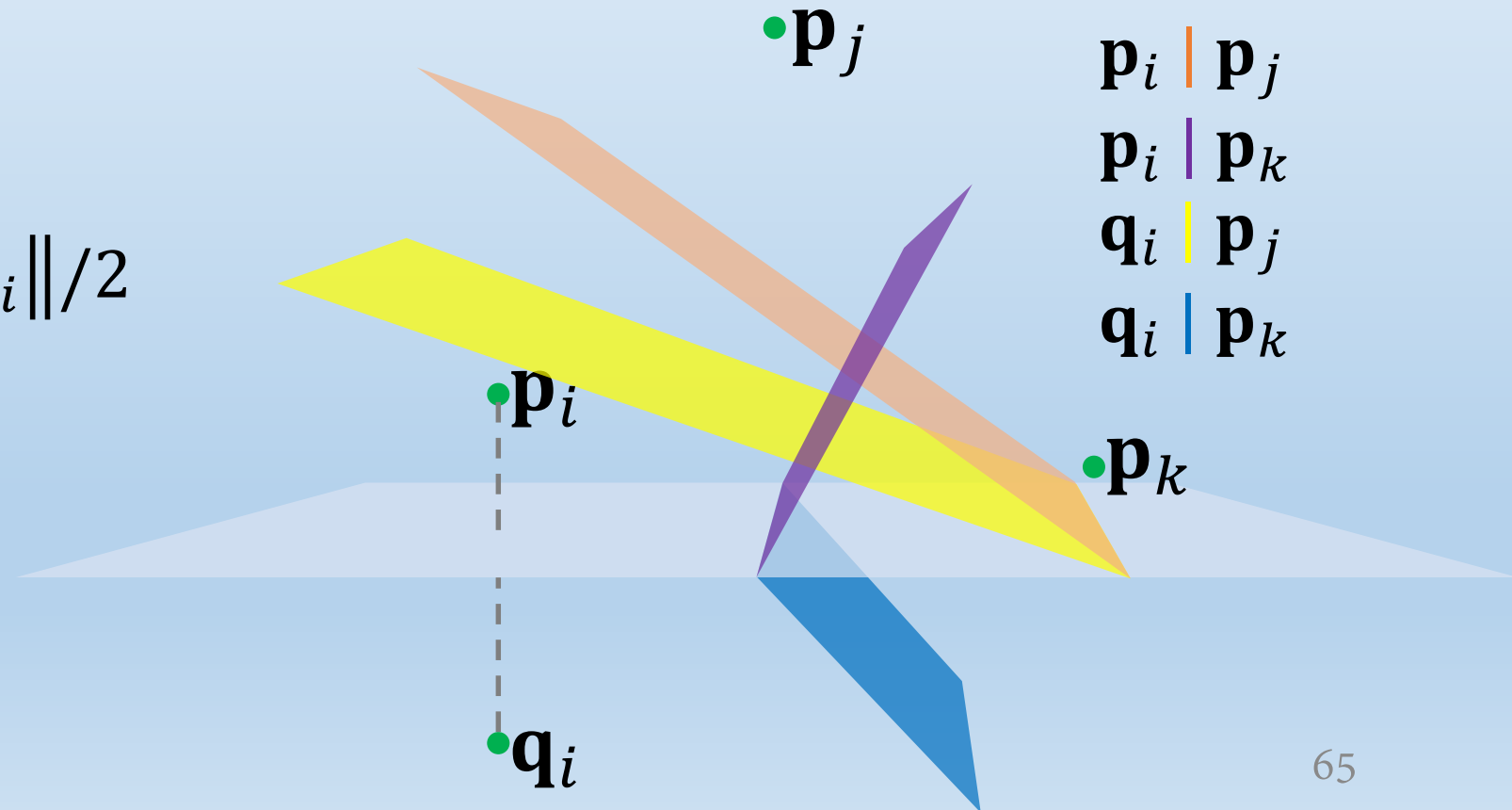
# Power图的快速构造：加速技巧

- 如果构造 $p_i$ 的胞元：先用 $p_i p_j$ 中垂面，再用 $p_i p_k$ 中垂面
- 如果构造 $q_i$ 的胞元：先用 $q_i p_k$ 中垂面，再用 $q_i p_j$ 中垂面



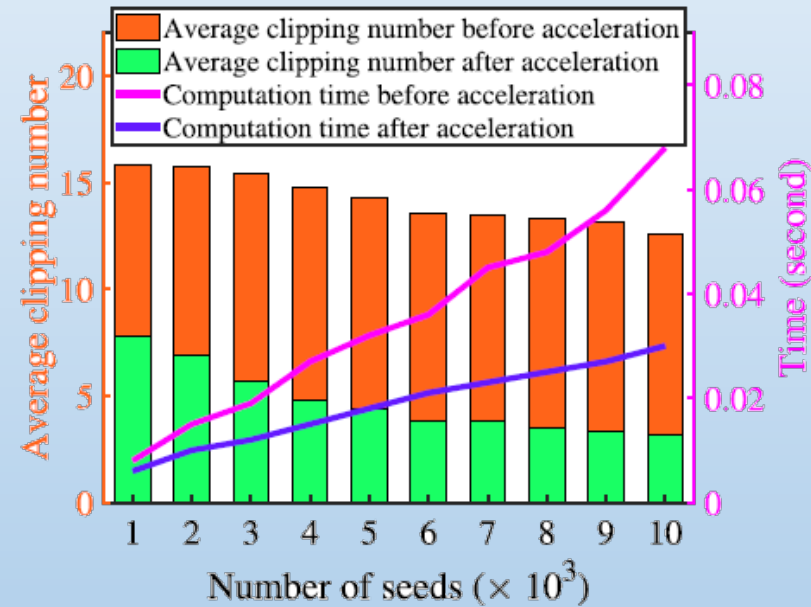
$$D_{max}(q_i, \Omega_i) \leq \|p_j - q_i\|/2$$

可以更早达到

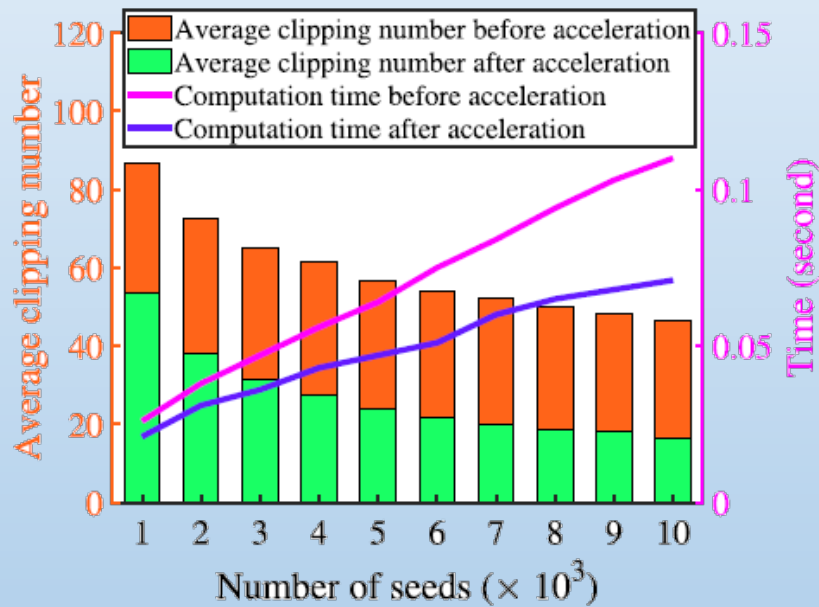


# Power图的快速构造：加速技巧

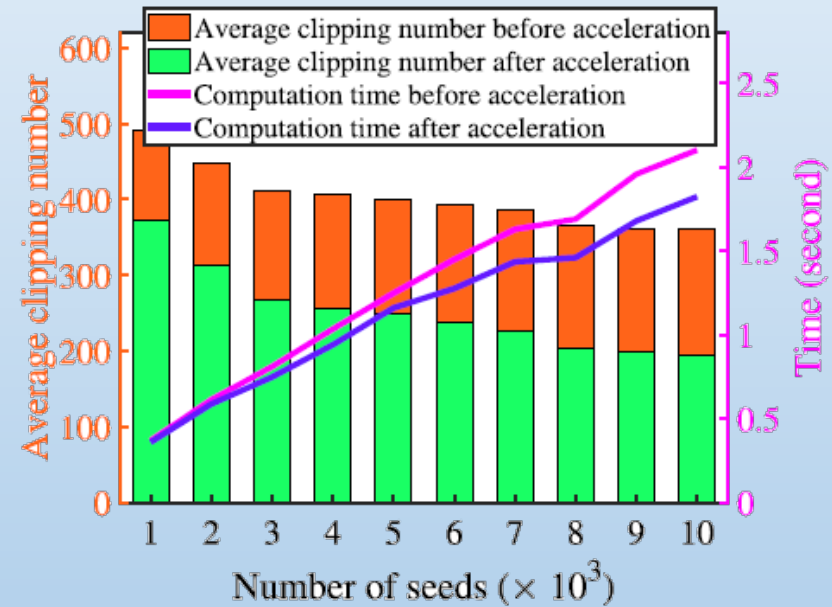
- 实施：提升点集 $\{p_i\}_{i=1}^n$ 构建kd树，搜索 $q_i$ 的k近邻以构造 $\Omega_i$



(a) 2D case



(b) Surface case

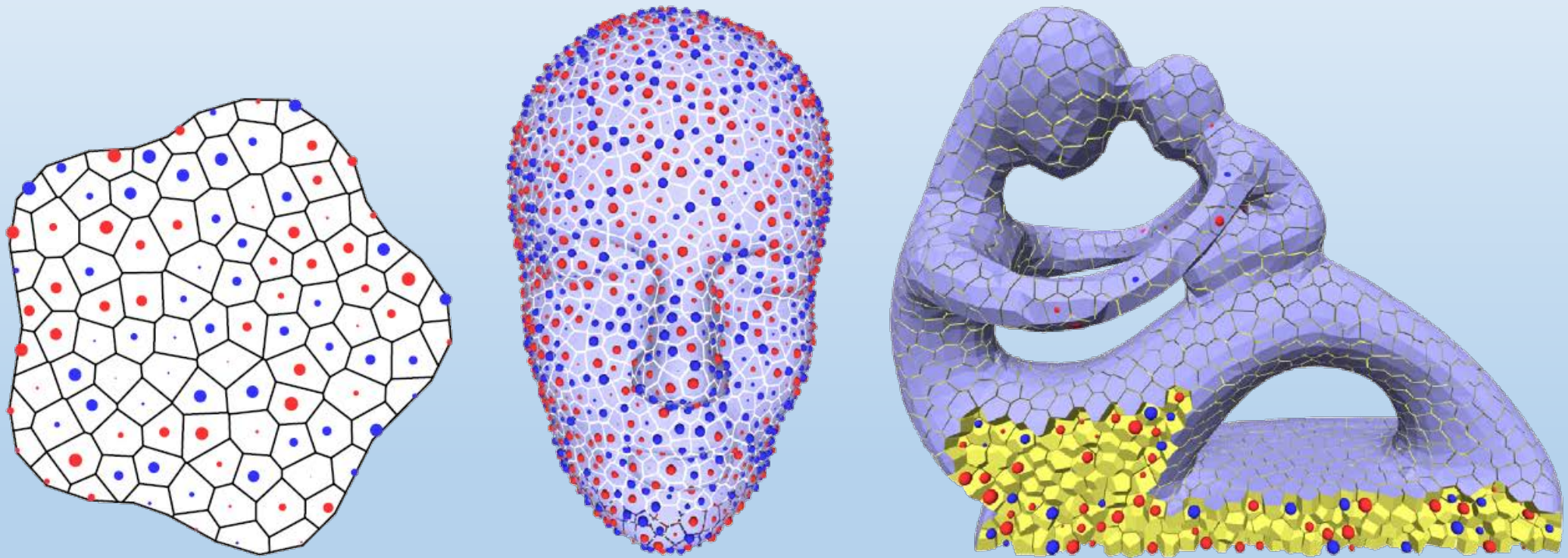


(c) 3D case

加速前后的效率对比

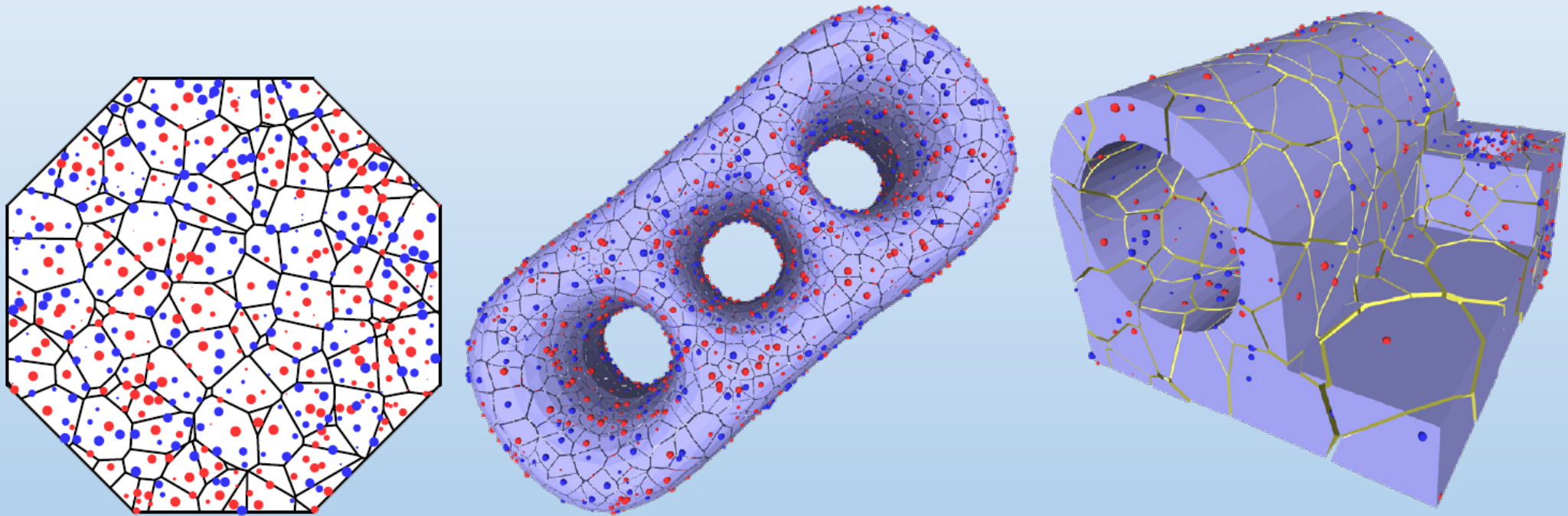
# Power图的快速构造：基于kNN的方法

- 结果：均匀位置随机权重



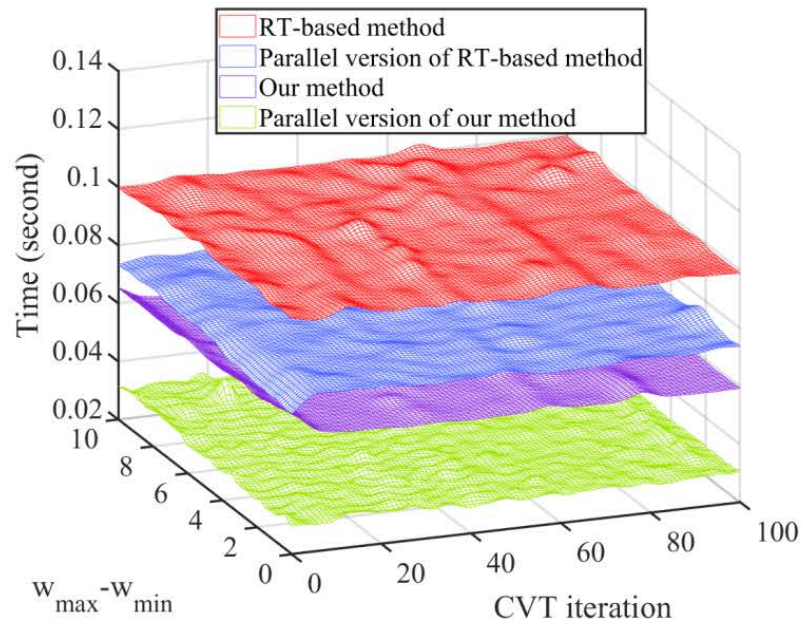
# Power图的快速构造：基于kNN的方法

- 结果：随机位置随机权重

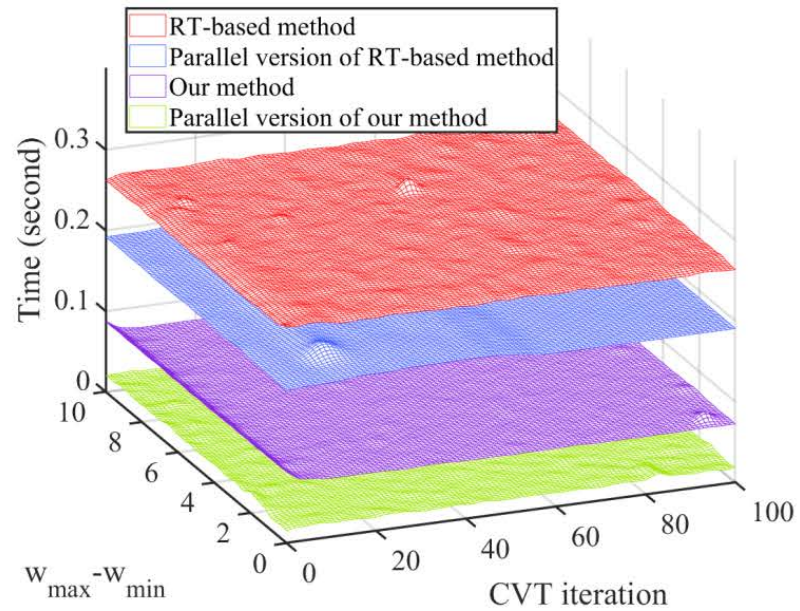


# Power图的快速构造：基于kNN的方法

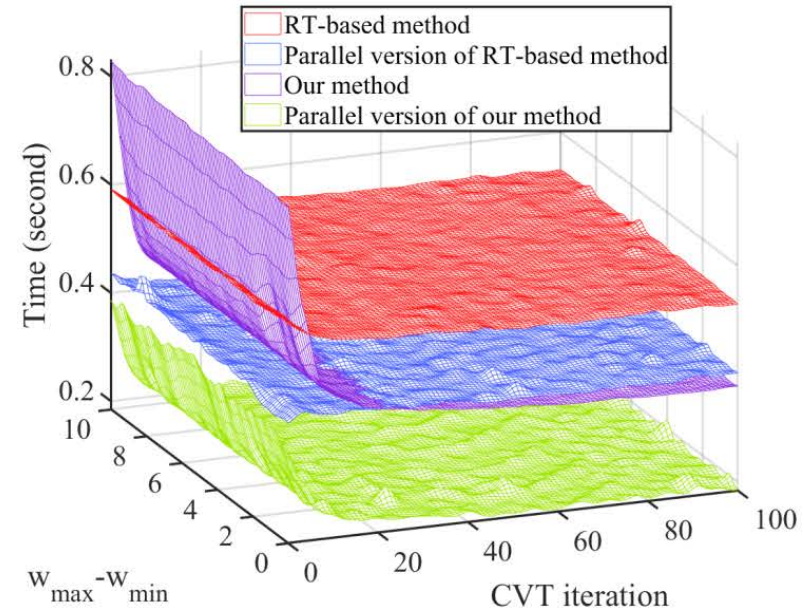
- 结果：运行速度比较



(a) 2D case



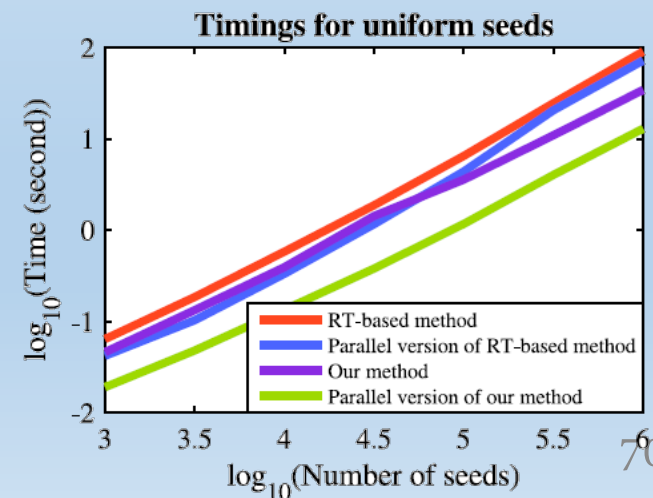
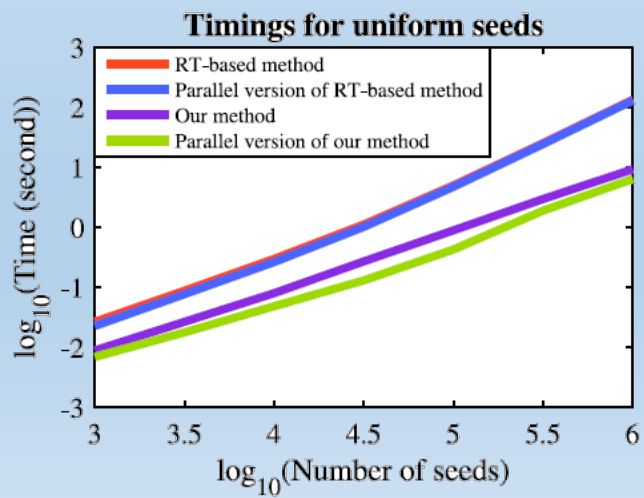
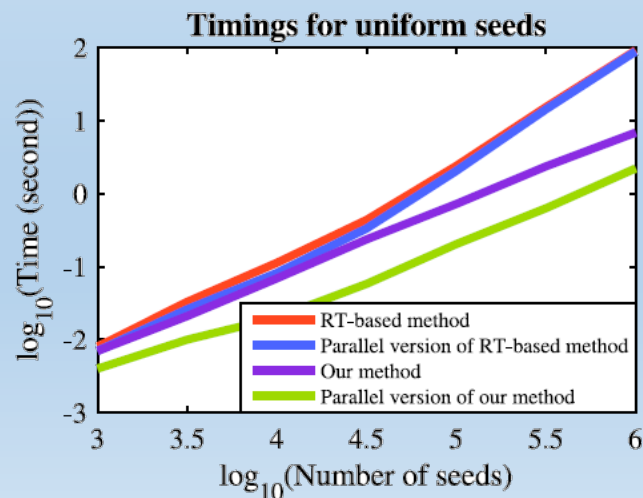
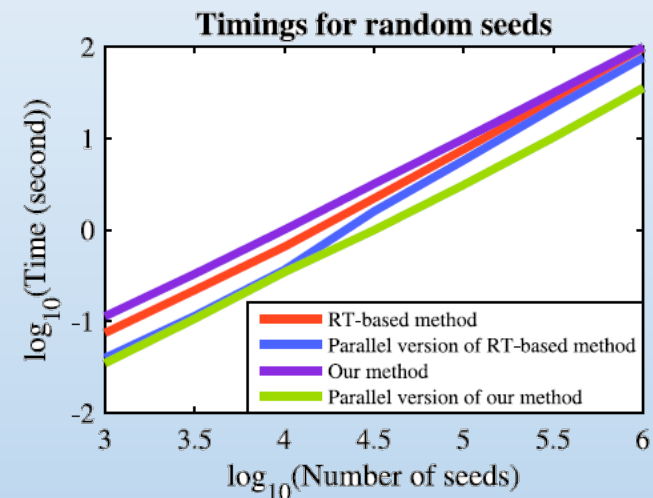
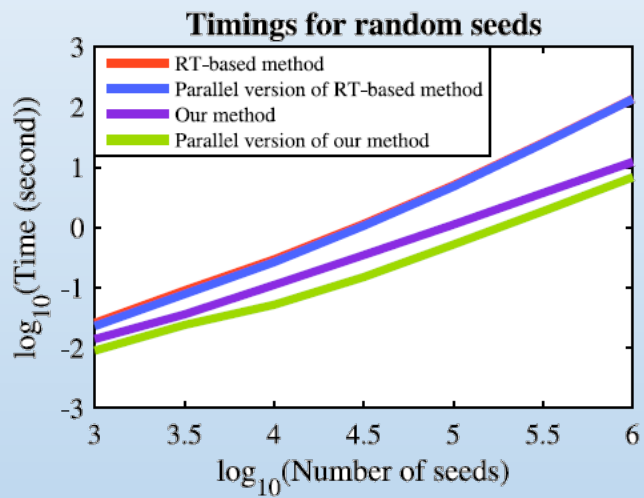
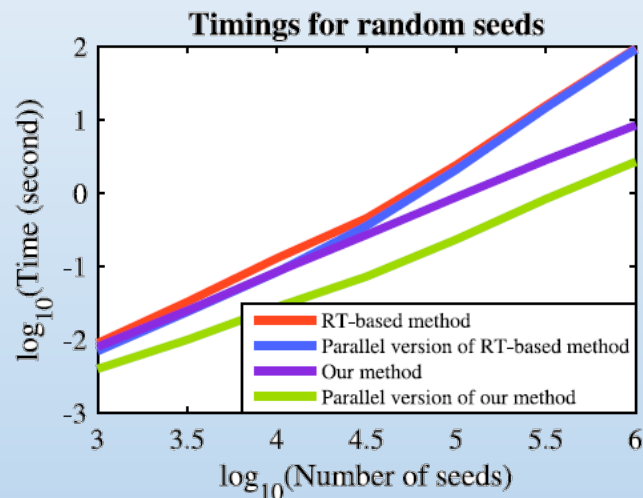
(b) Surface case



(c) 3D case

# Power图的快速构造：基于kNN的方法

- 结果：运行速度比较



谢谢