CENG 789 – Digital Geometry Processing

06- Surface Reconstruction,

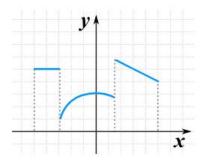
Scientific Visualization and Information Visualization

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Explicit Representation

- ✓ RECALL: Polygon meshes are piecewise linear surface representatins.
- ✓ Analogous to piecewise functions:



$$f(x) = \begin{cases} 6 & \text{if } x < -2\\ x^2 & \text{if } x > -2 \text{ and } x \le 2\\ 10 - x & \text{if } x > -2 \end{cases}$$

✓ Think surface as (the range of) a "shape" function.

$$\mathbf{f}: [0, 2\pi] \to \mathbb{R}^2$$

$$\mathbf{f}(t) = \begin{pmatrix} r\cos(t) \\ r\sin(t) \end{pmatrix}$$

$$\mathbf{f}:[0,2\pi]\to\mathbb{R}^2$$

$$\mathbf{f}(t) = \begin{pmatrix} ? \\ ? \end{pmatrix}$$

Explicit Surface Representation

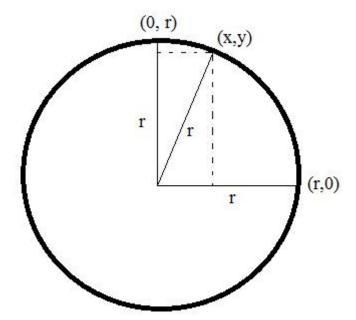
- ✓ For varying t, we get 2D shape (circle) points: t in [0, 2pi].
- ✓ Parameterization f maps a 1D parameter domain, e.g., [0, 2pi], to the curve (surface) embedded in R^2 (R^3).

$$\mathbf{f}: [0, 2\pi] \to \mathbb{R}^2$$

$$\mathbf{f}(t) = \begin{pmatrix} r\cos(t) \\ r\sin(t) \end{pmatrix}$$

Implicit Surface Representation

- ✓ Implicit or indirect surface representation.
- \checkmark Surface is defined to be the zero-set of a scalar-valued function F.
 - ✓ That is, we have $F: \mathbb{R}^2 \to \mathbb{R}$, and then surface $\mathcal{S} = \{x \in \mathbb{R}^2 \mid F(x) = 0\}$.
 - ✓ Circle of radius r: $(x,y) \mapsto \sqrt{x^2 + y^2} r$ is defined by (x,y) pairs that make the right-hand-side 0



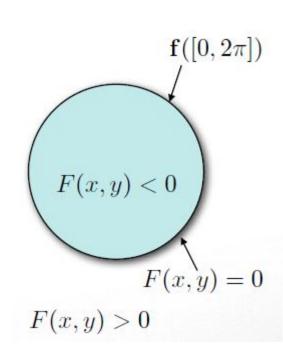
Explicit vs. Implicit

$$\checkmark$$
 Explicit: $\mathbf{f}(t) = \begin{pmatrix} r\cos(t) \\ r\sin(t) \end{pmatrix}$

✓ Range of a parameterization function.

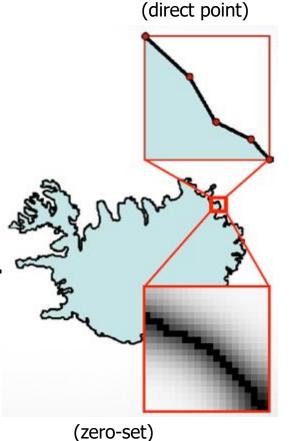
✓ Implicit:
$$F(x,y) = \sqrt{x^2 + y^2} - r$$

✓ Kernel of an implicit function.



- ✓ Explicit: for non-mathematical/arbitrary shapes.
 - ✓ Range of a parameterization function.
 - ✓ Piecewise approximation.

- ✓ Implicit: for non-mathematical/arbitrary shapes.
 - ✓ Kernel of an implicit function.
 - ✓ Piecewise approximation.



Explicit vs. Implicit

✓ Explicit:

- ✓ Range of a parameterization function.
- ✓ Piecewise approximation.
- ✓ Splines, triangle meshes, points.
- ✓ Easy rendering.
- \checkmark Easy geom. modif. (deformation or new t).

✓ Implicit:

- ✓ Kernel of an implicit function.
- ✓ Piecewise approximation.
- ✓ Scalar-valued 3D grid (mesh lies here).
- \checkmark Easy in/out test (just evaluate F).
- ✓ Easy topology modification.

(a) The line in R² through the points (1, 2) and (2, 3).

```
explicit: (1, 2), (2, 3)
implicit: x - y = -1
```

(b) The point (0, 1, 2) in ℝ³.

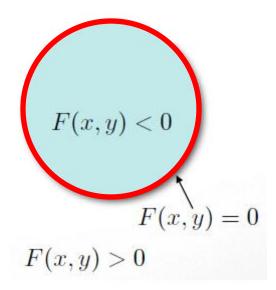
```
explicit: (0, 1, 2)
implicit: x = 0 \land y = 1 \land z = 3
```

(c) The plane in R³ through the point (0,1,1) and perpendicular to the vector (2,1,0).

```
explicit: (0, 1, 0), (0, 1, 1), (-1, 3, 0)
implicit: 2x + y = 1
```

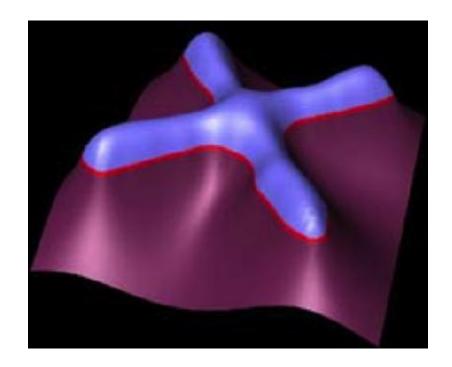
Implicit/Indirect Surfaces

- ✓ Level-set of a function defines the shape.
- ✓ Level means function values are the same = at the same level. Traditionally, level is 0, hence 0-set of the function F is sought.



Implicit Surfaces

✓ Level-set of 2D function F(x, y) defines 1D curve (embedded in 2D).

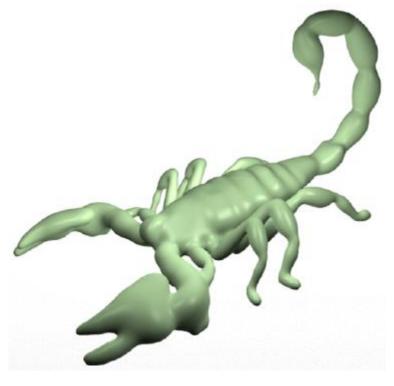


Implicit Surfaces

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 \checkmark Level-set of 3D function F(x, y, z) defines 2D surface (embedded in

3D).

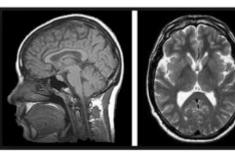


- ✓ Most common and natural representation is Signed Distance Function.
- \checkmark Maps each 3D point x to its signed distance F(x) from the surface.

$$F: \mathbb{R}^3 \to \mathbb{R}$$

- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ Other than Signed Distance Function (SDF), continuous intensity function from CT/MRI scans are also common. Here, we will focus on the computation of SDF as it is a geometric problem. CT/MRI devices provide intensity info with their underlying radiologic technology.





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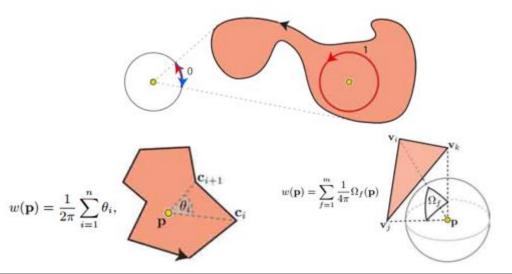
$$F: \mathbb{R}^3 \to \mathbb{R}$$

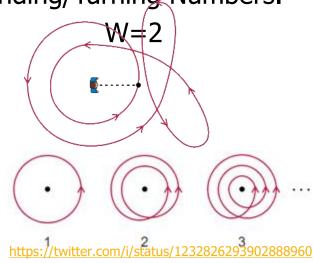
- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ Other than Signed Distance Function (SDF), continuous intensity function from CT/MRI scans are also common. Here, we will focus on the computation of SDF as it is a geometric problem. CT/MRI devices provide intensity info with their underlying radiologic technology.
 - ✓ Intensity: amount of vibration caused by magnets in MRI (no radiation).
 - ✓ Intensity: x-rays (x radiation) are beamed & received along the tunnel in CT.

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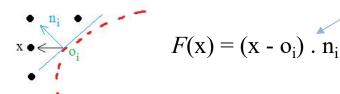
- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ Another function for inside/outside test: Winding/Turning Numbers.
- ✓ Originally defined for closed curves (2D) and surfaces (3D).
- ✓ Made robust to self-intersections, open boundaries, and non-manifold pieces by Jacobson et al., 2013.
- ✓ Still needs some sort of surface input (tests point in/out of a surface), so not suitable for point cloud to surface conversion.

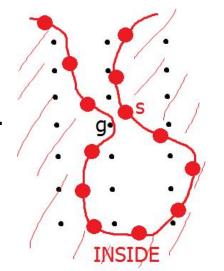
$$w(\mathbf{p}) = \frac{1}{2\pi} \sum_{i=1}^{n} \theta_i, \qquad \mathbf{p}$$

- ✓ Most common and natural representation is Signed Distance Function.
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$$F: \mathbb{R}^3 \to \mathbb{R}$$

- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ Another function for inside/outside test: Winding/Turning Numbers.
 - ✓ More robust than a signed distance function.
 - ✓ Although inside, grid point g will be wrongly treated as outside as it is coupled w/ the closest sample, which yields a positive signed distance (see slide 39).
 - ✓ No such problem w/ Winding Number test.

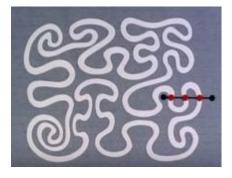




- ✓ Most common and natural representation is Signed Distance Function.
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$$F: \mathbb{R}^3 \to \mathbb{R}$$

- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ Another function for inside/outside test of a closed surface: ray count.
- ✓ Shooting a ray from the point and count # of times it intersects the surface: odd number means the point is inside, even means outside.





- ✓ Most common and natural representation is Signed Distance Function.
- ✓ Maps each 3D point x to its signed distance F(x) from the surface.

$$F: \mathbb{R}^3 \to \mathbb{R}$$

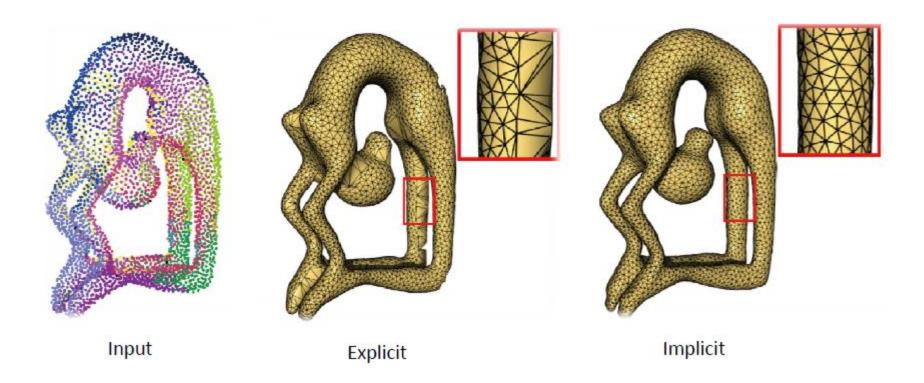
- ✓ Sign indicates inside/outside. F(x)=0 means x is on the surface.
- ✓ A function for unsigned distance to a point cloud: UDF vs. SDF.
- \checkmark Average the sum of squared distances to K-nearest neighbors.

$$d_U(x) = \sqrt{\frac{1}{K} \sum_{p \in N_K(x)} ||x - p||^2}$$

- ✓ Doesn't need a surface input and also pretty robust ☺.
- ✓ Can you sign this up to make it useful for Marching Cubes?
 - ✓ First do UDF (robust) and then sign it using the signs (not values) in SDF?

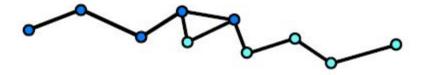
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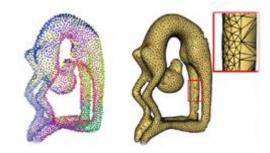
✓ Given a set of 3D points, compare Explicit vs. Implicit reconstruction.



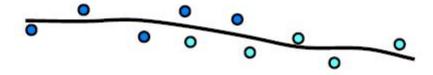
✓ Implicit algorithms *approximate*, explicit ones *interpolate* input data.

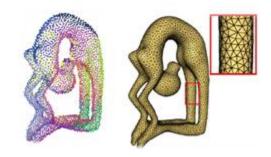
- ✓ Given a set of 3D points, compare Explicit vs. Implicit reconstruction.
- ✓ Explicit reconstruction method:
 - ✓ Connect sample points by triangles (connect the dots).
 - ✓ Exact interpolation of sample points.
 - ✓ Bad for noisy or misaligned data (common in scans).
 - ✓ May lead to holes or non-manifoldness.



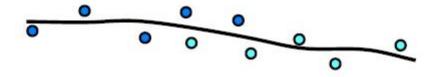


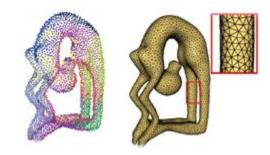
- ✓ Given a set of 3D points, compare Explicit vs. Implicit reconstruction.
- ✓ Implicit reconstruction method:
 - ✓ Estimate signed distance function (SDF) for each grid point (scalar-valued grid).
 - ✓ Extract level zero iso-surface from this grid (Marching Cubes).
 - ✓ Approximation of input points (better in noisy situations).
 - ✓ Manifoldness by construction.



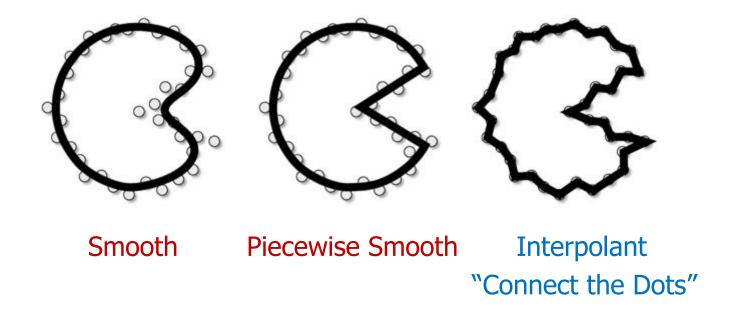


- ✓ Given a set of 3D points, compare Explicit vs. Implicit reconstruction.
- ✓ Implicit reconstruction method:
 - ✓ The distance function is interpolated and polygonalized by the marching squ/cubes algorithm.
 - ✓ The distance function is, however, based on an approximation of the input surface (via tangent planes), hence the whole process is an approximation.





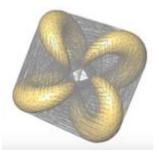
- ✓ Given a set of 3D points, compare Explicit vs. Implicit reconstruction.
- ✓ Implicit vs. Explicit:



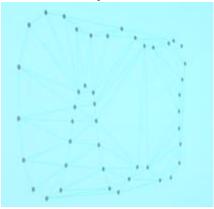
- ✓ Surface reconstruction is an ill-posed problem: want sharp corner?
- ✓ Solution: regularize via priors, e.g., smooth, piecewise smooth, simple.

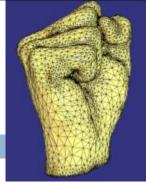


✓ Crust Algorithm: Since Delaunay triangulation encodes the proximity
b/w the points, if points are dense enough, we should have the desired
triangles within the Delaunay triangulation. Tri → Tetrahedron in 3D.



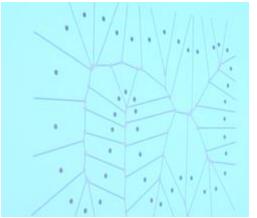
- ✓ Compute Delaunay triangulation of the input point set.
- ✓ So we have the edges we need, but also the extras.



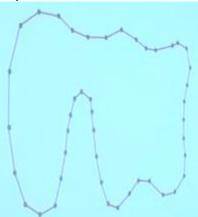


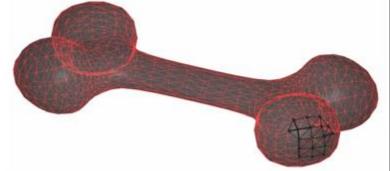
✓ Crust Algorithm: Since Delaunay triangulation encodes the proximity
b/w the points, if points are dense enough, we should have the desired
triangles within the Delaunay triangulation. Tri → Tetrahedron in 3D.

✓ Get rid of extras: Compute Voronoi diagram. Insert Voronoi vertices
(pink) to the Delaunay triangulation. Keep edges b/w black dots only.





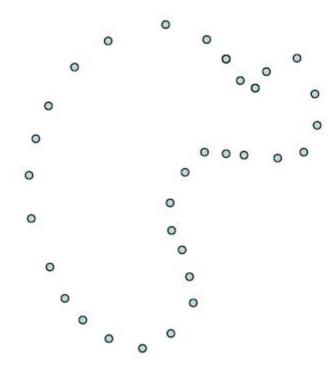




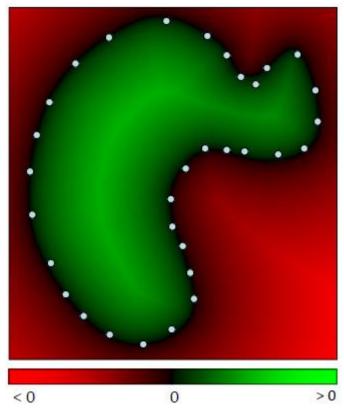
- \checkmark Find local neighborhood L_i of each point p_i in the 3D point cloud input.
 - \checkmark Closest k points (using a k-d tree).
- \checkmark For each L_i compute tangent plane using PCA.
 - ✓ If the input is oriented, just take the average of all normals for the plane normal. Use the mean pnt as the plane pnt (for both oriented/unoriented).
- \checkmark Project all points in L_i to the tangent plane and compute their 2D Delaunay triangulation D_i .
- ✓ Final triangulation is the composition of all these local triangulations.

✓ Yet another explicit algorithm is Poisson Reconstruction.

✓ Implicit function approach.

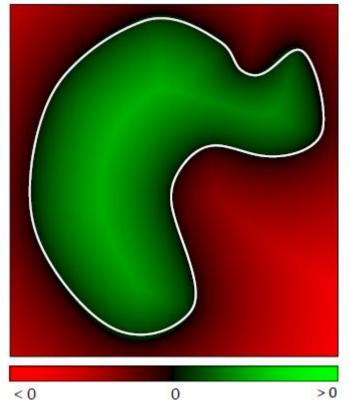


✓ Implicit function approach.



✓ Define a function $F: \mathbb{R}^3 \to \mathbb{R}$ with value <0 outside, >0 inside, =0 on.

✓ Implicit function approach.

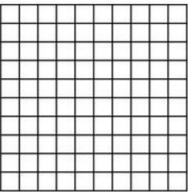


✓ Extract the zero-set isosurface, i.e., $S = \{x \text{ in } R^3 \mid F(x) = 0\}$.

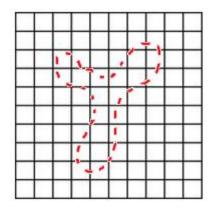
- ✓ Implicit function: Signed distance function $F: \mathbb{R}^3 \to \mathbb{R}$.
- ✓ Construction algorithm.
 - ✓ Input: point samples representing the object to be reconstructed.



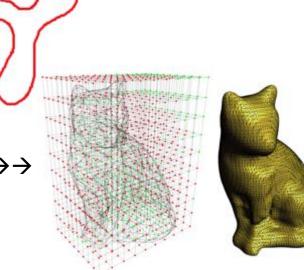
✓ Output: *F* value at each grid point, i.e., signed distance of that grid pnt to the sampled surface.



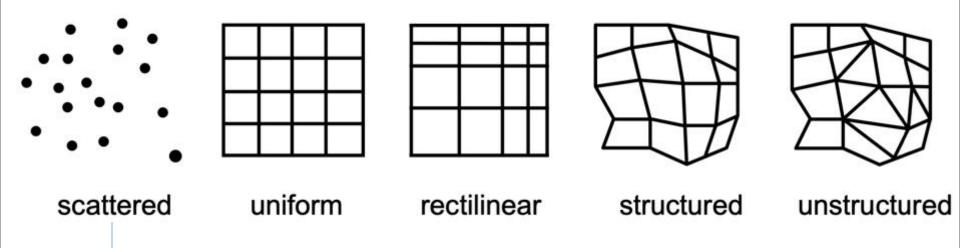
✓ So we need a grid that encapsulates the sampled surface.



- ✓ Uniform 2D grid.
 - ✓ Mesh to be extracted: 1D (closed) curve \rightarrow
- ✓ Uniform 3D grid.
 - \checkmark Mesh to be extracted: 2D (closed) surface $\rightarrow \rightarrow \rightarrow \rightarrow$



✓ Other grid types.

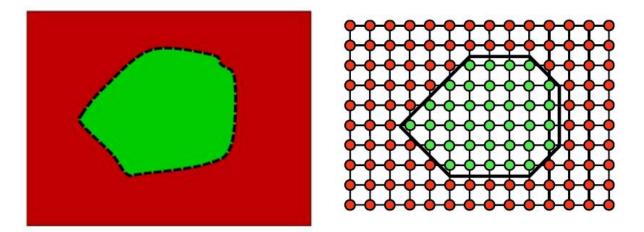


Not a grid at all: no connectivity.

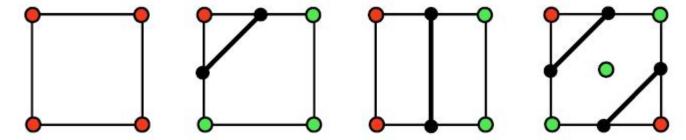
Uniform aka regular grid.

curvilinear

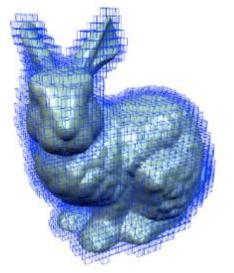
- ✓ Mesh extraction idea.
- ✓ Marching Squares (2D), Marching Cubes (3D).

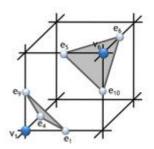


 \checkmark 24 cases. May be reduced by symmetry, e.g., all red and all gre. equal.

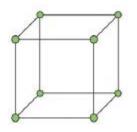


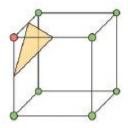
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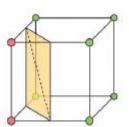


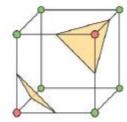


✓ 28 cases. Sym. applies. Fast look up: use 8-bit case index: **dex - **DOI 100 0 0 0 1 - 33

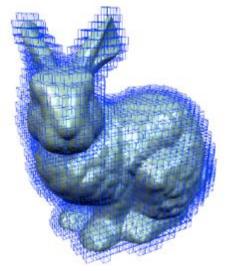


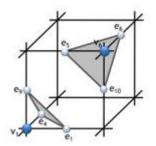






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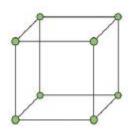


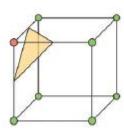


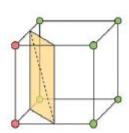
- ✓ 28 cases. Sym. applies. Fast look-up: use 8-bit case index: **ndex **DOI 10 00 00 01 33
- ✓ Case index brings connectivity from the look-up table.
 - ✓ Cut edges are e1, e4, e5, e6, e9, e10.
 - ✓ Output triangles are (e1, e9, e4), (e5, e10, e6).

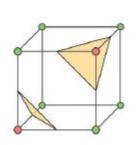
Marching X

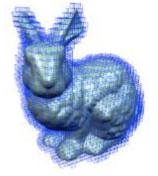
- √ Steps for Marching Squares/Cubes
 - ✓ Discretize space (use a regular grid enclosing the surface).
 - ✓ Evaluate signed distance function on grid.
 - ✓ Classify grid points (inside/outside w.r.t. surface).
 - ✓ Classify grid edges (one endpoint inside, one outside).
 - ✓ Compute intersections.
 - ✓ Connect intersections.







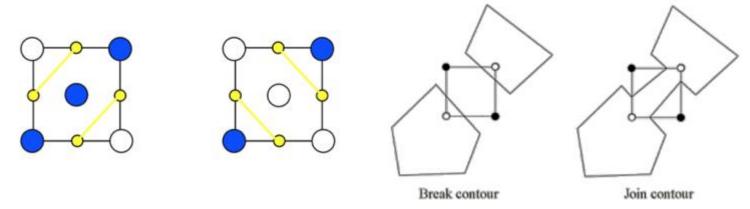




Marching X

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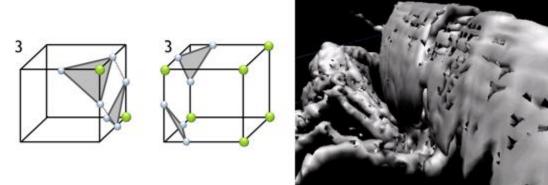
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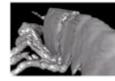


 \checkmark Handle by subsampling inside a cell, or randomly picking 1 of the 2 possibilities.

Marching X

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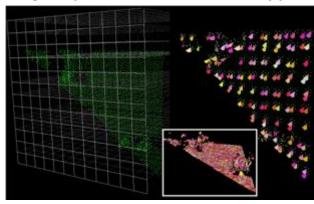


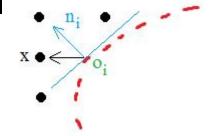
✓ If random pick, then make choices consistently or this happens. Fixed:

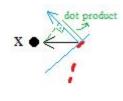
Signed Distance Function (SDF)

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- ✓ Back to the construction of the Signed Distance Function $F: \mathbb{R}^3 \to \mathbb{R}$.
- ✓ Input: sample points.
- ✓ Output: F value at each grid point.
- ✓ Algo:
 - ✓ Associate a tangent plane with each sample point.
 - ✓ Why? Tangent planes are local linear approximations to the surface.

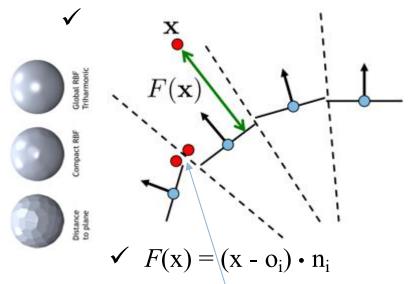


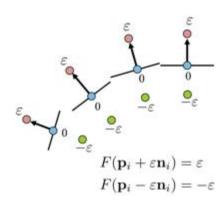




 \checkmark Compute $F(\mathbf{x}) = (\mathbf{x} - \mathbf{o_i}) \cdot \mathbf{n_i}$

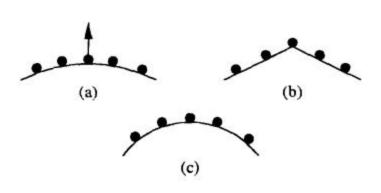
- ✓ Back to the construction of the Signed Distance Function $F: \mathbb{R}^3 \to \mathbb{R}$.
- ✓ Input: sample points.
- ✓ Output: F value at each grid point.



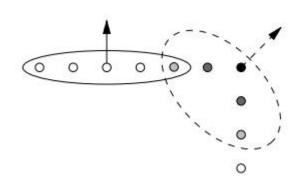


- \checkmark F(x) is discontinuous. How to fix? Hint: consider off-set constraints.
 - ✓ RBF, MLS, DeepSDF, <your idea here>.
 - ✓ Reconstruction and representation of 3D objects with radial basis functions, 2001.
 - ✓ Interpolating and Approximating Implicit Surfaces from Polygon Soup, 2004.
 - ✓ DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, 2019.

- ✓ Tangent plane for sample point s is found as follows:
 - ✓ Find k-nearest neighbors of s.
 - ✓ Apply principle component analysis on this set of close points.
 - ✓ Find the covariance matrix of the set.
 - ✓ Take the eigenvectors of this matrix as the principal axes.
 - ✓ Use the third best axis (w/ smallest eigenvalue) as the normal of the tangent plane, i.e. n_i .
 - ✓ Use the mean of this point set as the centering point of the plane, i.e., o_i .
 - \checkmark The smaller the 3rd eigenvalue, the more confident the plane is, a is confident, b,c are not. ($\lambda_3/\lambda_1 < \Gamma$)



Darker = more ambiguous



- ✓ Tangent planes have arbitrary normal signs; need a normal-orienter for smooth/consistent normals across the point set.
- ✓ MST-based: Surface Reconstruction from Unorganized Points, 1992.
- ✓ Ray cast-based: A Simple Method for Correcting Facet Orientations, '15.
- ✓ BFS-based: breadth-first search to enfrce a consistent facet orientation.
 - ✓ Last two are designed for surface/mesh inputs, thus not directly applicable.

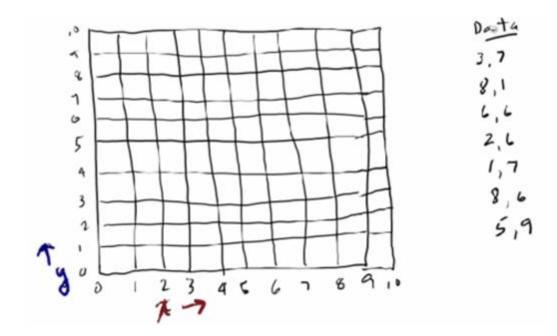


k-d Tree for Nearest Neighbors (NN)

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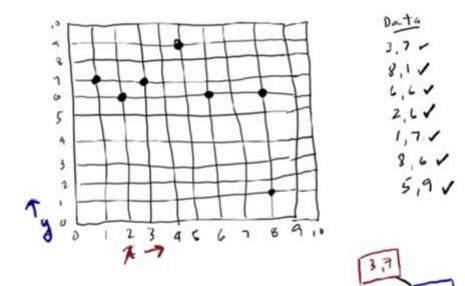
- √ k-nearest points.
- ✓ Brute force: O(k * N) when we have N samples. $//10^3$ steps
- ✓ Can be done in O(k * IgN) using k-d trees. //10 steps.
- √ k-d tree: cells are axis-aligned bounding boxes.
 - √ k-d dimensional binary search tree.
 - ✓ Not to be confused w/ the k in k-nearest neighbors.

- \checkmark k-d tree insertion. k = # of dimensions = 2 in example below.
- ✓ Idea: every time you go down in tree, you toggle decision-making dimension.



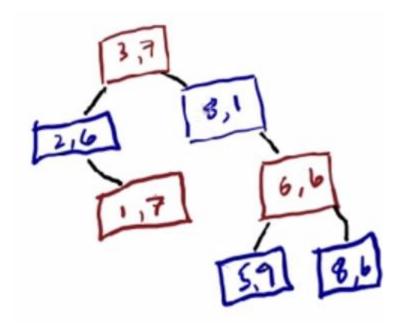
- ✓ k-d tree insertion. k = # of dimensions = 2 in example below.
- ✓ Idea: every time you go down in tree, you toggle decision-making dimension.

- 1) 3,7 is inserted
- 2) 8 > 3 (1st dimension) of 3,7, so put 8,1 to right; colored in blue 'cos if may have to make a decision at this point, i'll be deciding at the 2nd dim (red means 1st dim)
- 3) 6 > 3 go right, 6 > 1 go right
- 4) 2 < 3 go left
- 5) 1 < 3 go left, 7 > 6 go right
- 6) 8 > 3 go right, 6 > 1 go right, 8 > 6 go right
- 7) 5 > 3 go right, 9 > 1 go right, 5 < 6 go left



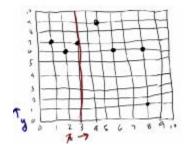
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- \checkmark k-d tree search operation. Search (5, 2) below.
- \checkmark 5 > 3 go right, 2 > 1 go right, 5 < 6 go left, 2 < 9 look left, not found.

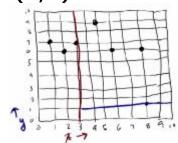


- √ k-d tree partitioning.
- ✓ Going left or right means partitioning the space.

(3,7) inserted



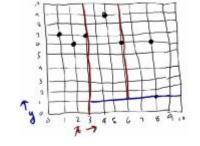
partition the space into 2 axis-aligned bounding boxes, i.e., everything <= 3 to left everything > 3 to right. (8,1) inserted



(6,6) right of the

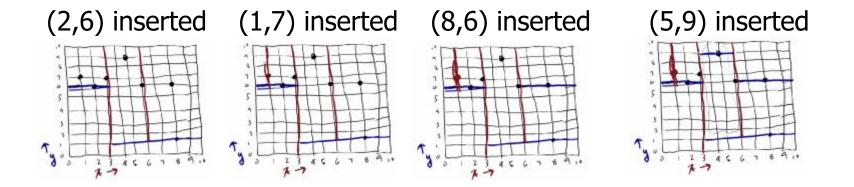
3-line, top of the

1-line:



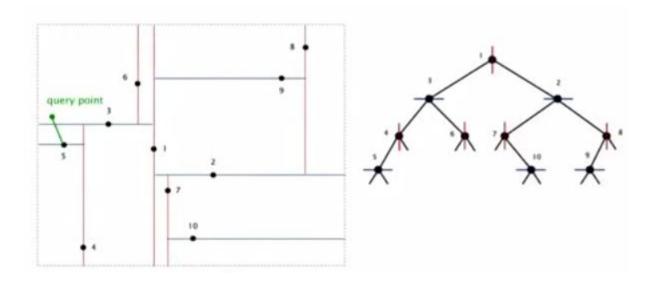
everything <= 1
everything > 1
(w.r.t. y dimension)

- ✓ k-d tree partitioning.
- ✓ Going left or right means partitioning the space.



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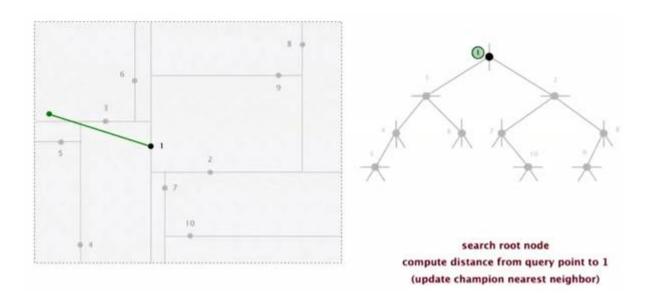
- √ k-d tree nearest-neighbor to a query point (see Note below).
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Our algo should return point 5 (as the nearest one to the query).

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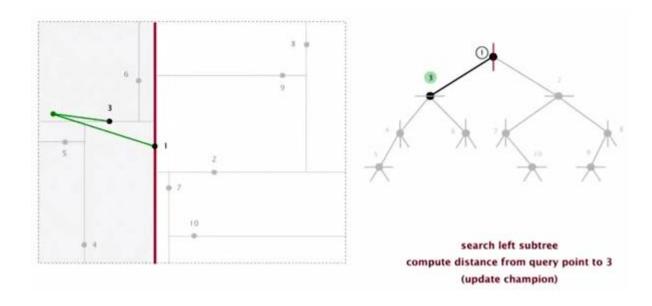
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Go towards query point, i.e., left. (there might be a closer pnt than 1 in the right; at least we think so now).

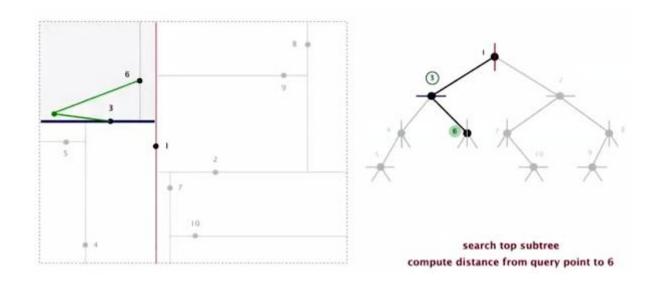
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- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



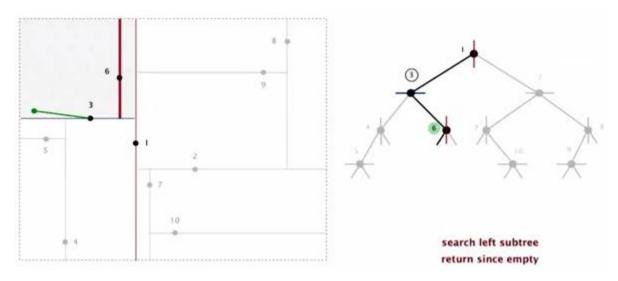
✓ When recursion gets back to pnt 1, we won't search the right subtree 'cos there could be no point closer to query than 3. //cutting out ©

- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



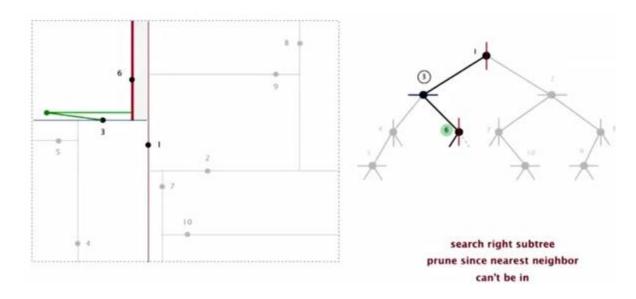
✓ Going towards the query point, so checking the top of 3. Pnt 6 is not better so do not update the champion.

- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



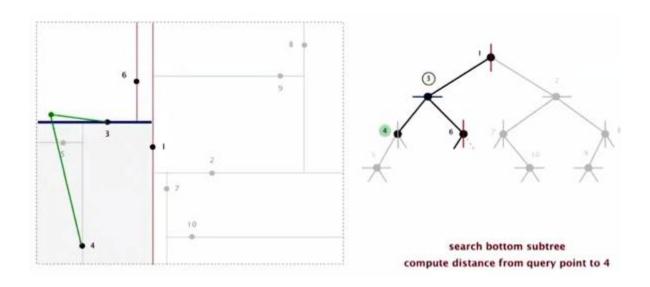
✓ Check left subtree of pnt 6 (going towards qury), empty, so do nothing.

- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Do not check the right subtree of pnt 6 'cos they can't be closer than 3.

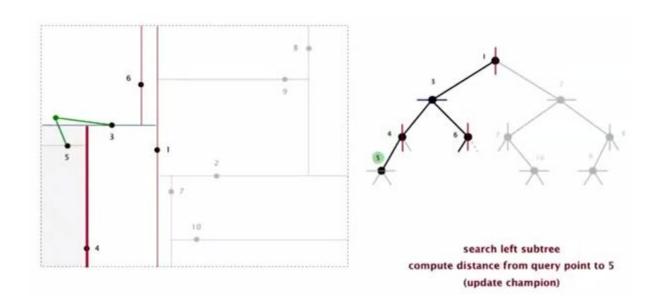
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Recursion checks the bottom subtree of pnt 3, which takes us to pnt 4, which is not closer; so 3 is still the champion.

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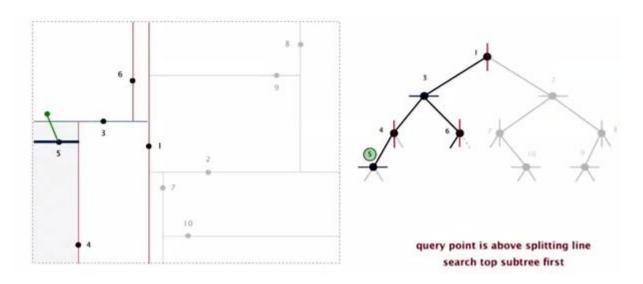
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Check left subtree of pnt 4 (towards query), where we have pnt 5, the new champion.

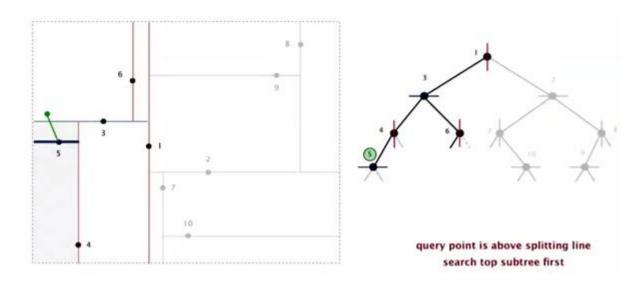
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- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Check top of pnt 5 (no pnts there), do nothing.

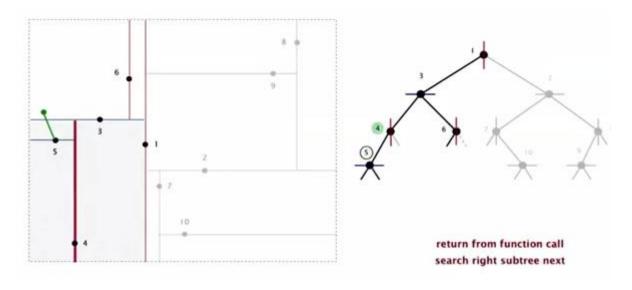
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Check bottom of pnt 5 (no pnts there), do nothing.

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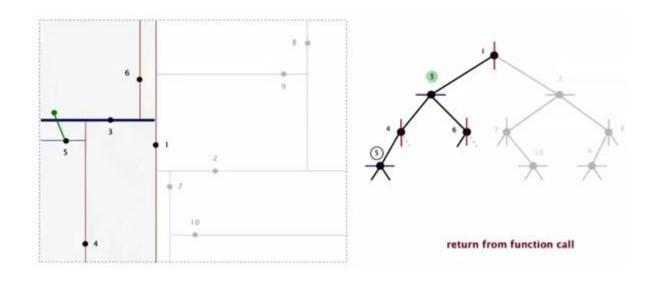
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Recursion comes back to the right subtree of pnt 4, but cut it out (no search) 'cos there can't be a closer pnt there than pnt 5.

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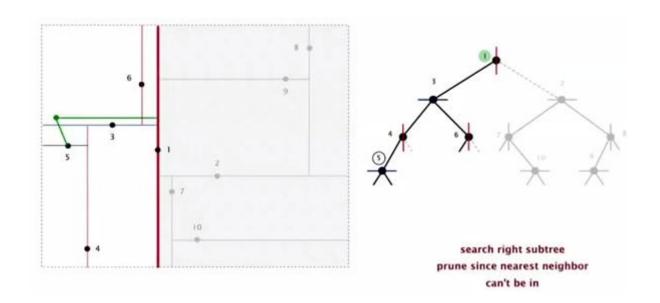
- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.



✓ Recursion comes back to pnt 3, whose both subtrees are handled.

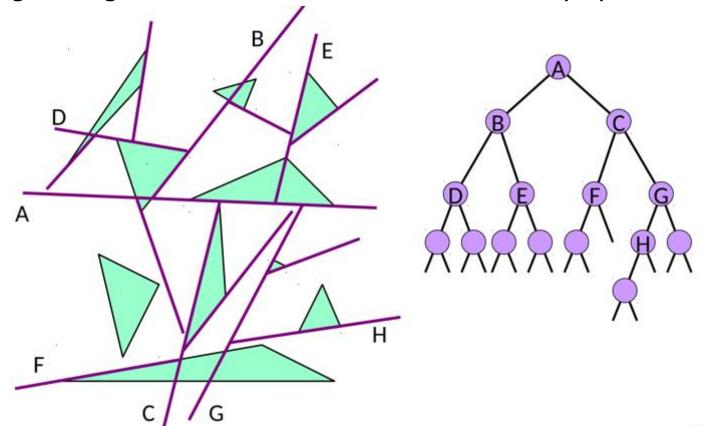
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- √ k-d tree nearest-neighbor to a query point.
- ✓ Idea: As we get closer to the query point, we are cutting out all the subtrees that are away.

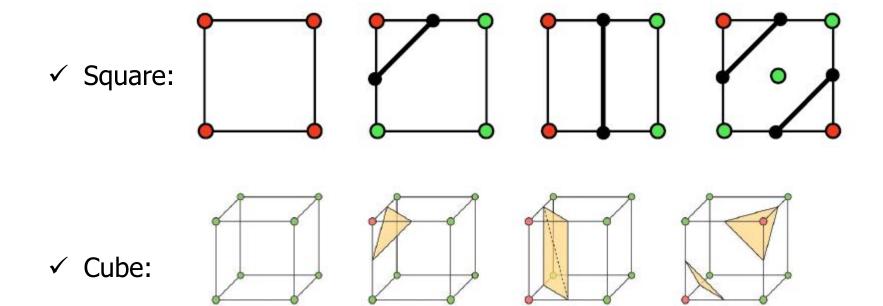


✓ Recursion comes back to pnt 1, right subtree is next, but cut it out (no search) 'cos there can't be a closer pnt there than pnt 5.

- √ k-d tree: cells are axis-aligned bounding boxes.
- ✓ BSP-tree: cells are arbitrarily shaped; splitting lines/planes through edge/triangles of the set to be stored. BSP: Binary Space Partitioning.



- \checkmark We efficiently (k-d tree) computed signed distance function F.
- ✓ The only thing left is to find the intersection point on the square/cube edge:

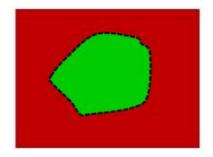


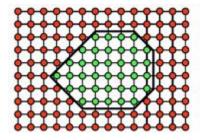
Marching X

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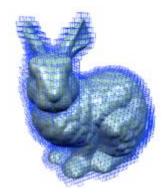
- \checkmark We efficiently (k-d tree) computed signed distance function F.
- ✓ The only thing left is to find the intersection point on the square/cube edge:

✓ Square:

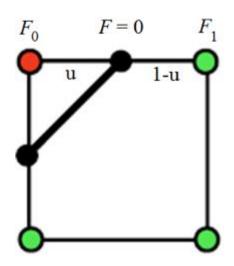




✓ Cube:



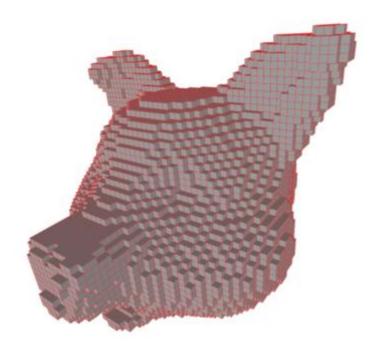
- \checkmark We efficiently (k-d tree) computed signed distance function F.
- ✓ The only thing left is to find the intersection point x on the square/cube edge: x_0 x = ? x_1

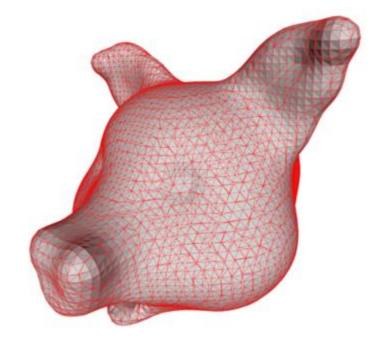


- ✓ $F = F_0 * (1-u) + F_1 * u$ → for F=0, $u = F_0 / (F_0 F_1) / / F$ is linear on edges.
- ✓ $x = x_0 + u * (x_1 x_0)$ → use u computed above and locate $x \odot$.
- ✓ Interpolation schemes discussed in Deformation lecture slides 26-31.

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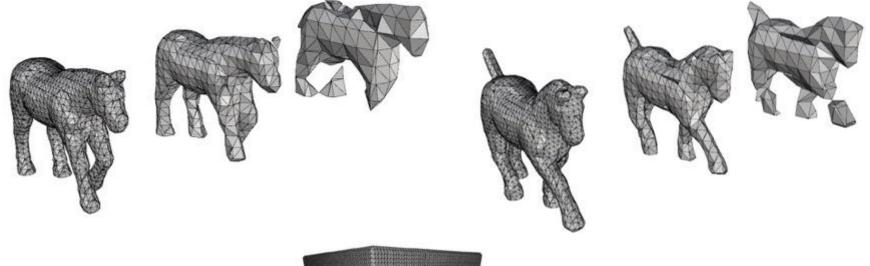
- \checkmark We efficiently (k-d tree) computed signed distance function F.
- ✓ Once we have this function, one can use the Cuberille method (1979) for a cruder approximation than Marching Cubes (1987).





Check function at each cube center.

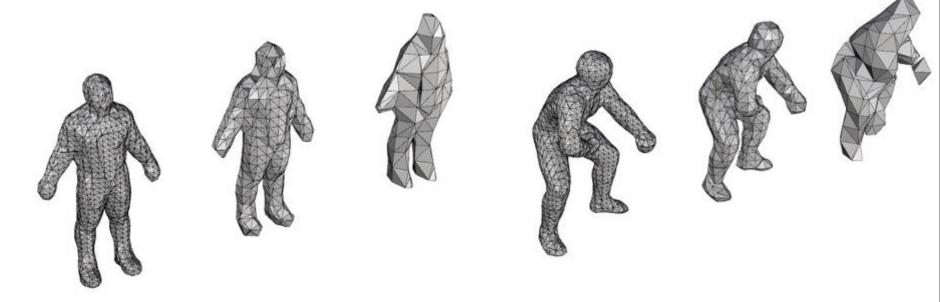
✓ Size of each voxel in the uniform grid determines level-of-detail.



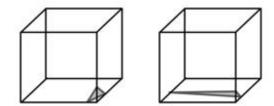
✓ Grid not adaptive ⊗.



✓ Size of each voxel in the uniform grid determines level-of-detail.

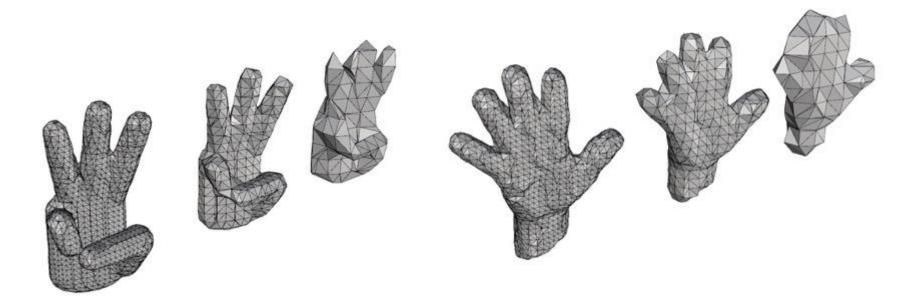


✓ Grid sampling can cause short triang edges, rendering tri uninformative.



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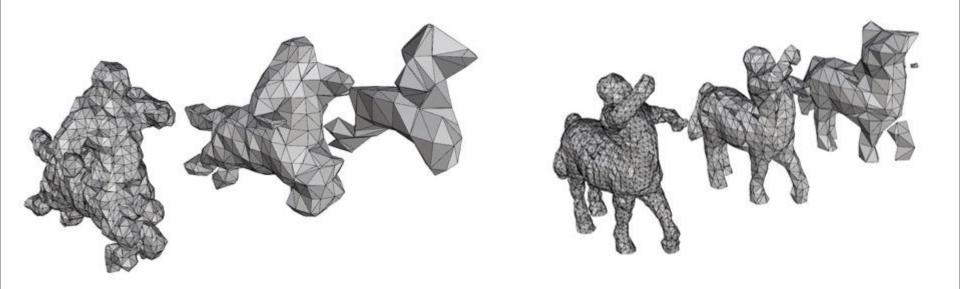
✓ Size of each voxel in the uniform grid determines level-of-detail.



✓ Solution: if such an edge arises, snap the edge vertex to cube corner. If more than 1 vertex of ________n discard triangle.

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✓ Size of each voxel in the uniform grid determines level-of-detail.



Marching Cubes Case Study: CT Scan View

- ✓ In medical imaging, uniform grids are built based on CT/MRI scans.
- ✓ SDF is replaced by intensity values captured by radiology technology.
- ✓ CT scans generally come in DICOM format. Here is one way to convert them to NIfTI (nii) format, which can be parsed easily.
 - ✓ Use dcm2nii.exe software: https://people.cas.sc.edu/rorden/mricron/dcm2nii.html
 - ✓ E:\Postdoc\skull\mricron>dcm2nii.exe ..\CTsample\DIC
- ✓ Unzip output above somescan.nii.gz
- ✓ Learn target intensity using a software like ITK-SNAP, say it is e.
 - ✓ E.g., move cursor around skull and read intensities to decide on e.
- ✓ Marching cubes will extract the level-set corresponding to value e.



Marching Cubes Case Study: CT Scan View

- ✓ Read header and data.
 - ✓ #include "nifti1.h"

```
nifti1.h
/** \file nifti1.h
    \brief Official definition of the nifti1 header. Written by Bob Cox, SSCC, NIMH.
    HISTORY:
       29 Nov 2007 [rickr]
         - added DT RGBA32 and NIFTI TYPE RGBA32

    added NIFTI_INTENT codes:

              TIME SERIES, NODE INDEX, RGB VECTOR, RGBA VECTOR, SHAPE
#ifndef NIFTI HEADER
#define _NIFTI_HEADER_
 ** This file defines the "NIFTI-1" header format.
      ** It is derived from 2 meetings at the NIH (31 Mar 2003 and
                                                               skok
      ** 02 Sep 2003) of the Data Format Working Group (DFWG),
      ** chartered by the NIfTI (Neuroimaging Informatics Technology
      ** Initiative) at the National Institutes of Health (NIH).
      ** Neither the National Institutes of Health (NIH), the DFWG,
                                                               3kok
      ** nor any of the members or employees of these institutions
                                                               地址
      ** imply any warranty of usefulness of this material for any
                                                               冰冰
      ** purpose, and do not assume any liability for damages,
      ** incidental or otherwise, caused by any use of this document.
                                                               3636
      ** If these conditions are not acceptable, do not use this!
      ** Author: Robert W Cox (NIMH, Bethesda)
      ** Advisors: John Ashburner (FIL, London),
                                                               米米
                 Stephen Smith (FMRIB, Oxford),
                                                               sksk
                 Mark Jenkinson (FMRIB, Oxford)
```

Marching Cubes

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- ✓ Read header and data.
 - ✓ #include "nifti1.h"

```
void VoxelSet::loadNii(char* miiFile)
    //binary nii format reader adapted from http://sourceforge.net/projects/niftilib/
    cout << "Voxel grid initializing (to " << niiFile << ")..\n";</pre>
    nifti 1 header hdr;
   FILE *fp;
    int ret, i;
    double totalIntensity;
   MY_DATATYPE *data = NULL;
    /******** open and read header */
    fp = fopen(niiFile,"rb"); //seeing this took my 2 hours :(
    if (fp = NULL) {
            fprintf(stderr, "\nError opening header file %s\n", niiFile);
           exit(1);
    ret = fread(&hdr, MIN_HEADER_SIZE, 1, fp);
    if (ret != 1) {
            fprintf(stderr, "\nError reading header file %s\n",niiFile);
           exit(1);
    fclose(fp); //close here 'cos i'll reopen it below with a jump to the start of the image data
    /******** print a little header information */
    fprintf(stderr, "\nnii file header information:");
    fprintf(stderr, "\nXYZT dimensions: %d %d %d %d",hdr.dim[1],hdr.dim[2],hdr.dim[3],hdr.dim[4]);
    fprintf(stderr, "\nDatatype code and bits/pixel: %d %d",hdr.datatype,hdr.bitpix);
    fprintf(stderr, "\nScaling slope and intercept: %.6f %.6f",hdr.scl_slope,hdr.scl_inter);
    fprintf(stderr, "\nByte offset to data in datafile: %ld",(long)(hdr.vox_offset));
    fprintf(stderr, "\nVoxel spacing: %f, %f, %f\n", hdr.pixdim[1], hdr.pixdim[2], hdr.pixdim[3]);
    /******* open the datafile, jump to data offset */
    fp = fopen(niiFile,"rb");
    if (fp = NULL) {
            fprintf(stderr, "\nError opening data file %s\n", niiFile);
           exit(1):
    ret = fseek(fp, (long)(hdr.vox_offset), SEEK_SET); //jump
    if (ret != 0) {
            fprintf(stderr, "\nError doing fseek() to %ld in data file %s\n",
                (long)(hdr.vox_offset), niiFile);
           exit(1):
    /********* allocate buffer and read first 3D volume from data file */
    data = (MY_DATATYPE *) malloc(sizeof(MY_DATATYPE) * hdr.dim[1]*hdr.dim[2]*hdr.dim[3]);
    if (data = NULL) {
            fprintf(stderr, "\nError allocating data buffer for %s\n",niiFile);
           exit(1);
    fread(data, sizeof(MY DATATYPE), hdr.dim[1]*hdr.dim[2]*hdr.dim[3], fp);
    fclose(fp);
```

Marching Cubes Case Study: CT Scan View

that contain skull intensities Create voxels useful to Marching Cubes, the ones

```
//learn width, height, depth of each voxel and then initialize each one (new Voxel)
width = hdr.pixdim[1];
height = hdr.pixdim[2];
depth = hdr.pixdim[3]; //of each cell to be added to voxels[] below
int toRight = 0, toUp = 0, toFront = 0;
float x, y, Z;
//all voxels that includes bones, brains, eyes, .. everything; just need skull bones here
for (i = 0; i < hdr.dim[1]*hdr.dim[2]*hdr.dim[3]; i++)
    //id, intensity, and coord of this current voxel
    x = toRight * hdr.pixdim[1]; //voxel spacing, space b/w x coords, i.e. pixdim[1]
    toRight ++:
    y = toUp * hdr.pixdim[2]; //voxel spacing, space b/w y coords, i.e. pixdim[2]
    z = toFront * hdr.pixdim[3]; //voxel spacing, space b/w z coords, i.e. pixdim[3]
    if ( isSkullVoxel(data[i], x, y, z) ) //returns true if (intensity > 200 && intensity < 1000) where intensity is data[i]
        if (toRight % 5 == 0 && toUp % 5 == 0 && toFront % 5 == 0) //extra thresholding to downsample the bone voxels by picking
                                                                   //every fifth in x-direction and in y-direction and in z-direction
            float* coords = new float[3];
            coords[0] = x;
            coords[1] = y;
            coords[2] = z;
            voxels.push back( new Voxel(i, data[i], coords) ); //coords is the center of this voxel
    //direction/pointer adjustments
    if (toRight >= hdr.dim[1])
        toRight = 0; //reset to the left end
        toUp++; //1 level up
        if (toUp >= hdr.dim[2])
            toFront++; //1 slice towards me, that is towards front
            toUp = 0: //start from the bottom level
} //end of i
//you may then create coarse voxels by merging every non-overlapping 3x3x3 box (of 27 voxels)
//in data[] to 1 big coarseVoxel if 1+ constituent element is a segmented skull/bone voxel
11 ...
```

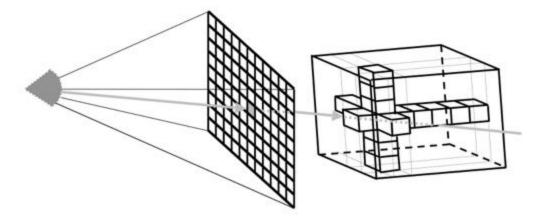
Scientific Visualization

- ✓ Scalar field: a scalar value is associated with each point in n-d space.
 - ✓ Can be obtained by associating SDF or intensity values to grid points.
- ✓ Vector field: an n-d vector is associated with each point in n-d space.
 - ✓ Can be obtained by simulations.
- ✓ Scalar fields can be visualized via
 - ✓ indirect (volume) rendering: isosurface/mesh extraction and rendering (corresponding to a certain scalar value Marching Cubes in 3D).
 - √ We handled this already.
 - √ direct (volume) rendering ray casting.
 - ✓ Upcoming.
- ✓ Vector fields can be visualized via
 - ✓ vector arrows located at each point.
 - ✓ Upcoming.

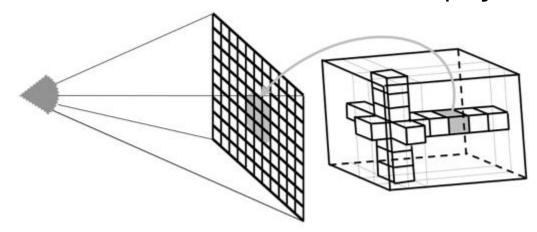
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- ✓ So far we've dealt with visualizing a scalar field indirectly, via isosurface extraction and rendering.
- ✓ Let's now do it directly via ray casting.
- ✓ Aka direct volume rendering (DVR) if the field is defined in 3D.

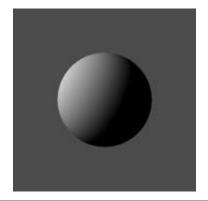
✓ Ray casting is a backward method where we send rays from the eye.

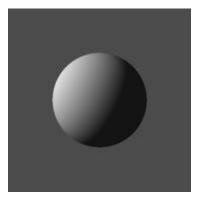


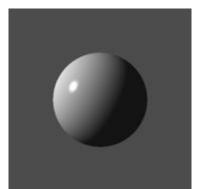
✓ Opposite of the forward method where we use projections to the eye.



- ✓ Ray casting is similar to ray tracing in surface-based computer graphics.
 - ✓ Ray tracing deals with primary rays (first rays cast into the scene from the camera/eye) and secondary rays (recursive rays to generate shadows, reflections, refractions, etc.)
 - ✓ 1979, Turner Whitted.
 - ✓ Ray casting deals only with primary rays.
 - ✓ 1968, Arthur Appel.
- ✓ Check out CENG477 Computer Graphics course for details.
 - √ http://user.ceng.metu.edu.tr/~ys/ceng477-gfx/
 - ✓ Look at Ray Tracing parts 1 and 2, up to the Recursive Ray Tracing section.

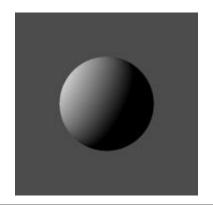


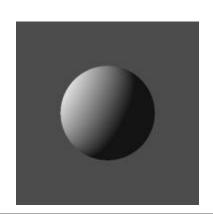


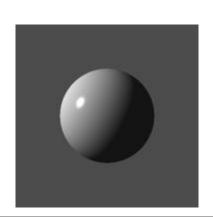


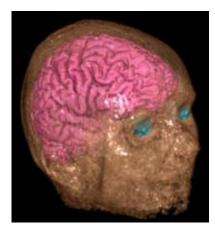
Additional color due to lighting.

- ✓ How to calculate ray-surface intersection since we've no surfaces here.
- ✓ Step through the volume.
- ✓ A ray is cast into the volume, sampling the volume at certain intervals.
- ✓ Sampling intervals are usually equidistant, but don't have to be (e.g. importance sampling).
- ✓ At each sampling location, a sample is interpolated / reconstructed from the voxel grid.
- ✓ Opacity and color in each cell is predefined according to classification.



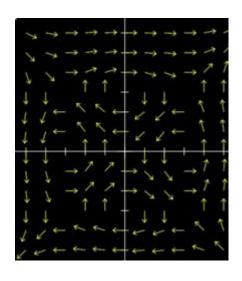


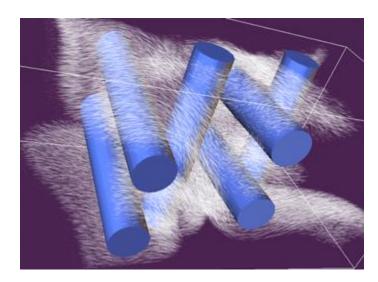


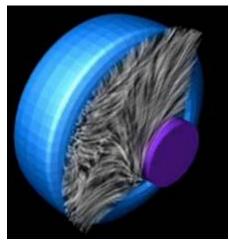


- ✓ So far we've dealt with visualizing a scalar field, i.e., a grid with function values at each grid point, for a given scalar value.
 - ✓ Arises frequently in medical imaging, 3D point cloud to surface conversions.
- ✓ Let's now extend this to vector field visualization, where we have an n-dimensional space with n-dimensional vectors attached at each point.
 - ✓ Arises frequently in fluid simulation, air flow simulation, or in general visualizing functions that have the same # of dimensions in their input as in their output.

✓
$$f(x, y) = [x^2 + 5y \ xy]^T$$
, $f(x, y, z) = [4x \ x^3(y^2 - 5) \ 33]^T$, and so on.

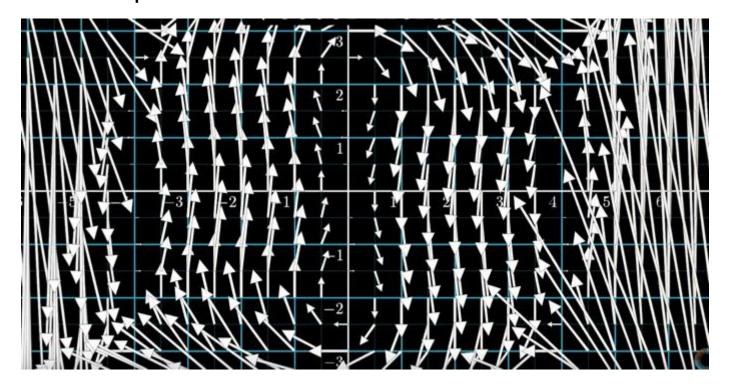






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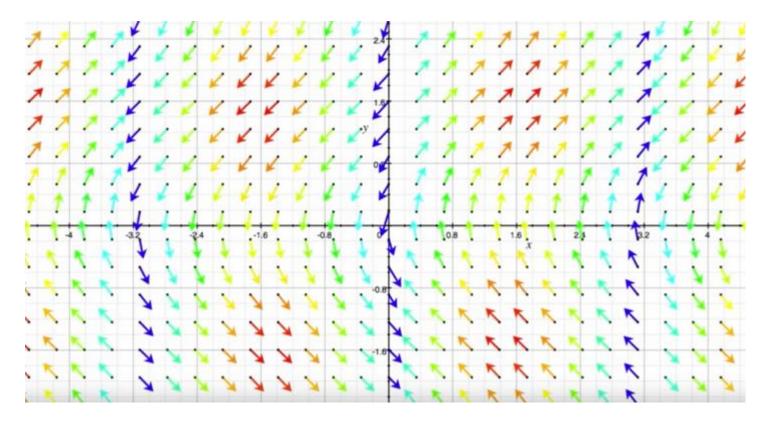
✓ If all vectors are drawn proportional to their magnitudes, the longer ones mess up the screen.



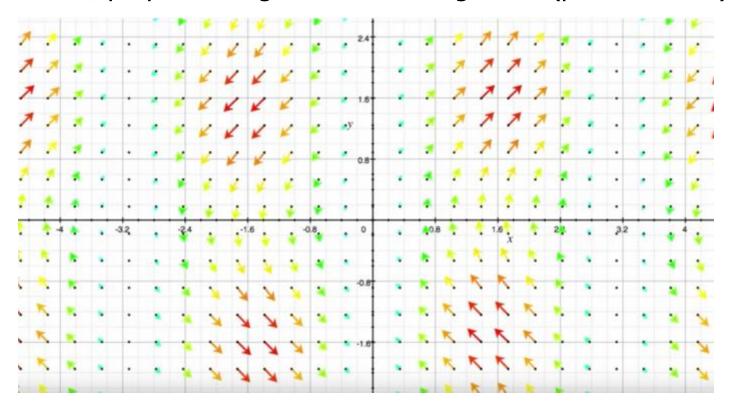
✓ This one and the subsequent visuals're collected from the fluid flow youtube series of Khan Academy and 3Blue1Brown.

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- ✓ All vectors are made unit (length 1) for visual clarity.
- ✓ We can still infer their magnitudes via color coding: red long blue short.

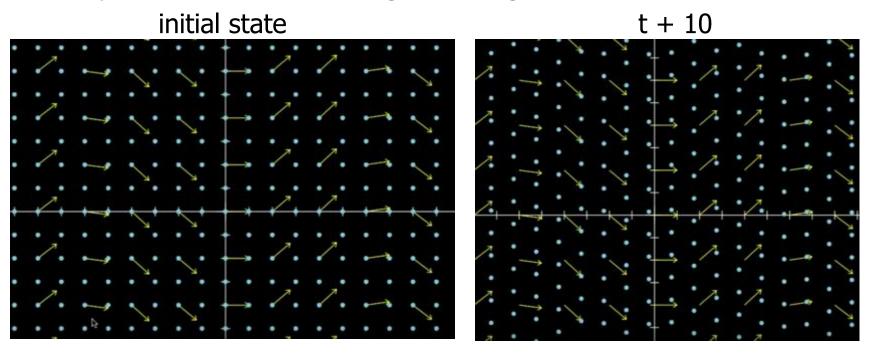


- ✓ All vectors are made unit (length 1) for visual clarity.
- ✓ Combined w/ proper scaling where max length is 1 (prevent mess).



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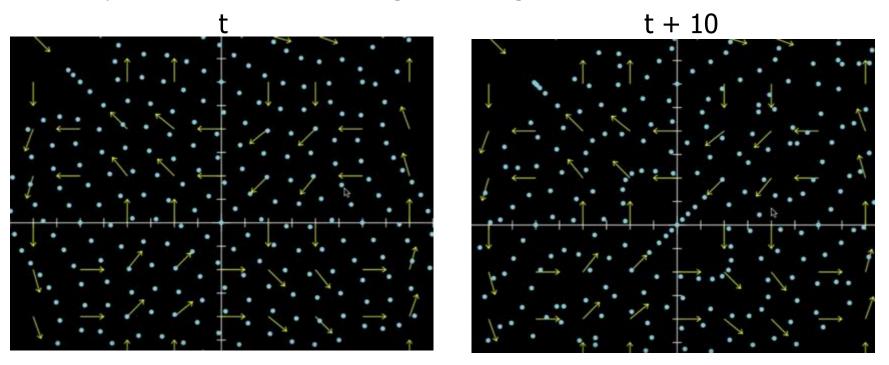
- ✓ Case study: fluid flow.
- ✓ Droplets of water are moving according to the vectors visualized.



- ✓ Vectors are representing the velocities of particles of fluids here.
 - ✓ Alternatives: force of gravity, magnetic field, etc.

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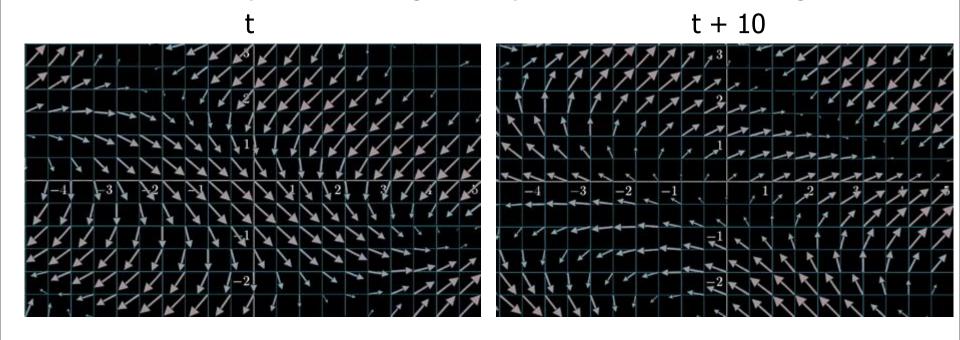
- ✓ Case study: fluid flow.
- ✓ Droplets of water are moving according to the vectors visualized.



✓ This is a static vector field depicting a steady state system.

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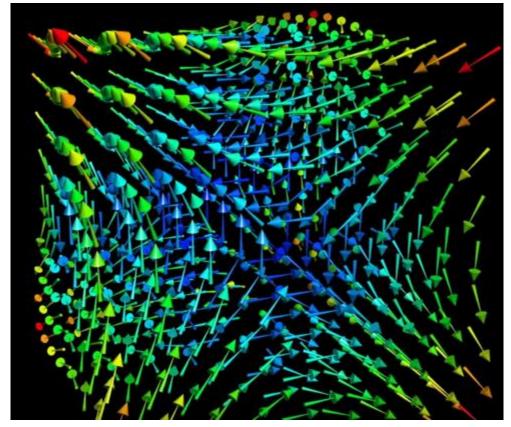
- ✓ Case study: fluid flow.
- ✓ Vector fields may change over time, e.g., in real-world fluid flow, the velocities of particles change in response to the surrounding context.



- ✓ This is a dynamic vector field depicting a more realistic fluid flow.
 - ✓ Wind is not constant; electric field not constant (charged particles move).

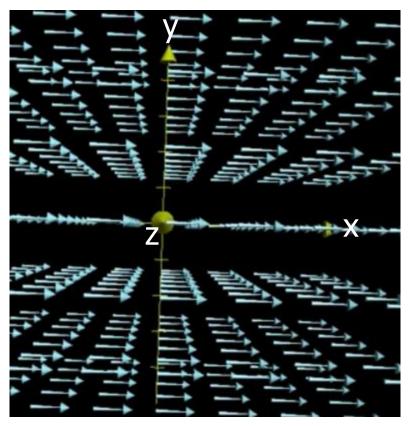
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- ✓ n-d spaces are equipped with n-d vectors.
- ✓ So far we studied n=2. Here n=3:



✓ Vectors at each point are defined as $f(x, y, z) = [yz xz xy]^T$.

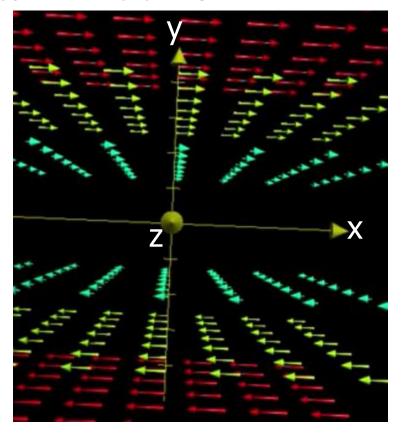
- ✓ n-d spaces are equipped with n-d vectors.
- ✓ So far we studied n=2. Here n=3:



✓ Vectors at each point are defined as $f(x, y, z) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T$.

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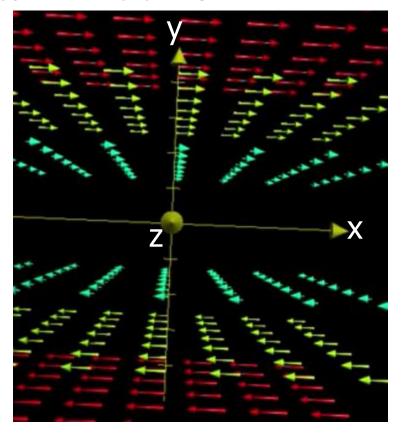
- ✓ n-d spaces are equipped with n-d vectors.
- ✓ So far we studied n=2. Here n=3:



✓ Vectors at each point are defined as f(x, y, z) = ?. Color ~ magnitude.

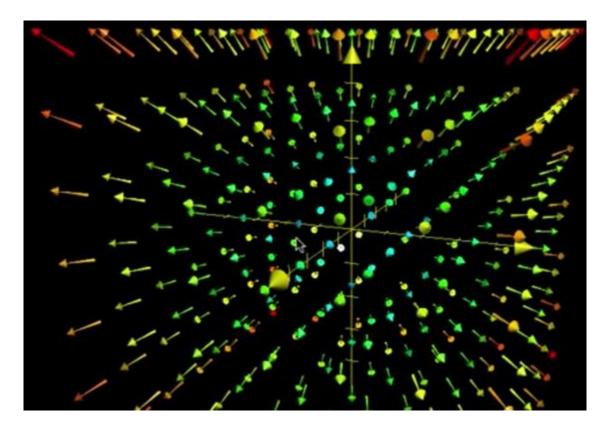
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- √ n-d spaces are equipped with n-d vectors.
- ✓ So far we studied n=2. Here n=3:



✓ Vectors at each point are defined as $f(x, y, z) = [y \ 0 \ 0]^T$.

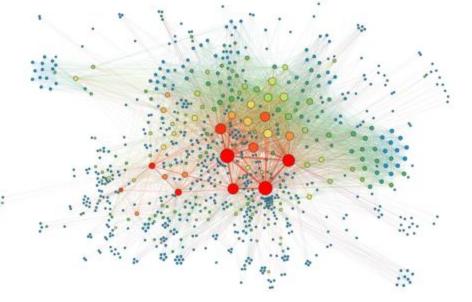
- ✓ n-d spaces are equipped with n-d vectors.
- ✓ So far we studied n=2. Here n=3:

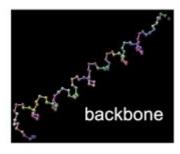


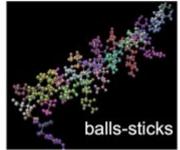
✓ Vectors at each point are defined as $f(x, y, z) = [x \ y \ z]^T$.

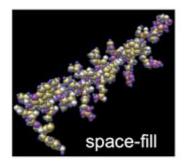
Information Visualization

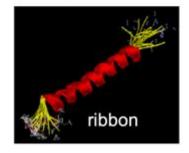
- ✓ Study of visual representations of abstract data to reinforce human cognition.
- ✓ Differs from Scientific Visualization: it is infovis (information visualization) when the spatial representation is chosen, and it is scivis (scientific visualization) when the spatial representation is given.
- ✓ Some examples include social network analysis, protein visualization.





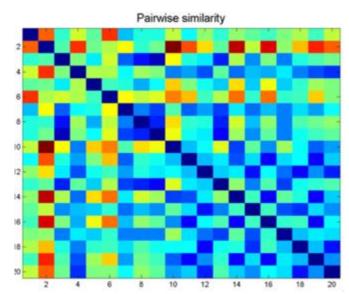




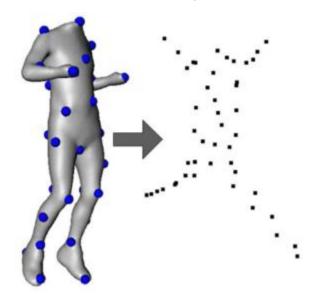


Information Visualization - MDS

- ✓ Multidimension Scaling (MDS) is a powerful tool to visualize pairwise dissimilarity data.
- ✓ Translates "info about the pairwise 'distances' among a set of n objects" into a configuration of n points mapped into the Euclidean space.
 - ✓ A form of non-linear dimensionality reduction: see more in Shape Gen. slides.



Geodesic distances b/w sample pairs.



MDS mapping of samples.

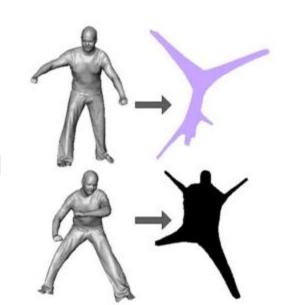
Information Visualization - MDS

✓ Given a distance matrix with the distances $\delta_{i,j}$ between each pair of objects, and a chosen number of dimensions k, an MDS algorithm places each object into k – dimensional Euclidean space such that the between-object distances $||x_i - x_j||$ are preserved as well as possible. For k = 1, 2, and 3, the resulting points can be visualized on a scatter plot.

$$\min_{x_1,\dots,x_I} \sum_{i < j} (\|x_i - x_j\| - \delta_{i,j})^2$$

Information Visualization - MDS

- ✓ Main MDS techniques are as follows.
- \checkmark Least-squares MDS: minimizes the energy: $\min_{x_1,\dots,x_I} \sum_{i < j} (\|x_i x_j\| \delta_{i,j})^2$
- ✓ Classical MDS: uses k leading eigenvectors of the associated affinity matrix () to obtain the k-d configuration.
- ✓ Landmark MDS: embeds a small number of landmark points via least-squares or classical method, and then computes the embedding coordinates of the remaining data points based on their distances from the landmark points.



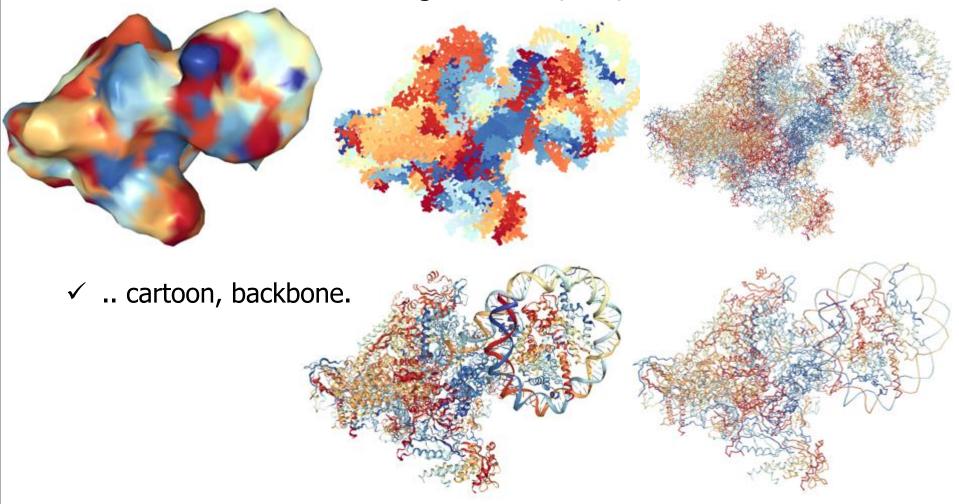
Information Visualization – Protein Vis.

- ✓ Some popular visualization modes:
 - ✓ Ball+stick: Atoms are displayed as spheres (balls) and bonds as cylinders (sticks). Aspect ratio defines how much bigger sph radius compred to cyl radius.
 - ✓ Licorice: Ball+stick variant where balls and sticks have the same radius.
 - ✓ Line: Bonds are displayed by a flat, unshaded line.
 - ✓ Point: Atoms are displayed by textured points.
 - ✓ Spacefill: Atoms are displayed as a set of space-filling spheres.
 - ✓ Trace: A flat, unshaded line is displayed along the main backbone trace.
 - ✓ Ribbon: A thin ribbon is displayed along the main backbone trace.
 - ✓ Cartoon: A smooth trace connect successive residues of unbroken chains by their main backbone atoms.
 - ✓ Backbone: Cylinders connect successive residues of unbroken chains by their main backbone atoms.
 - ✓ Backbone chain of a polymer is the longest series of covalently bonded atoms that together create the continuous chain of the molecule.
 - Surface: Displays the molecular surface.

Information Visualization – Protein Vis.

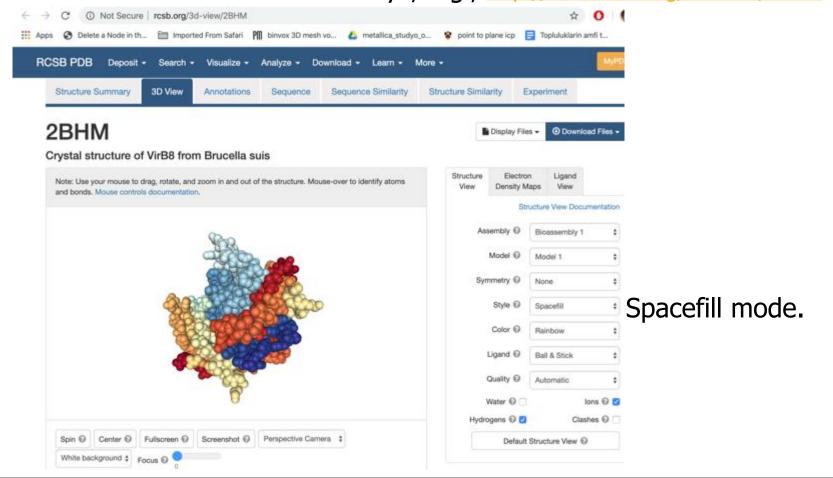
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✓ Other modes from left to right: surface, line, licorice ...



Information Visualization – Protein Vis.

√ https://www.rcsb.org/ provides state-of-the-art visualizations of protein structures in different intuitive ways, e.g., http://www.rcsb.org/3d-view/2BHM



- ✓ Implement Marching Cubes algorithm for implicit surface reconstructin.
 - ✓ Address the related research questions posed in Slide 17* and Slide 39**.
 - * Rather than contouring the surface with 0 isovalue, take the isovalue as the median signed distance value over the input points, suggested by the paper Signing the Unsigned: Robust Surface Reconstruction from Raw Pointsets.
 - ** Fixing the discontinuity issue in the original SDF.
- ✓ Implement Crust algorithm for explicit surface reconstruction.
- ✓ Implement MDS by casting it as a mass-spring problem.