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Learning from volumetric depth

Geometric Computer Vision
GCV v2021.1, Module 5

Alexey Artemov, Spring 2021

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Lecture Outline

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Lecture Outline

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§1. Volumetric 3D representations

Volumetric 3D shapes

1.1. Volumetric 3D data

§1. Volumetric 3D representations

- Dealing with **volumetric representations** of 3D objects and scenes
- **Conceptually simple and most similar** to color 2D images / range-images: defined by sampling a function on a regular grid
- **Fast inside-outside tests** (with distance functions)
- **Fast data modifications** with new information
- **Trivially converted** from different sources of 3D data
  - LIDAR point clouds, RGB-D point clouds, CAD models...
- Acts as a **data source for downstream** tasks (both reconstruction and understanding)
  - Mesh extraction, segmentation / detection / classification, ...

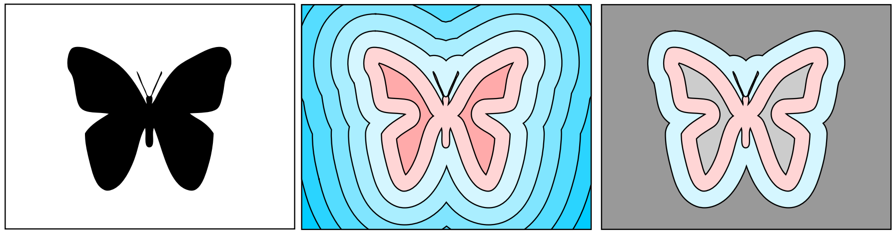
1.1. Volumetric 3D functions

§1. Volumetric 3D representations

- **Occupancy map**: a binary function $\text{OCC}(\mathbf{x}) : \Omega \to \{0,1\}$
- **Signed distance function** (SDF): an array of signed distance values $\text{SDF}(\mathbf{x}) : \Omega \to \mathbb{R}$
  - Positive values outsize the shape (free space), negative inside (occupied space)
- **Truncated SDF** (TSDF): $\text{TSDF}(\mathbf{x}) : \Omega \to [-\sigma, \sigma]$
  - Set max value to a fixed value $\text{TSDF}(\mathbf{x}) = \min(\max(\text{SDF}(\mathbf{x}), -\sigma), \sigma)$

1.1. Volumetric 3D functions

§1. Volumetric 3D representations



Occupancy map SDF TSDF

Figure credit: Representing geometry

1.1. Depth images as TSDFs

§1. Volumetric 3D representations

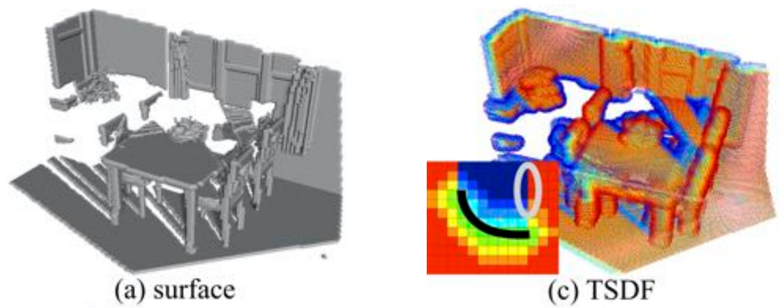


Figure credit: SSCnet

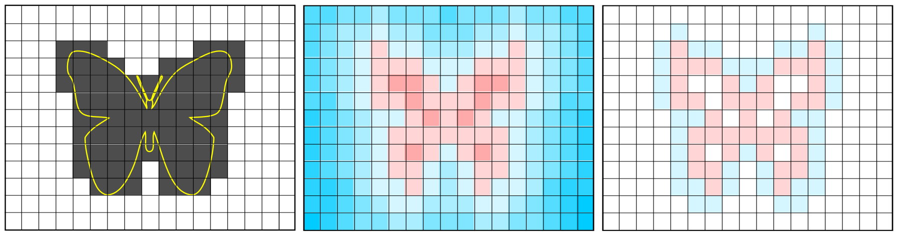
1.1. Volumetric 3D computational representations

§1. Volumetric 3D representations

- Sometimes: a **combination of basis functions** $f(\mathbf{x}) = \sum_i c_i b_i(\mathbf{x})$
- **Dense volumetric grid:** a set $\Omega = \{0,\ldots,n_x\} \times \{0,\ldots,n_y\} \times \{0,\ldots,n_z\} \subset \mathbb{R}^3$ **of voxels** (VOlumetric PIXELs: axis aligned cubes)
- **Hierarchical grid (quadtree / octree):** store function values at progressively finer levels
- **Sparse grid / hash grid:** stores only important cells or blocks of volumetric data

1.1. Volumetric 3D functions

§1. Volumetric 3D representations



Occupancy map SDF TSDF

- Dense volumetric grid: need $O(N^3)$ voxels where N is the spatial resolution

Figure credit: Representing geometry

Connections to other 3D modalities

1.2. Connections to other 3D modalities

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§1. Volumetric 3D representations

- Volumetric 3D representations can be…
- Built from:
  - Point sets / meshes / CAD models / you name it: **voxelization** (OCC)
  - Surface modalities: **distance-to-surface queries** (SDF, TSDF)
  - **Fusion** of (registered) range-images into a global surface model (OCC, SDF, TSDF)
- Used for:
  - Implicit surface modeling
  - (Explicit) Mesh extraction

1.2. Voxelization

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§1. Volumetric 3D representations

- Voxelizing **triangle meshes/CAD models:** all voxels that are intersected by a triangle are set to 1, all others are set to 0
- Voxelizing **point clouds:** occupy a voxel if at least one point of the point cloud is within the voxel
- Surface geometry only (no interior occupancy)

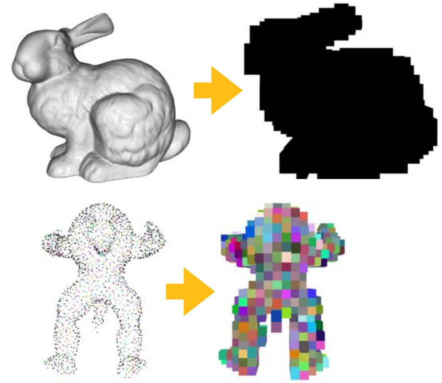

Figure credit: Open3D

1.2. Voxelization: space carving

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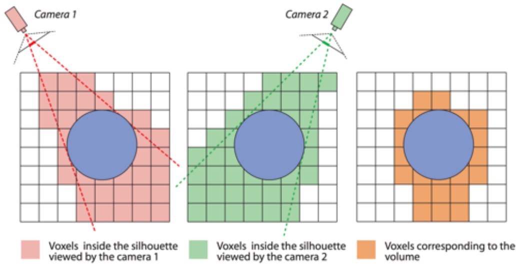
§1. Volumetric 3D representations



- Shape-from-silhouette: discard voxels projecting outside silhouette
- Need multiple views of the same shape

Figure credit: A Real-Time System for Full Body Interaction with Virtual Worlds

1.2. Voxelization: space carving

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§1. Volumetric 3D representations

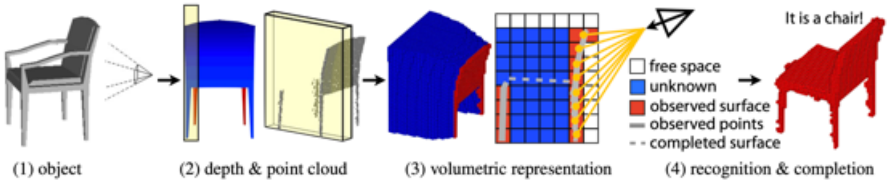


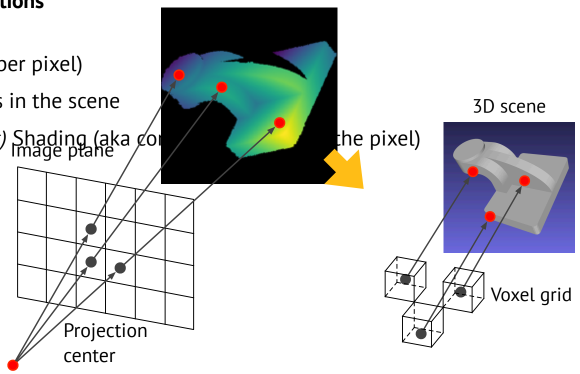
Figure credit: 3DShapeNets

- Useful for sequential tasks (e.g. determining the next-best-view from current reconstructing + a list of previous camera poses)
- Obtain depth maps (raycasting/sensors) → voxelize entire space with several occupancy labels (simplest: free/occupied, but unknown is important, too)

1.2. Distance-to-surface queries: raycasting

§1. Volumetric 3D representations

1. Generation of rays (one per pixel)
2. Intersection with objects in the scene
3. *(For graphics applications)* Shading (aka co the pixel)



Constructing volumetric 3D shapes from range-images

1.3. Constructing volumetric 3D shapes from range-images

§1. Volumetric 3D representations

- **Input:** a sequence of range-image measurements $d_1, \ldots, d_n$
- **Goal:** to build a single 3D model (preferably a surface) $D(\mathbf{x})$ **(a fused TSDF volume)**
- **Constrains:**
  - Camera poses can be known (frames registered) or unknown (SLAM variant)
  - Dense 3D modeling
  - Real-time performance (e.g. Kinect / RealSense: depth @30FPS)

Figure credit: Andy Zeng

Figure credit: ScanComplete

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

- Start with range-surfaces (proxy surfaces obtained from range-images)
- Perform rolling averaging in each spatial location on the grid:

$$D_{i+1}(\mathbf{x}) = \frac{W_i(\mathbf{x})D_i(\mathbf{x}) + w_{i+1}(\mathbf{x})d_{i+1}(\mathbf{x})}{W_i(\mathbf{x}) + w_{i+1}(\mathbf{x})}$$

where $W_i(\mathbf{x}), w_i(\mathbf{x})$ represent cumulative and instantaneous weights

$$W_{i+1}(\mathbf{x}) = W_i(\mathbf{x}) + w_i(\mathbf{x})$$

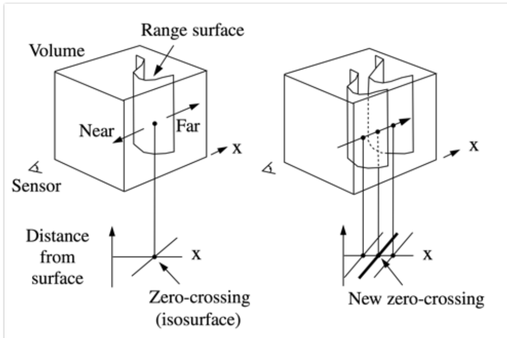
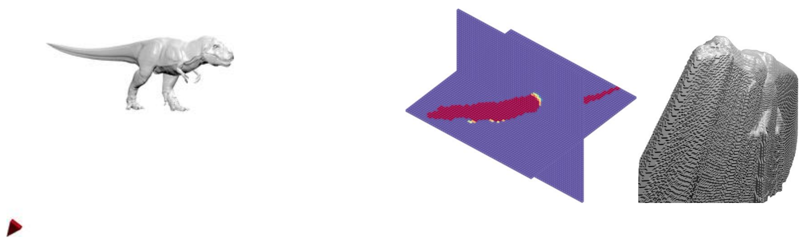


Figure credit: Curless & Levoy

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations



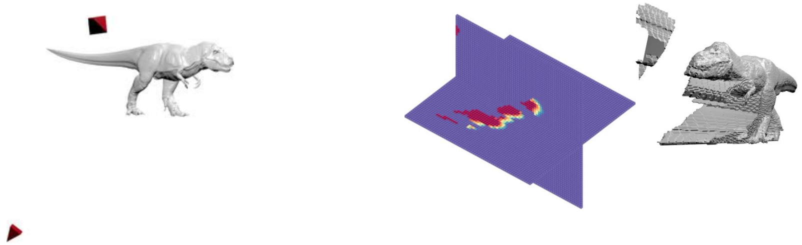
View / camera pose

Current reconstruction

Slide credit: Riegler et al., OctNet

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations



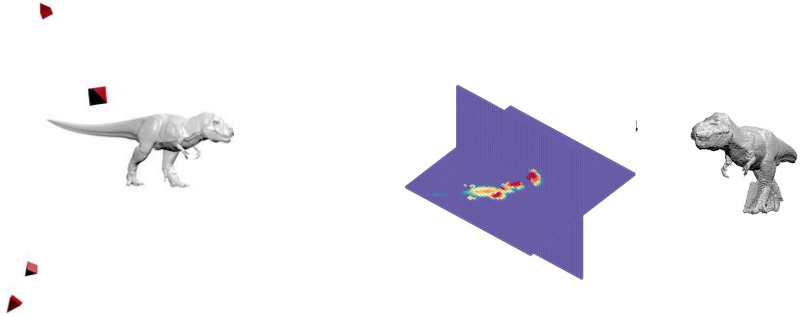
View / camera pose

Current reconstruction

Slide credit: Riegler et al., OctNet

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations



View / camera pose

Current reconstruction

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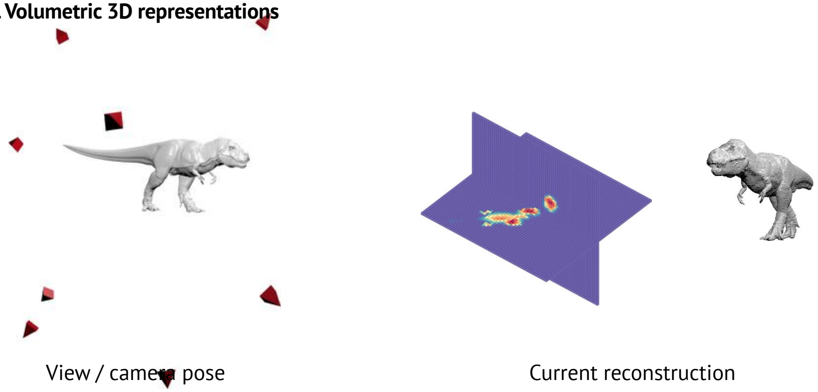
1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations



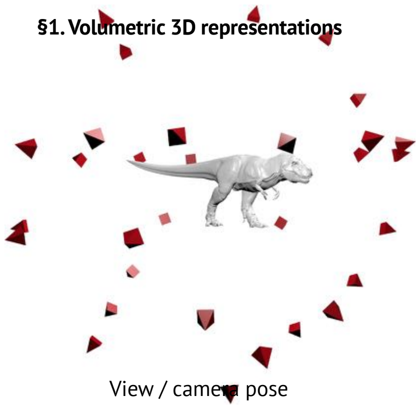
View / camera pose

Current reconstruction

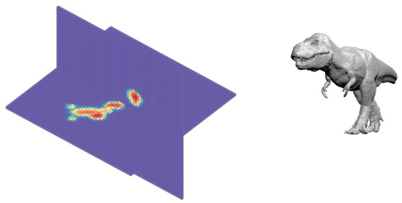
Slide credit: Riegler et al., OctNet

1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations



View / camera pose



Current reconstruction

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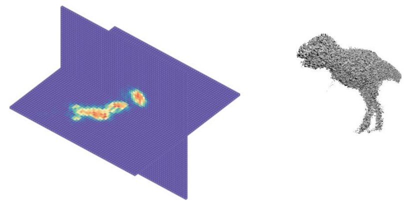
1.3. Depth fusion: Curless & Levoy fusion

§1. Volumetric 3D representations

- Pros
  - Simple
  - Fast
  - Easy implementation
- Cons
  - Many views required
  - Can not handle outliers
  - No surface completion



Final reconstruction

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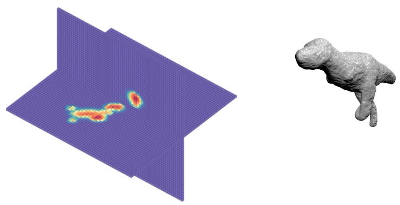
1.3. Depth fusion: TV-L1

§1. Volumetric 3D representations

- Obtained by minimizing a surface-shrinking functional during updates

$$\min_u \int_\Omega |\nabla u| + \lambda \sum_{i \in \mathcal{I}(x)} |u - f_i| \, dx$$

- Pros
  - Prior on surface area
  - Noise reduction
- Cons
  - Simplistic local prior, shrinkage bias
  - Can not complete missing surfaces



Final reconstruction

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1.3. Volumetric 3D data: summary

§1. Volumetric 3D representations

- Generic **regular representation** for 3D data
- **Distance-to-shape function** (or its variants) encoded on a volumetric grid
- Naive implementation **scales cubically** with the required resolution: $O(N^3)$
- Can be constructed with simple procedures from other types of 3D data (e.g., voxelization, space carving, ray-casting, or more complex depth fusion)

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§2. Spatial data structures

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Dense volumetric 3D grids

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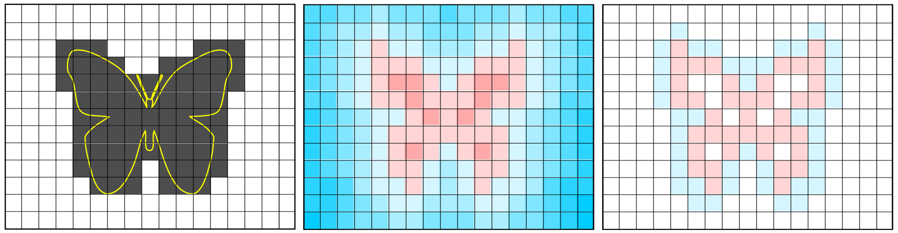
2.1. Dense volumetric 3D grids

§1. Volumetric 3D representations



Occupancy map SDF TSDF

- Dense volumetric grid: need $O(N^3)$ voxels where N is the spatial resolution

Figure credit: Representing geometry

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2.1. Dense volumetric 3D grids

§1. Volumetric 3D representations

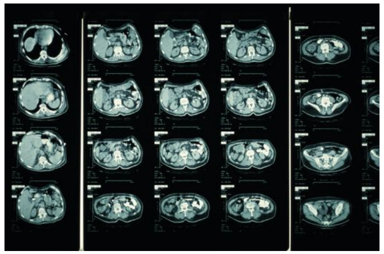


Figure credit: NBC News

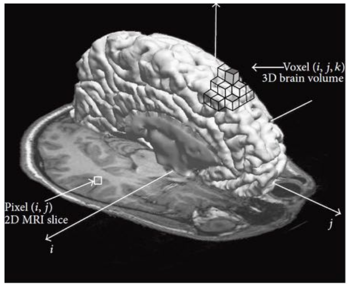
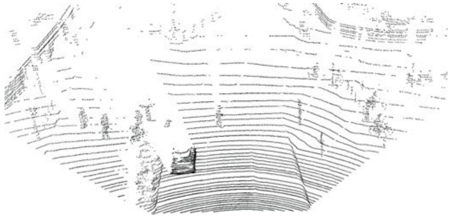


Figure credit: Despotovic et al., 2010

- "Truly dense" volumetric data is rare (e.g., CT/MRI scans)

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures

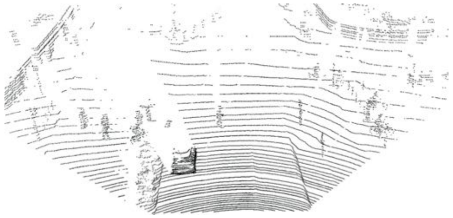


Point Cloud

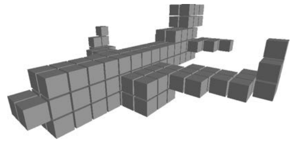
Mesh

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



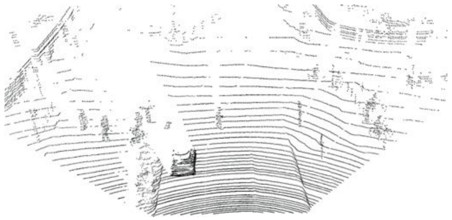
Point Cloud



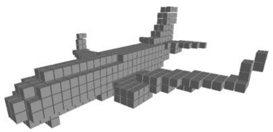
Voxelized 16^3 Occupancy 4.19%

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



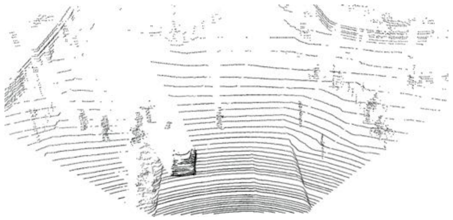
Point Cloud



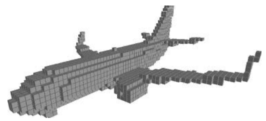
Voxelized 32^3 Occupancy 2.11%

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



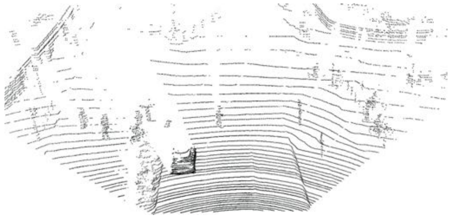
Point Cloud



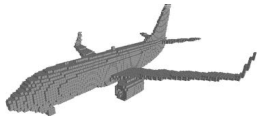
Voxelized 64^3 Occupancy 1.06%

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



Point Cloud

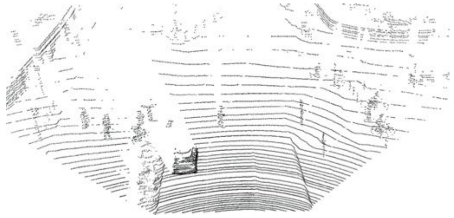


Voxelized 128^3 Occupancy 0.56%

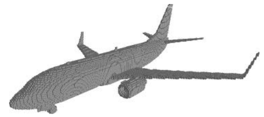
Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



Point Cloud

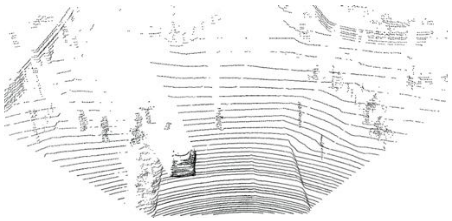


Voxelized 256^3 Occupancy 0.31%

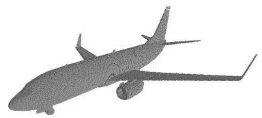
Slide credit: Riegler et al., OctNet

2.1. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



Point Cloud



Voxelized 512^3 Occupancy 0.16%

Slide credit: Riegler et al., OctNet

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Sparse data representations

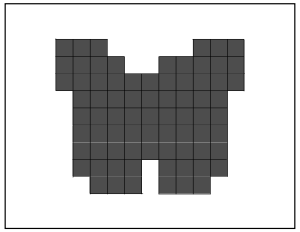
2.2. Sparse data representations

§2. Spatial data structures

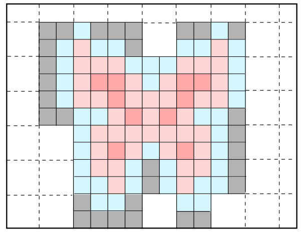
- Storage requirements for volumetric data: $O(N^3)$ where N is the spatial resolution
  - Need $O(N^3)$ for truly volumetric 3D data (e.g., MRI scans)
  - Encoding surfaces: $O(N^2)$
  - Point clouds: inherently sparse $O(N_{\text{points}})$
- Store data only in occupied locations (active values)
  - **Sparse tensor representation**
  - Which format to choose?

2.3. Disadvantages of dense volumetric 3D grid

§2. Spatial data structures



Occupancy map



TSDF

- Sparse volumetric grid: need $O(K)$ voxels where K is the number of nonempty voxels

2.2. Sparse data representations

§2. Spatial data structures

- Dense array storage

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

```
[ 10, 20,  0,  0,  0,  0,
   0, 30,  0, 40,  0,  0,
   0,  0, 50, 60, 70,  0,
   0,  0,  0,  0,  0, 80 ]
```

Memory array 24-floats

2.2. Sparse data representations

§2. Spatial data structures

- Coordinate list storage (COO)

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

Row	Column	Value
0	0	10
0	1	20
1	1	30
1	3	40
2	2	50
2	3	60
2	4	70
3	5	80

COO

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2.2. Sparse data representations

§2. Spatial data structures

- Compressed sparse row (CSR) and compressed sparse column (CSC)

10	20	0	0	0	0
0	30	0	40	0	0
0	0	50	60	70	0
0	0	0	0	0	80

Matrix 6×4

```
values      = [ 10, 20, 30, 40, 50, 60, 70, 80 ]
col_indices = [  0,  1,  1,  3,  2,  3,  4,  5 ]
row_indptr  = [  0,  2,  4,  7,  8 ]
```

CSR

```
row_idx = 2
col_start = row_indptr[row_idx]  # 4
col_end = row_indptr[row_idx]  # 7
col_idxs = col_indices[col_start:col_end]
vals = values[col_start:col_end]
```

Reading from a CSR

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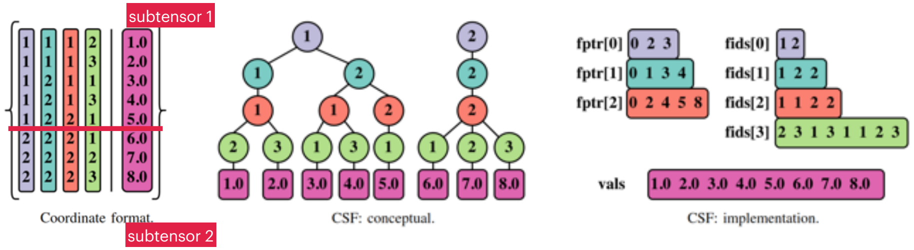
2.2. Sparse data representations

§2. Spatial data structures

- Compressed sparse fiber (CSF)



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Octrees

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2.3. Octrees

§2. Spatial data structures

- Memory-efficient data structure for spatial indexing
- Many applications:
  - Efficient 3D spatial indexing at high resolutions
  - Visualization (e.g. level of detail, frustum culling, raycasting)
  - Nearest neighbour search (e.g. needed by ICP)
  - Discrete geometry processing (e.g. meshing)

Figure credit: gifer.com

2.3. Octrees

§2. Spatial data structures

- A search tree with exactly 8 children in each node
- Recursively subdivide space into 8 octants at each spatial scale
- Point-region and matrix-based

- Insertion: $O(\log N)$
- Nearest-neighbour search: $O(\log N)$

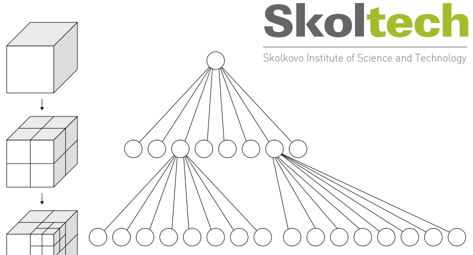
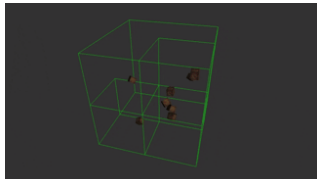
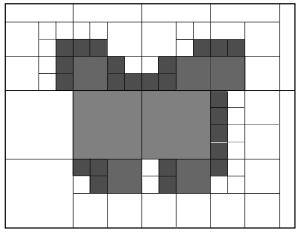


Figure credit: Wikipedia

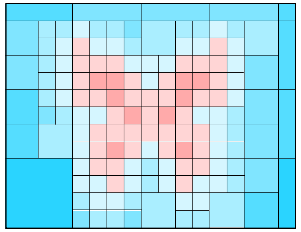


2.3. Octrees

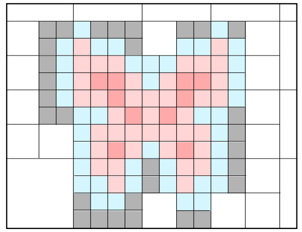
§2. Spatial data structures



Occupancy map



SDF

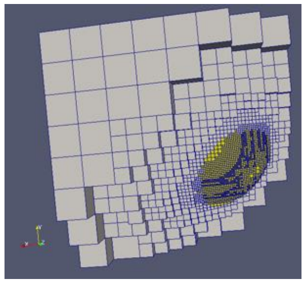


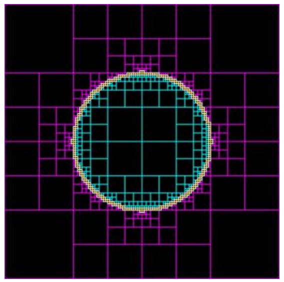
TSDF

- Quadtree/octree voxel grid: adaptively subdivide space to accommodate active sites

2.3. Octrees

§2. Spatial data structures





- Quadtree/octree voxel grid: resolution changes/dynamics

2.3. Spatial data structures: summary

§2. Spatial data structures

- **Dense volumetric grid:** a set $\Omega = \{0,\ldots,n_x\} \times \{0,\ldots,n_y\} \times \{0,\ldots,n_z\} \subset \mathbb{R}^3$ **of voxels**
  - Simplest, off-the-shelf, easy to use
  - Memory and computationally inefficient
- **Hierarchical grid (quadtree / octree):** store function values at progressively finer levels
  - Fast insertion and search: $O(\log N)$
  - Maintain a separate data structure, still pointwise-constant approximation
- **Sparse grid / hash grid:** stores only important cells or blocks of volumetric data
  - Removes redundancy be not storing / computing values in empty voxels
  - Separate sparse data-structures (e.g. COO-formatted sparse tensors)

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§3. Constructing neural networks on volumetric data

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Dense 3D CNNs

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3.1. Dense 3D CNNs

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- 2D convolutions: mainstream tool for processing signals
  - Images, video, RGBD, …
- Dense 3D volumetric data: directly extend 2D convolutions to 3rd dimension
  - No-brainer (add another loop into the code for convolution computation)

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3.1. Dense 3D CNNs: understanding 3D scans

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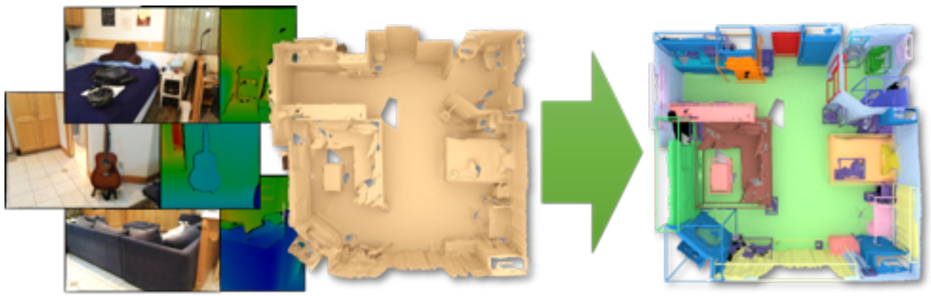

Slide credit: Matthias Niessner

3.1. Dense 3D CNNs: Deep Learning in 3D

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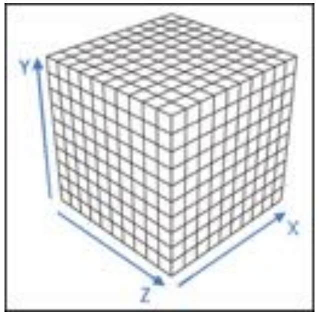
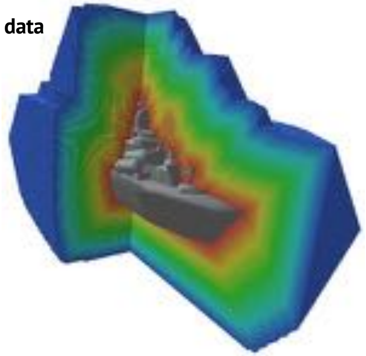


(binary) Voxel Grid



Implicit Function

3.1. Dense 3D CNNs: 3D Semantic Segmentation

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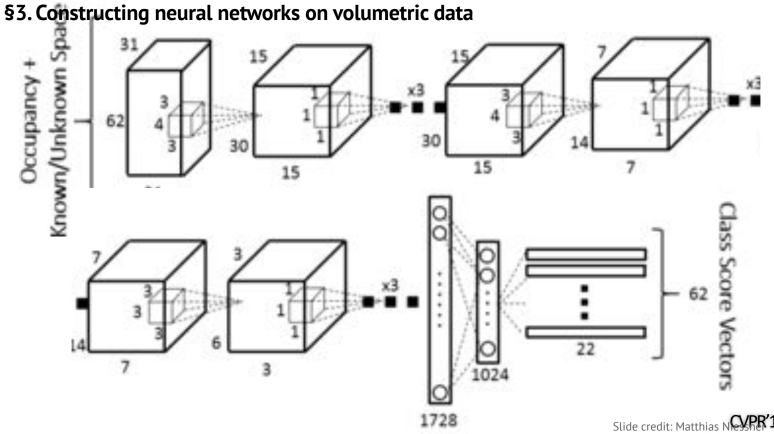

CVPR'17 (spotlight) [Dai et

3.1. Dense 3D CNNs: 3D Semantic Segmentation

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3.1. Dense 3D CNNs: 3D Reconstructions

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TOG'17 [Dai et al.]: Bu

3.1. Dense 3D CNNs: Incomplete Scan Geometry

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TOG'17 [Dai et al.]: Bu

3.1. Dense 3D CNNs: Completing 3D Shapes

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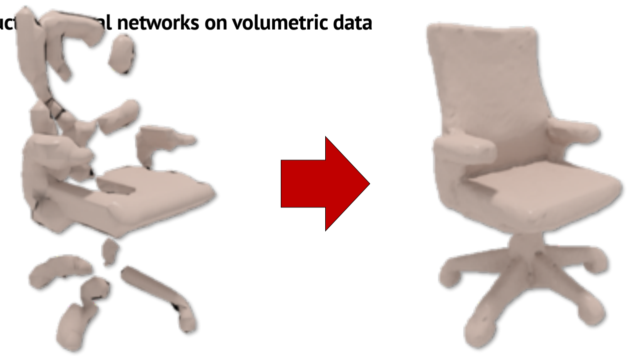
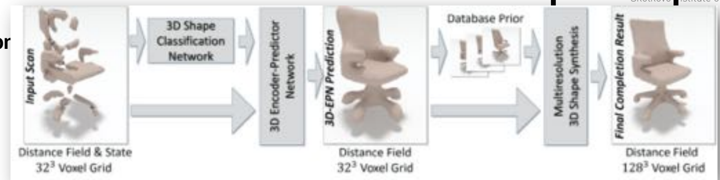


3.1. Dense 3D CNNs: Data-driven Shape Completion

§3. Cor



CVPR'17 (spotlight) [Dai et al.]

3.1. Dense 3D CNNs: Data-driven Shape Completion

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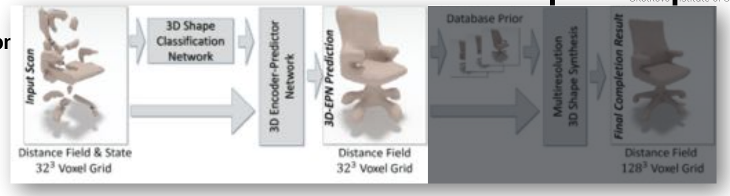
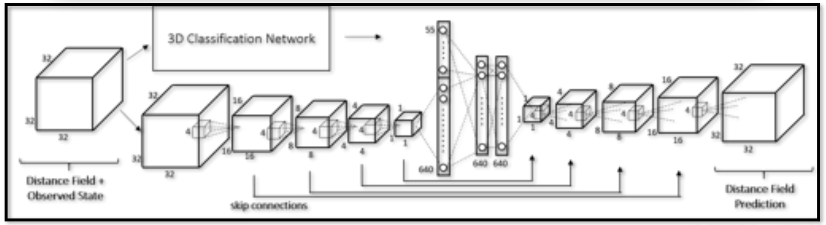




CVPR'17 (spotlight) [Dai et al.]

3.1. Dense 3D CNNs: Shape Completion Results

§3. Constructing ne

Input

Completion

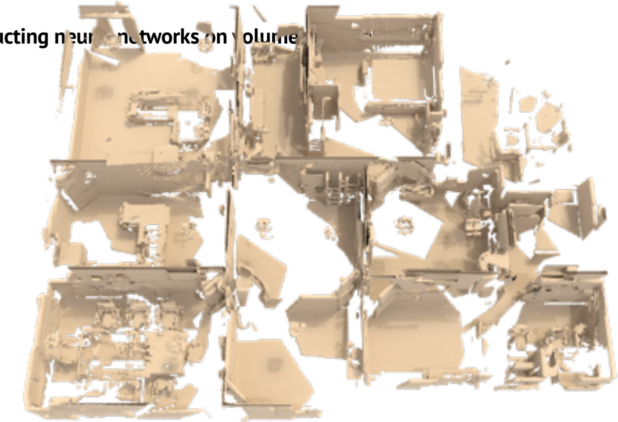
Ground Truth

Results on ShapeNet [Chang et al. 15]

CVPR'17 (spotlight) [Dai et al.]

3.1. What about Entire Scenes and Domain Transfer?

§3. Constructing neur networks on volume



3.1. Spatial Extent: Fully Convolutional for Arbitrary Sizes

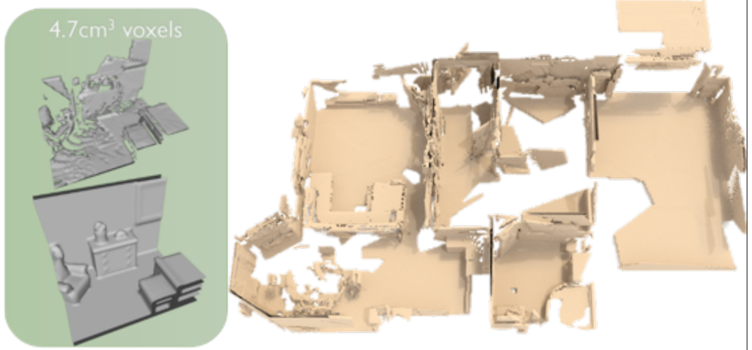
§3. Constructing neural networks on volumetric data

Train on crops of scenes

Test on entire scenes

Train Block Input Partial Scan

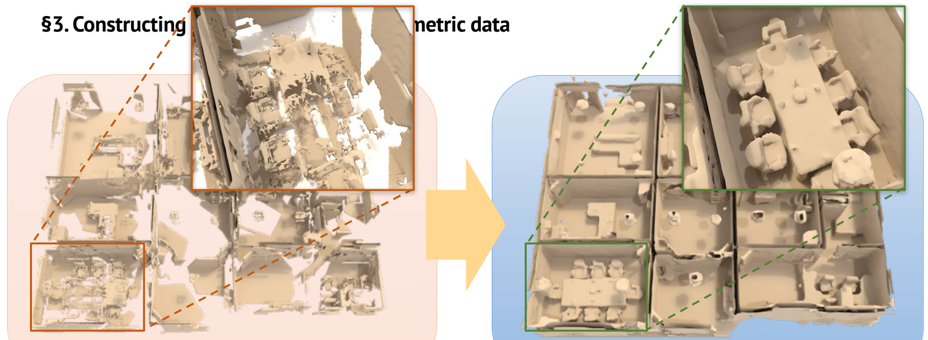
Train Block Complete Target



CVPR'18 [Dai et al.]: Sc

3.1. Dense 3D CNNs: ScanComplete: Scene Completion

§3. Constructing metric data



Input Partial Scan

Completed Scan

CVPR'18 [Dai et al.]: Sc

3.1. Dense 3D CNNs: ScanComplete

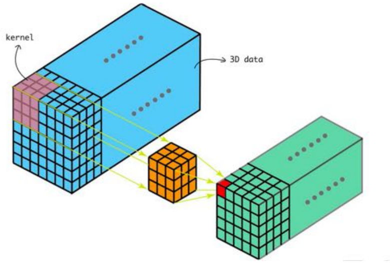
§3.

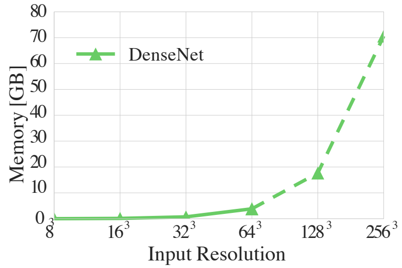
CVPR'18 [Dai et al.]: Sc

3.1. Dense 3D CNNs: memory requirements

§3. Constructing neural networks on volumetric data

- Network evaluation with batch size 32 (Voxelized ModelNet10 meshes)





Riegler et al., OctNet - 5

3.1. Naive 3D CNNs: summary

§3. Constructing neural networks on volumetric data

- Dense 3D CNNs: directly extend 2D convolutions to 3rd dimension
- **Computationally inefficient** (scale cubically with spatial resolution)
  - Process low-resolution shapes only (e.g., 32^3 or 64^3) or use shallower NNs
  - Many applications can leverage low-resolution volumes (e.g. semantic segmentation, scene completion…)
- **Sample inefficient** (perform worse compared to 2D CNNs)

Octree-based CNNs

3.3. Octree-based CNNs

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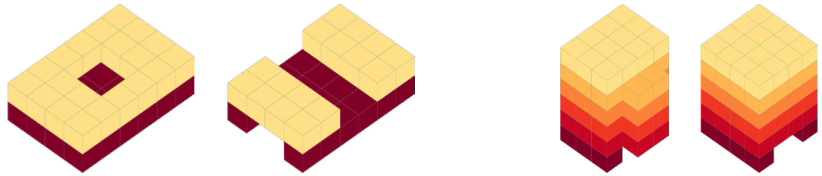
- **Goal:** train deep architectures at high spatial resolutions
  - Deeper models → higher learning efficiency
  - Higher resolution → more detail in input 3D shapes/scenes

3.3. Octree-based CNNs: effect of resolution

§3. Constructing neural networks on volumetric data



Voxelized 8^3

3.3. Octree-based CNNs: effect of resolution

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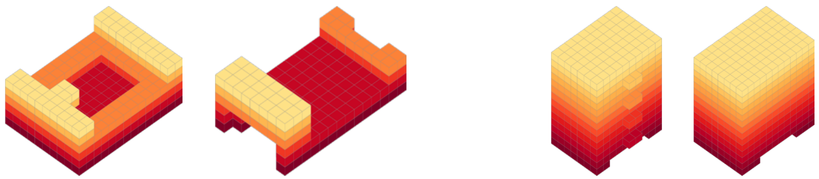

Voxelized 16^3

3.3. Octree-based CNNs: effect of resolution

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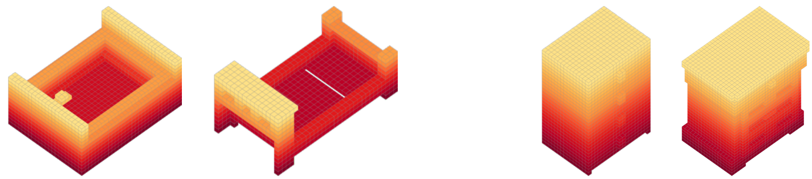

Voxelized 32^3

3.3. Octree-based CNNs: effect of resolution

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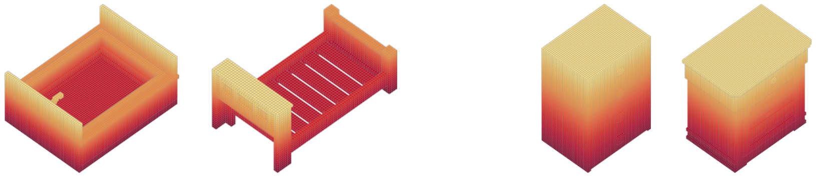
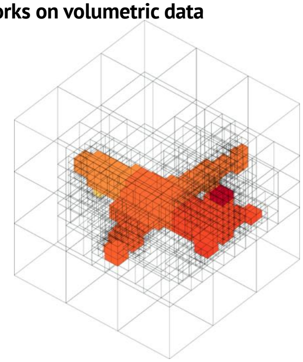


Voxelized 64^3

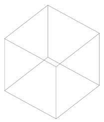
3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



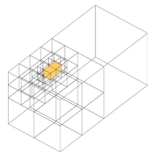
3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



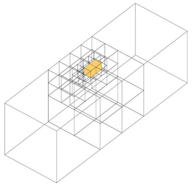
3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



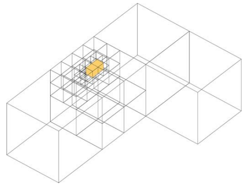
3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: grid of octrees

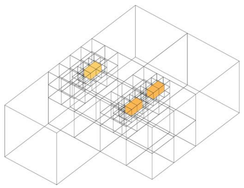
§3. Constructing neural networks on volumetric data



A. Miller et al. "Real-time rendering and dynamic updating of 3-d volumetric data". In: **GPGPU**. 2011.

3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



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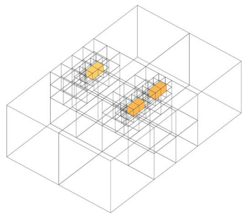
3.3. Octree-based CNNs: grid of octrees

§3. Constructing neural networks on volumetric data



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3.3. Octree-based CNNs: grid of octrees

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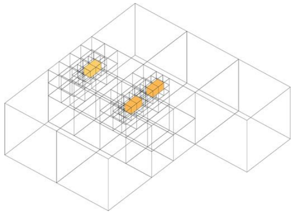
§3. Constructing neural networks on volumetric data



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3.3. Octree-based CNNs: grid of octrees

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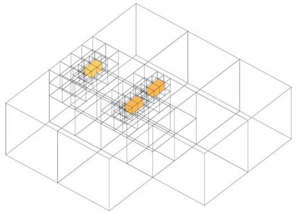
§3. Constructing neural networks on volumetric data



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3.3. Octree-based CNNs: grid of octrees

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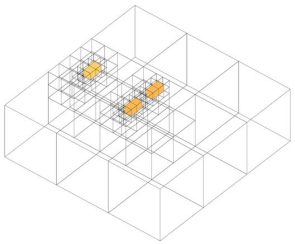
§3. Constructing neural networks on volumetric data



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3.3. Octree-based CNNs: grid of octrees

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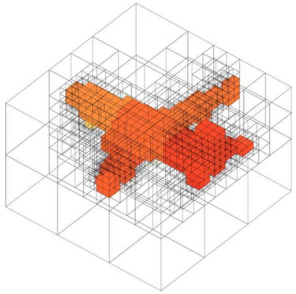
§3. Constructing neural networks on volumetric data



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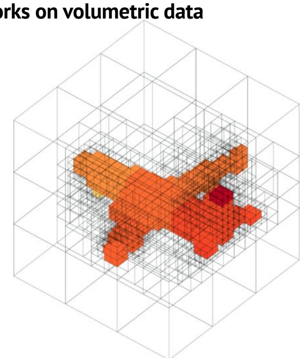
3.3. Octree-based CNNs: grid of octrees

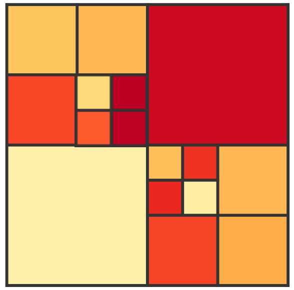
§3. Constructing neural networks on volumetric data



A. Miller et al. "Real-time rendering and dynamic updating of 3-d volumetric data". In: GPGPU. 2011.

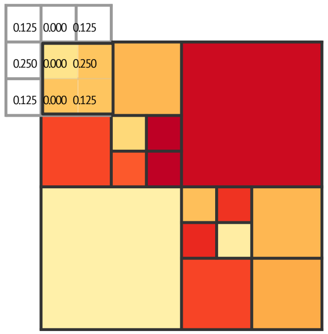
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



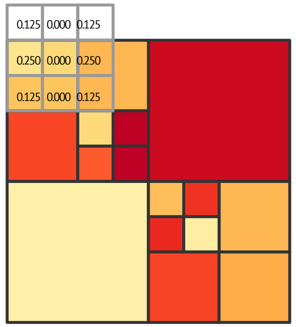
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



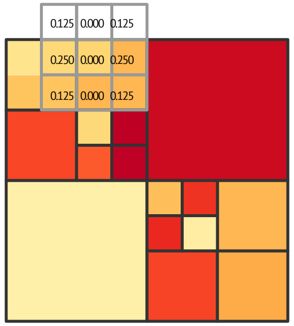
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

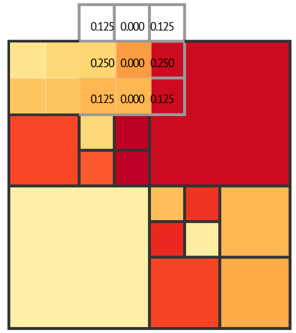
§3. Constructing neural networks on volumetric data



Slide credit: Riegler et al., OctNet

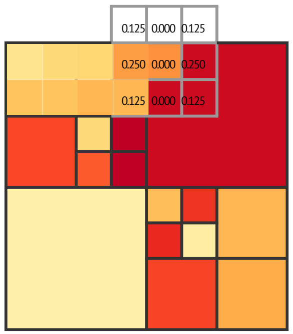
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

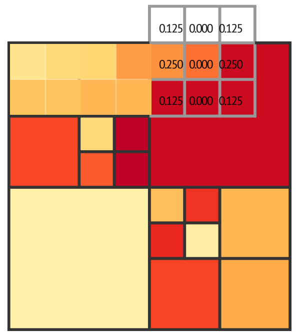
§3. Constructing neural networks on volumetric data



Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: convolution

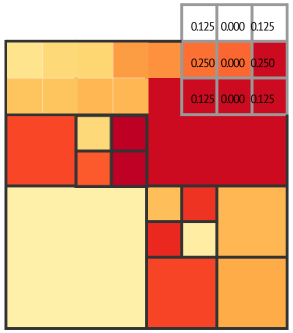
§3. Constructing neural networks on volumetric data



Slide credit: Riegler et al., OctNet

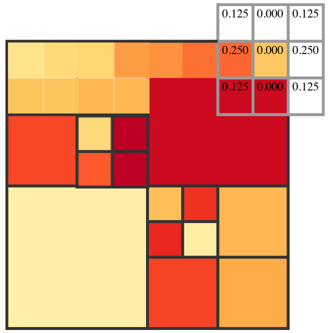
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



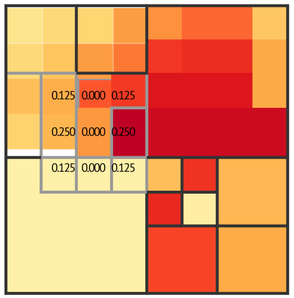
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



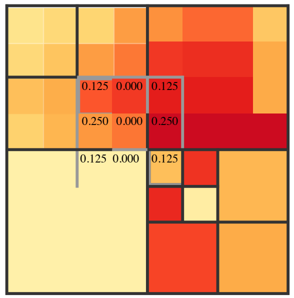
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



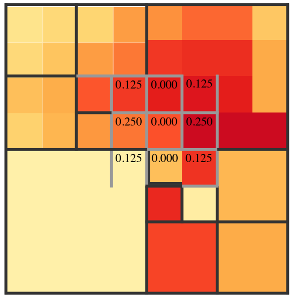
3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

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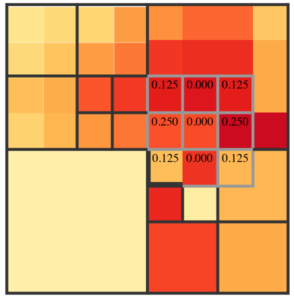

3.3. Octree-based CNNs: convolution

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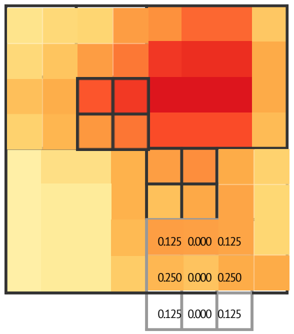
§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

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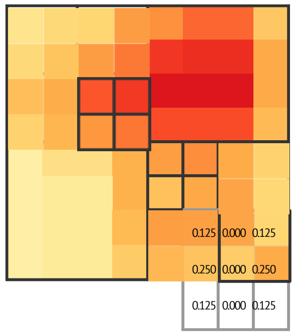
§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

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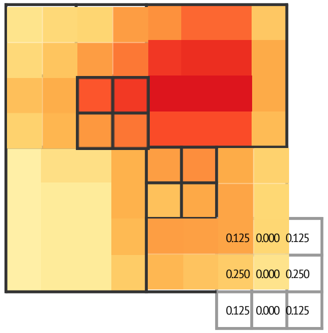
§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: convolution

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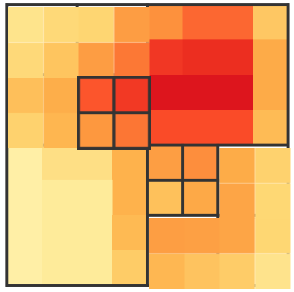

3.3. Octree-based CNNs: convolution

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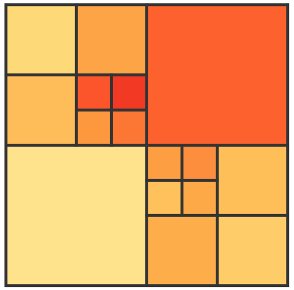

3.3. Octree-based CNNs: pooling

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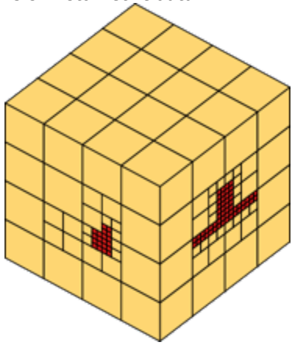
§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: pooling

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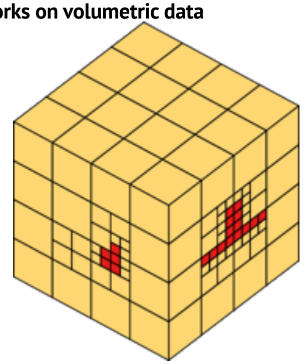
§3. Constructing neural networks on volumetric data



Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: pooling

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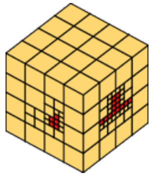
§3. Constructing neural networks on volumetric data



Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: pooling

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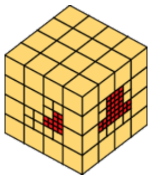

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: pooling

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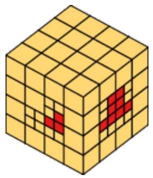

Slide credit: Riegler et al., OctNet

3.3. Octree-based CNNs: pooling

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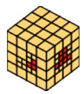
§3. Constructing neural networks on volumetric data



3.3. Octree-based CNNs: experiments

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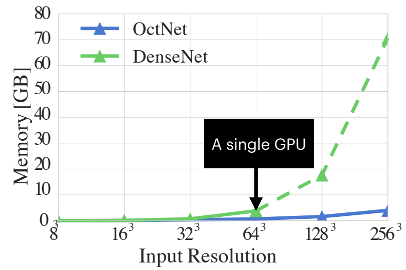
§3. Constructing neural networks on volumetric data



Network evaluation with batch size 32
Voxelized ModelNet10 meshes

3.3. Octree-based CNNs: experiments

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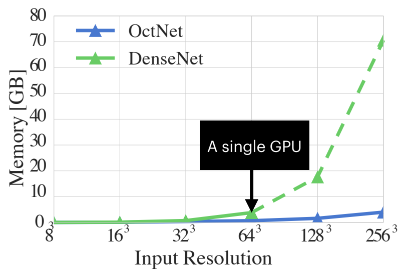
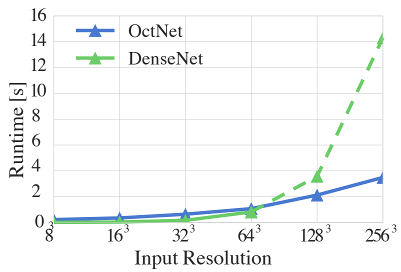
§3. Constructing neural networks on volumetric data





Network evaluation with batch size 32
Voxelized ModelNet10 meshes

3.3. Octree-based CNNs: experiments

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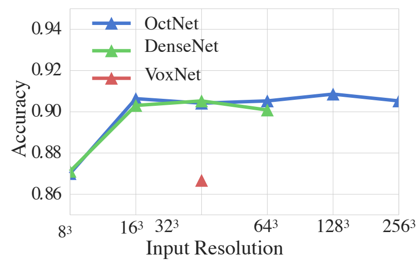

ModelNet10

D. Maturana and S. Scherer. "VoxNet: A 3D Convolutional Neural Network for real-time object recognition". In: **IROS**. 2015.

3.3. Octree-based CNNs: experiments

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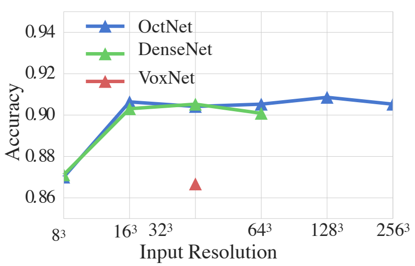
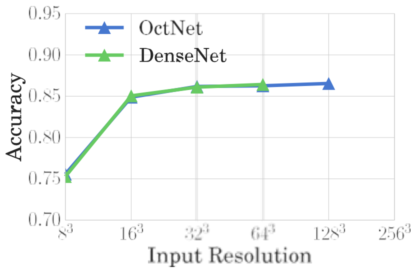


ModelNet10



ModelNet40

D. Maturana and S. Scherer. "VoxNet: A 3D Convolutional Neural Network for real-time object recognition". In: **IROS**. 2015.

3.3. Octree-based CNNs: summary

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§3. Constructing neural networks on volumetric data

- Define a convolutional / pooling operators on top of octree data structure
- Capability to train deeper architectures at higher spatial resolutions