3D Object Detection using Depth Images

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Team 6

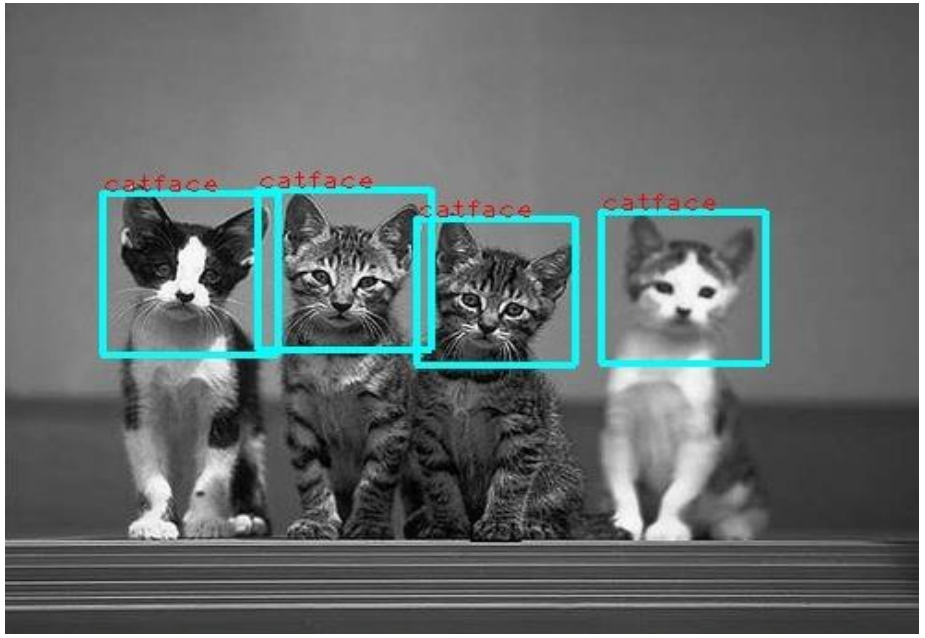
Introduction: Object Detection

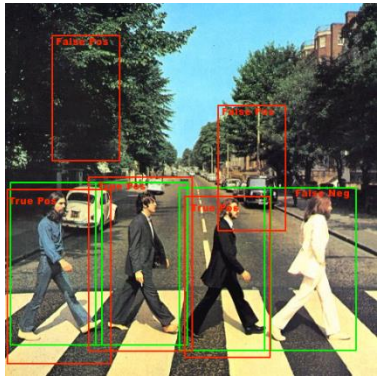
Need for object detection:

- Fundamental problem in CV!
- Application: Robotics, Image retrieval, Video surveillance

Traditional approaches

- Bounding box based
- Deep learning
  - ImageNet





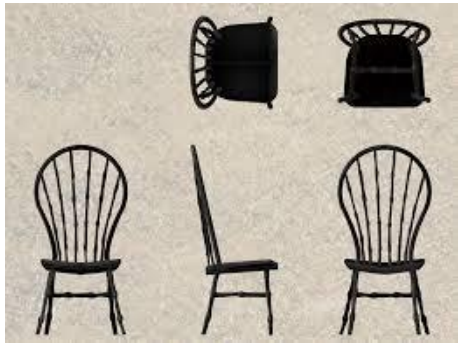
Object Detection is hard!

Variation

Object Detection is hard!

Variation

Viewpoint



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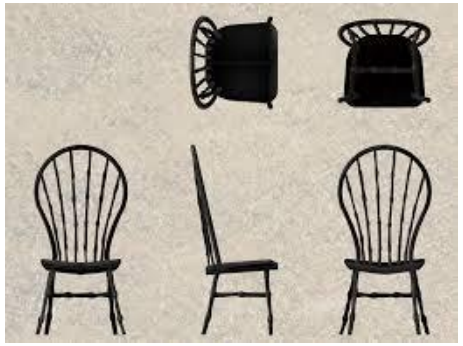
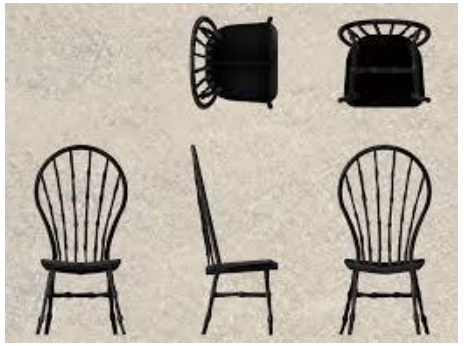


Illumination

Object Detection is hard!

Variation

Viewpoint



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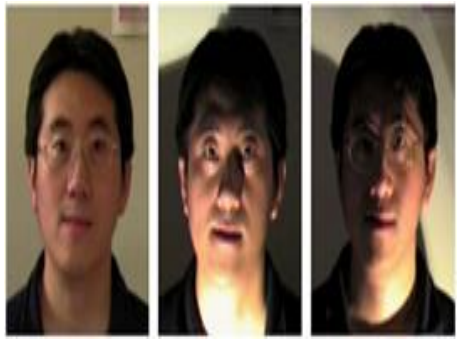
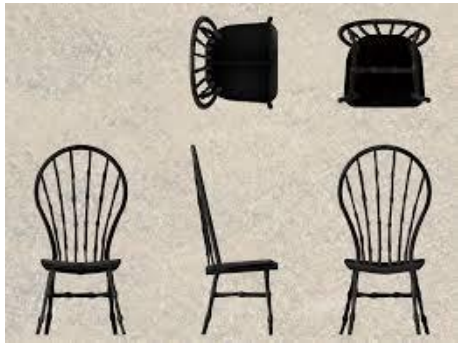


Clutter

Object Detection is hard!

Variation

Viewpoint



Illumination

Clutter

Occlusion

Depth Sensors

Asus Xtion Pro

Our problem statement: Detect objects in a scene using 3D depth images

3D Object Recognition: State of Art

Sliding Shapes

Suran Song, ECCV 2014

Used following features with exemplar SVM:

- Point density: no of points/voxel
- Shape: linearness, scatterness
- Normal: bin the orientation
- TSDF

Accuracy: 0.6 to 0.8

Kernel Descriptors

L. Bo, Dieter Fox, CVPR 2011

Uses 5 depth kernel descriptors that capture:

- Size
- Shape and edges
- Edges

Accuracy: 0.55

Algorithm: Training

- 3D Object detection is highly dependent on pose of the object.
- How do we obtain multiple poses?
- Solution??

Algorithm: Training with 3D CAD Models

- 3D Object detection is highly dependent on pose of the object.
- How do we obtain multiple poses?
- Solution??
- **Use CAD Models**
- Downloaded from Trimble 3D warehouse* and other freely available models
- Render the models(.ply) and capture point clouds of partial views

*https://3dwarehouse.sketchup.com/

Algorithm: Features

- Required: Set of correspondences between test point cloud and known cloud
- Features:
    - Compact, but rich representation of 3D data
    - Needs to be invariant to
        - Transformations and disturbances
        - Noise
        - Resolution invariant

Algorithm: Features

- Required: Set of correspondences between test point cloud and known cloud
- Features:
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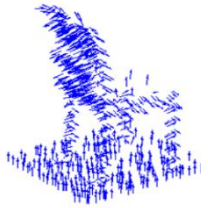
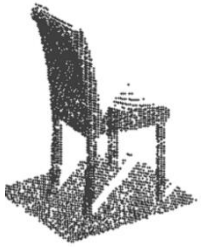
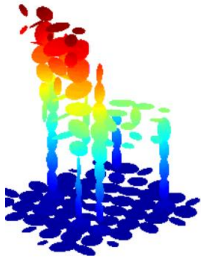
  - Needs to be invariant to
    - Transformations and disturbances
    - Noise
    - Resolution invariant
- Local Descriptors v/s Global Descriptors?



Normal



Points



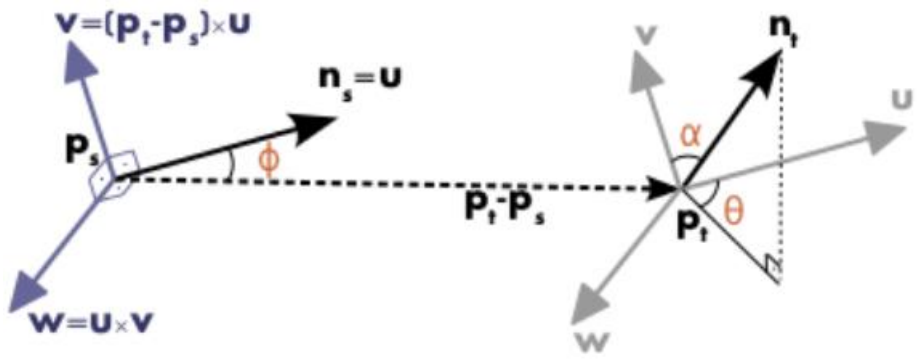
Shape

Algorithm: Point Feature Histogram

- PFH computes 3 values for each pair in the neighborhood
  - Captures information of the geometry surrounding the point
  - Finds the difference between directions of normals
- For each pair, computes a local reference frame(LRF) centered on p_s as:
  - The normal $u = n_s$
  - Cross product between n_s and the vector $(p_t - p_s)$ $v = n_s \times (p_t - p_s)$
  - Cross product between previous vectors $w = u \times v$
- Computes and accumulates

$$\alpha = cos^{-1}(v.n_t) \;\; ; \;\; \phi = cos^{-1}\left(u.\frac{(p_t - p_s)}{\|p_t - p_s\|_2}\right)$$

$$\theta = tan^{-1}(w.n_t, u.n_t)$$



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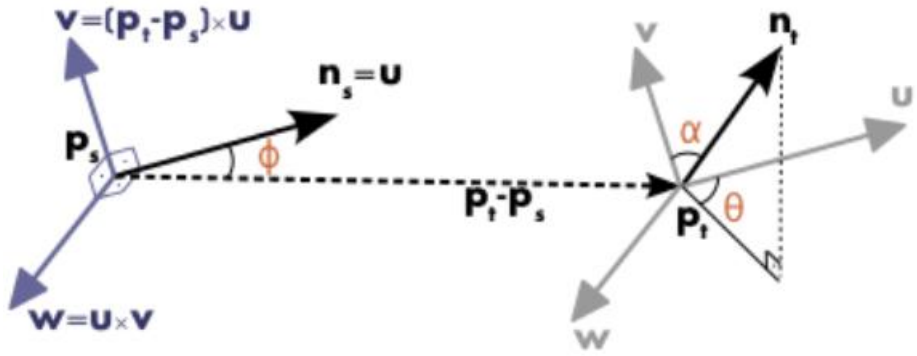
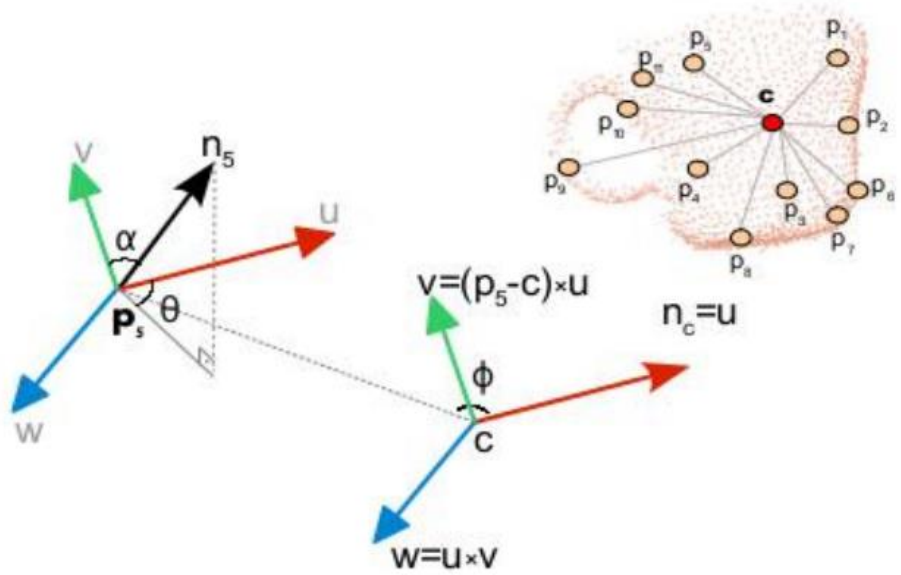
Extremely slow!

For *n* key points with *k* neighbors, complexity = $O(nk^2)$



Algorithm: Viewpoint Feature Histogram

- **Global Descriptor**
- Described by Rusu *et al.**
- Each view of the object provides a different descriptor
  - **Scale Invariant,** but encodes the viewpoint from where surface was captured
- For each pair ($\boldsymbol{p_c}$, $\boldsymbol{p_i}$):
  - Compute LRF for the centroid:
    - $u = n_s$
    - $v = \frac{p_i - p_c}{\|p_i - p_c\|} \times u$
    - $w = u \times v$
  - $\alpha = cos^{-1}(v.n)$
  - $\phi = cos^{-1}\left(u.\frac{(p_i - p_s)}{\|p_i - p_s\|_2}\right)$
  - $\theta = tan^{-1}(w.n, u.n)$



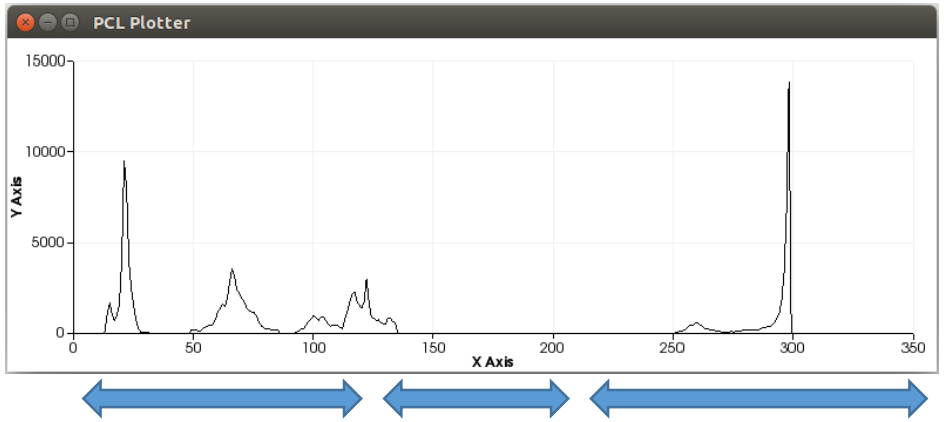
*Fast 3D Recognition and Pose Using the Viewpoint Feature Histogram, Rusu *et al.*, in Proc. Int. Conf. Intelligent Robots and Systems, 2010, pp. 2155–2162.

Algorithm: Viewpoint Feature Histogram

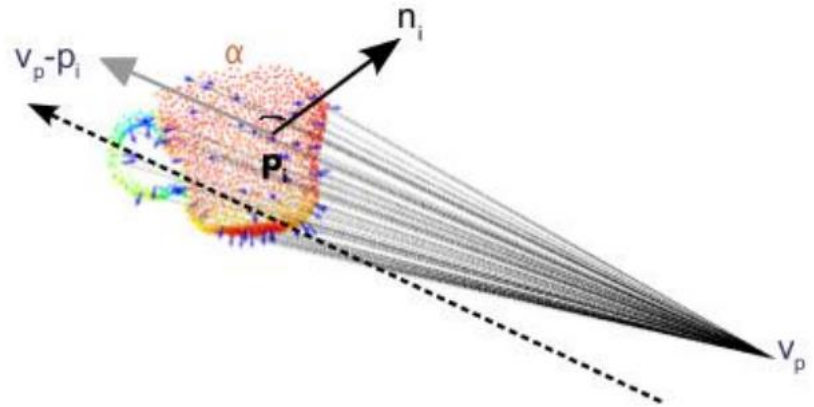
- Descriptor composition
  - 3 PFH angular values (α, θ, ϕ) with respect to centroid of object(45 bins each)
  - 1 shape distribution component with respect to centroid (45 bins)

$$SDC = \frac{(p_c - p_i)^2}{max((p_c - p_i)^2)}$$

  - 1 angular value which encodes angle b/w normal and central view direction α (128 bins)



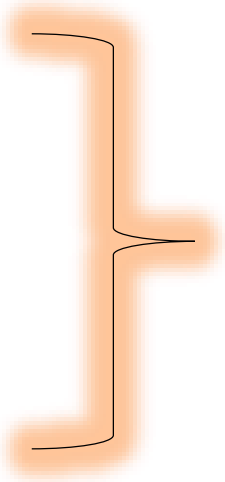
FPFH (α, θ, ϕ) Shape dist Viewpoint α



Algorithm: Global Radius-Based Surface Descriptor

- Described by Marton *et al.**
- Global feature is computed from each cluster by counting transitions between surface types
- Categorizes the point clouds into following shapes:
  - Cylindrical : minRadius = radius of cylinder, maxRadius = ∞
  - Spherical/Corner : minRadius and maxRadius are same
  - Planar
  - Noise/Corner
  - Edge

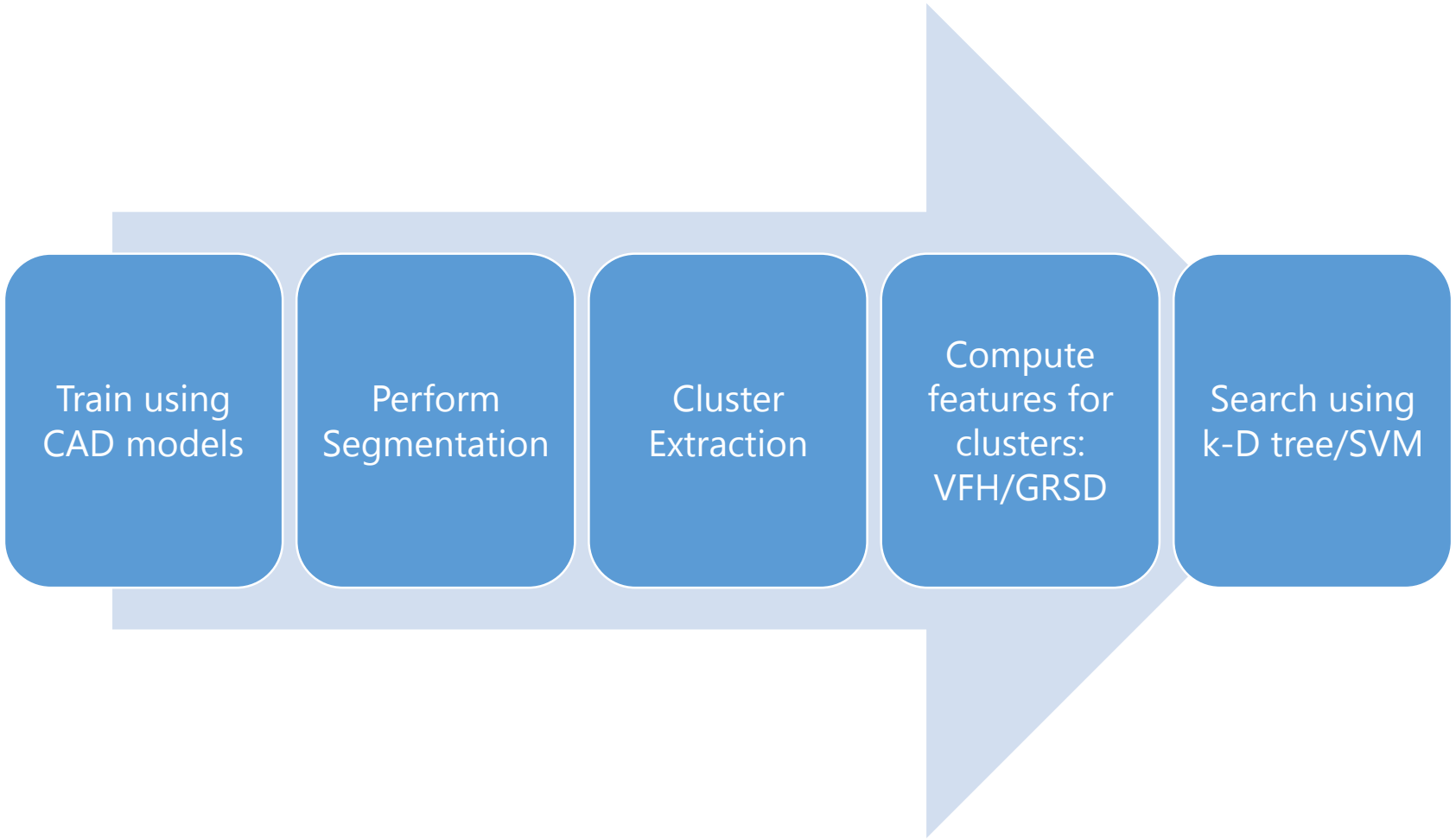
Based on minRadius, maxRadius



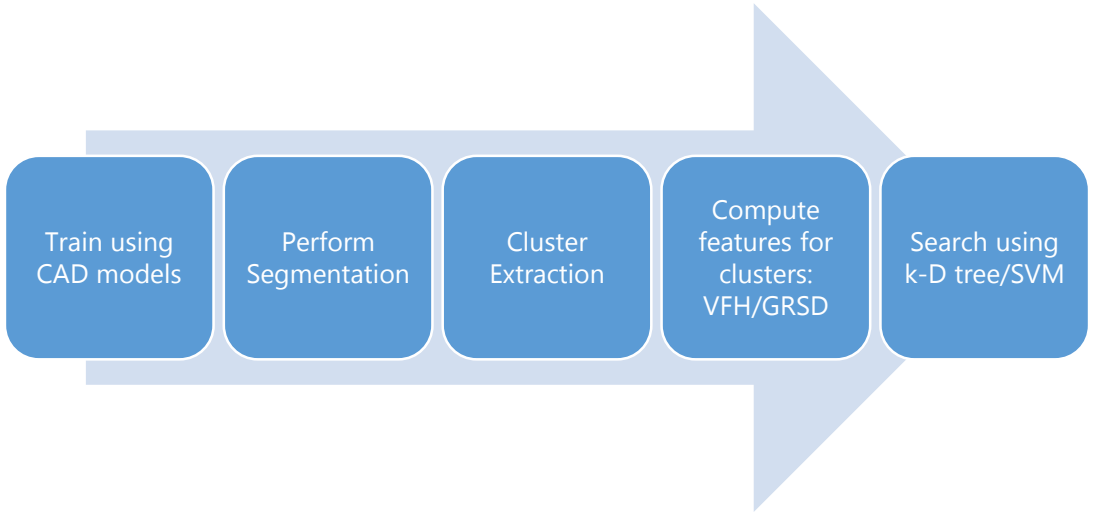
Use geometric class to decide on what model to fit.

*General 3D Modelling of Novel Objects from a Single View, Marton *et al.*, in IROS, 2010

Object Recognition Pipeline

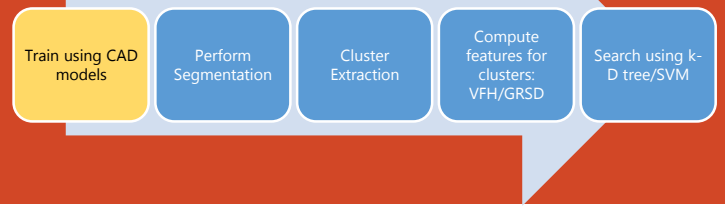


Object Recognition Pipeline: Platform

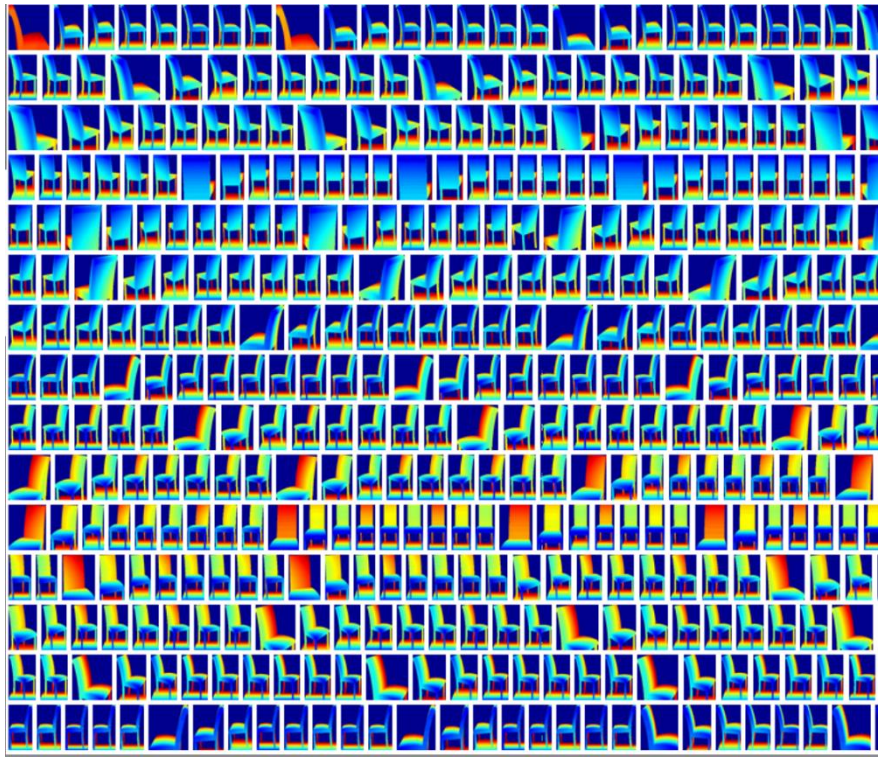


- Point Cloud Library implemented in C++
- Hardware: XBOX 360 Kinect
- OpenNI for Kinect image capture
- KD Tree : FLANN implementation

Object Recognition Pipeline: Training



- Generated 80 views using different angles
- Object categories comprised:
  - Chair
  - Coffee Mug
  - Bottle
  - Ball
  - Bowl
- Used Blender and Meshlab for editing and creating CAD dataset



Object Recognition Pipeline: Training

Segmentation process:

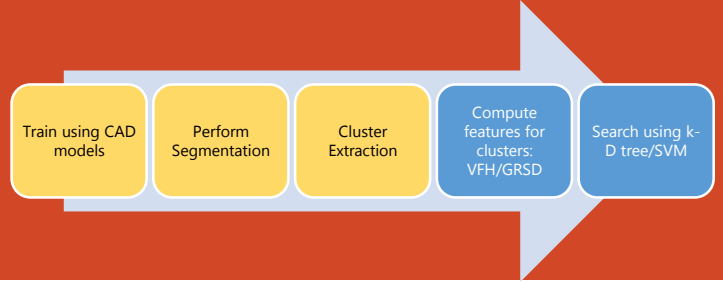
- SAC Segmentation: (**SA**mple **C**onsensus based)
  - Fit plane model
  - With constraints = orientation

- Once, plane is extracted:
  - Find objects standing on tables, shelves
  - Protruding objects such as door handles

  By

- Polygonal prism method:
  - Using convex hull of planar points
  - Extruding this outline along plane normal

Object Recognition Pipeline: Cluster Extraction



- Once the objects are detected
  - Need to segment remaining point cloud into clusters
  - Idea: Use region growing approach that cannot grow two points with a high distance
    - This merges locally dense areas and splits separate clusters
  - Basically, **Euclidean distance** based clustering
  - Up-sample and down-sample
    - to obtain clusters with different point cloud densities

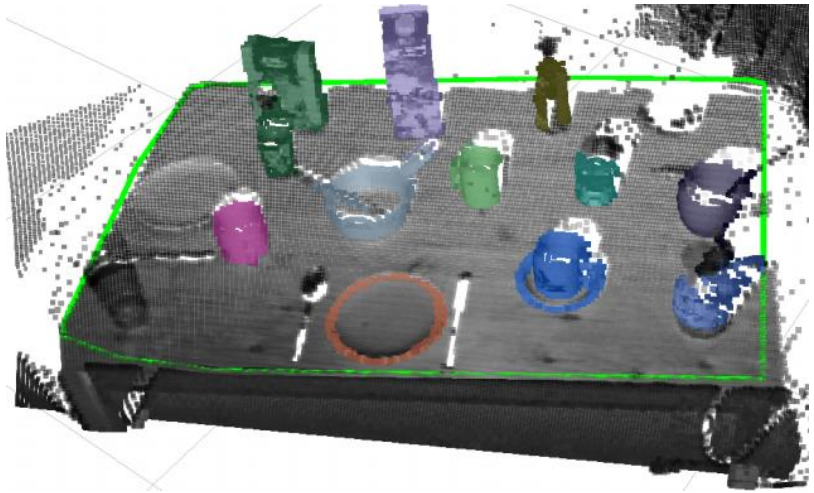
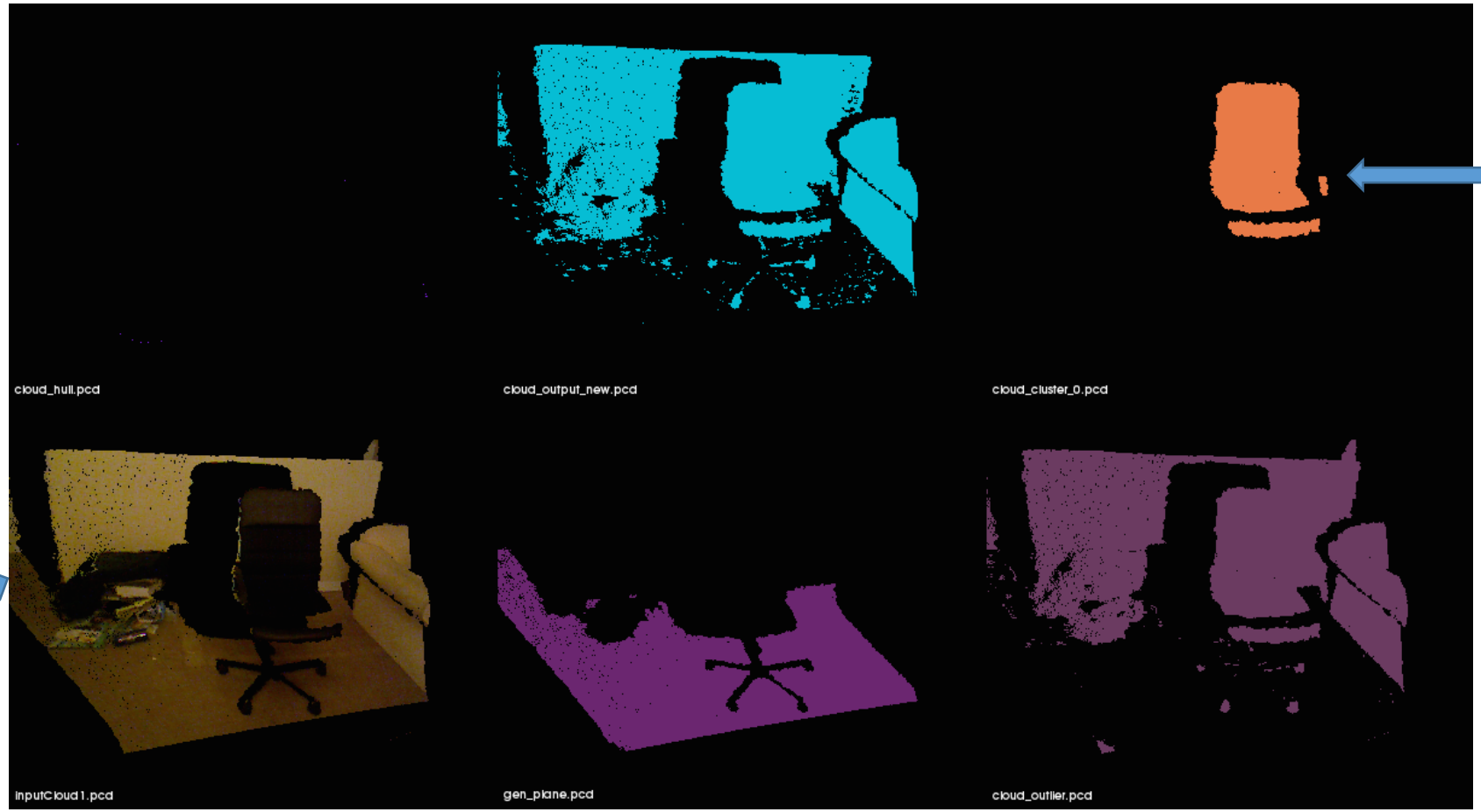


Table top clusters obtained after plane extraction

Object Recognition Pipeline: Cluster Extraction

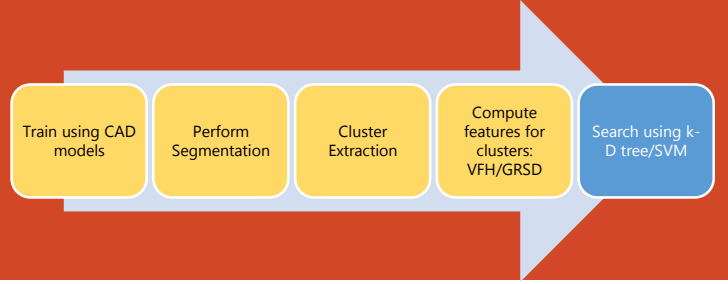
- Result



Final Segmented cluster

Input depth image

Object Recognition Pipeline: Compute Features

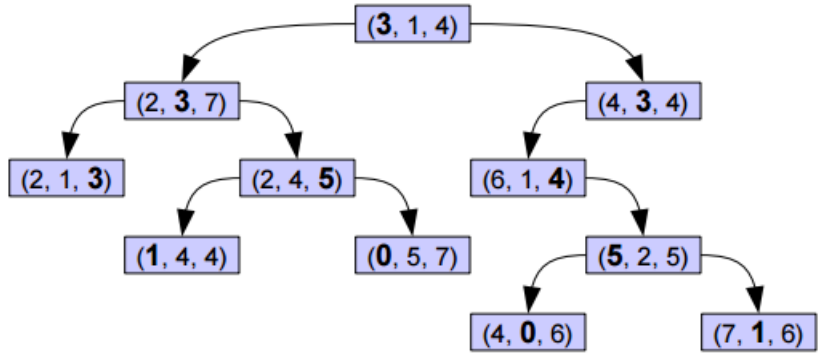


- Compute for each point cloud:
  - VFH/GRSD features
  - Single view might not provide differentiating features:
    - Perform feature extraction/recognition at regular intervals

Object Recognition Pipeline: Compute Features

- Once feature descriptors are computed for each clustered point cloud:
  - **Nearest neighbor search**
    - Run k-D tree based nearest match based on histogram distance
    - Histogram distance is calculated based on:
      - Chi-square metric

$$d(H_1, H_2) = \sum_i \frac{(H_1(i) - H_2(i))^2}{H_1(i)}$$



  - **One v/s all -SVM**
    - Computed using libSVM library
    - Perform this for all classes

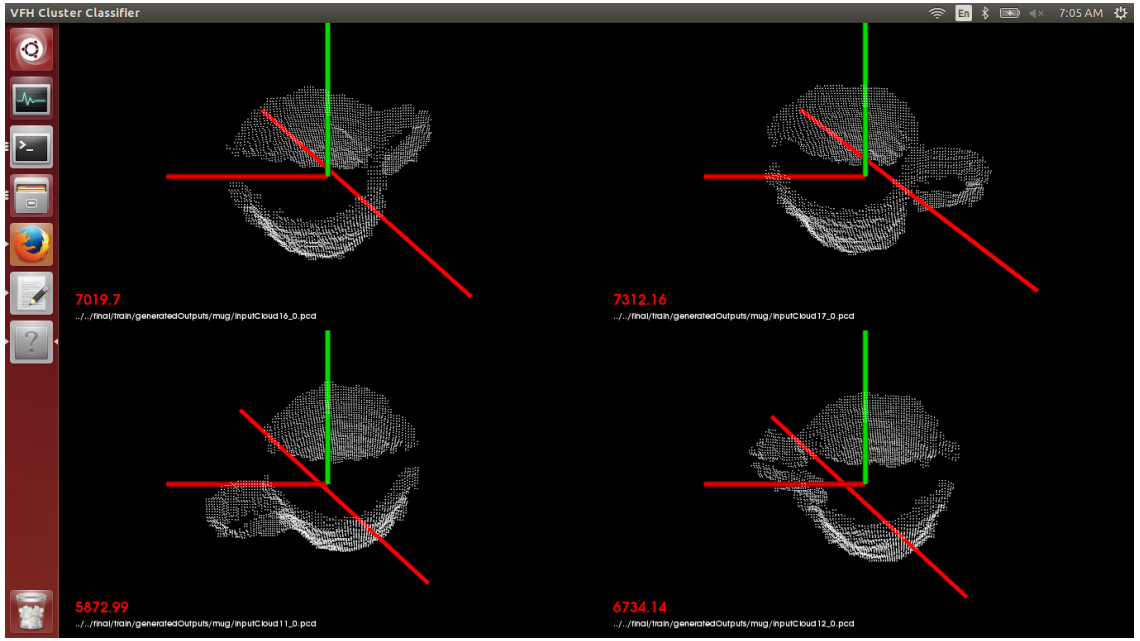
Demo: Segmentation

- Play video!

Demo: Object Recognition

- Using Kinect

Results

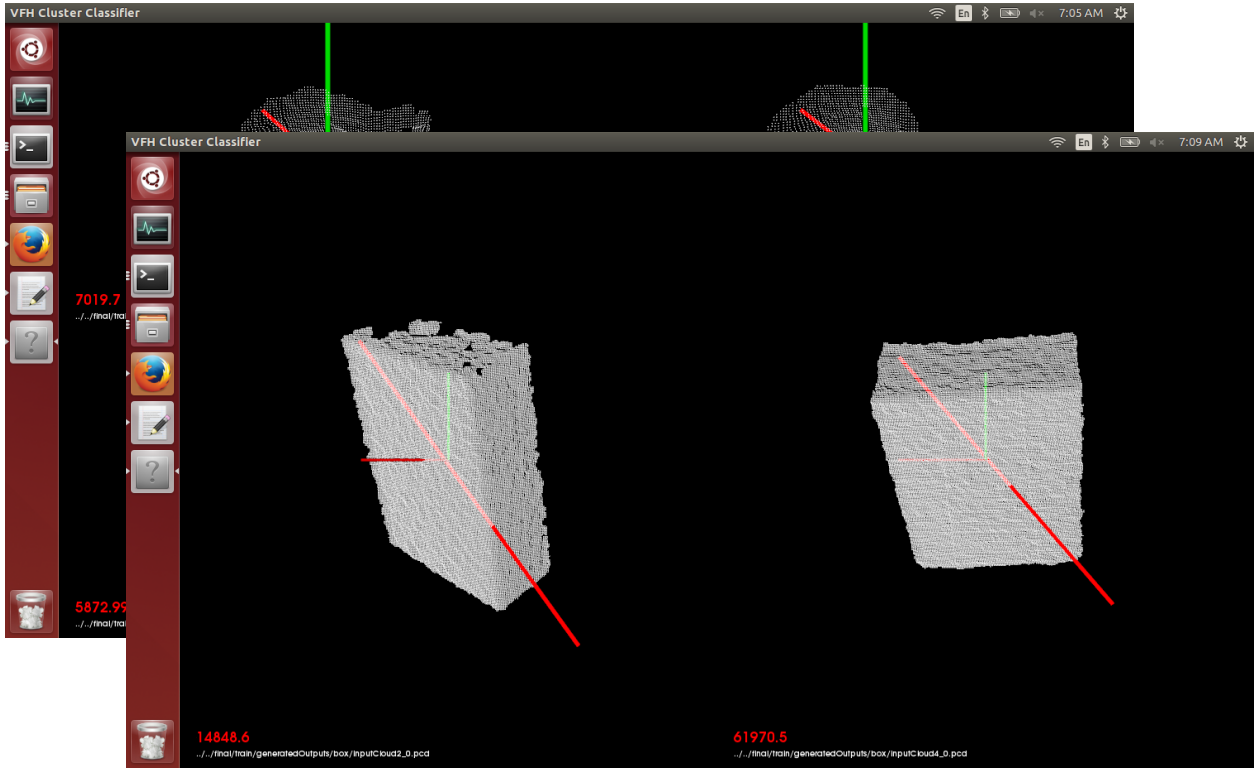


Matching obtained for Coffee Mug

Challenges

- Kinect dataset is too small
  - Compared to 2D datasets available online
- Kinect Data: Too noisy
- Need exact 3D models
- Need powerful segmentation
- One v/s all SVM wasn't good enough classifier
  - Only polynomial kernel provided good results

Results



Matching obtained for Cereal Box

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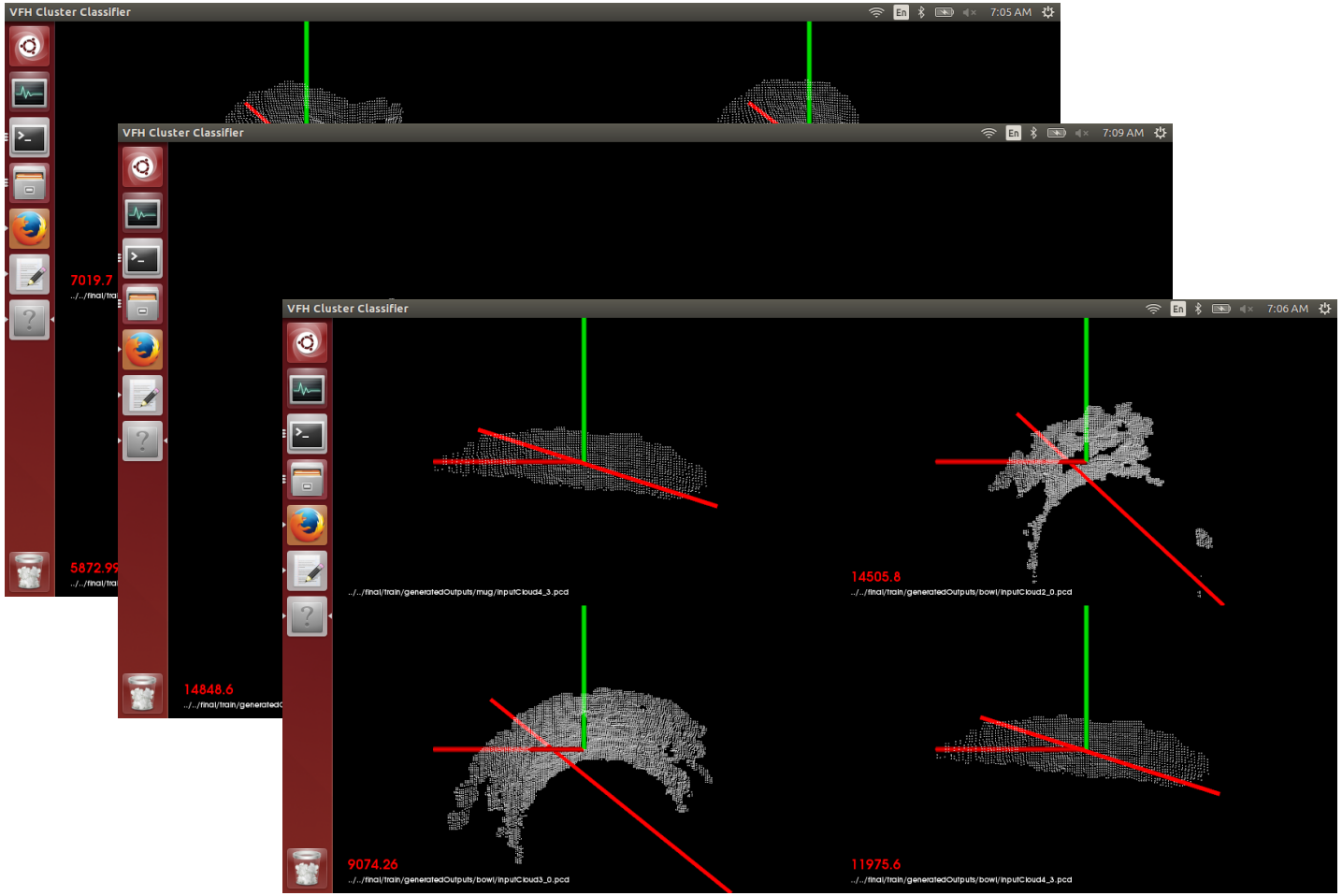
Results



Matching obtained for Bowl

Challenges

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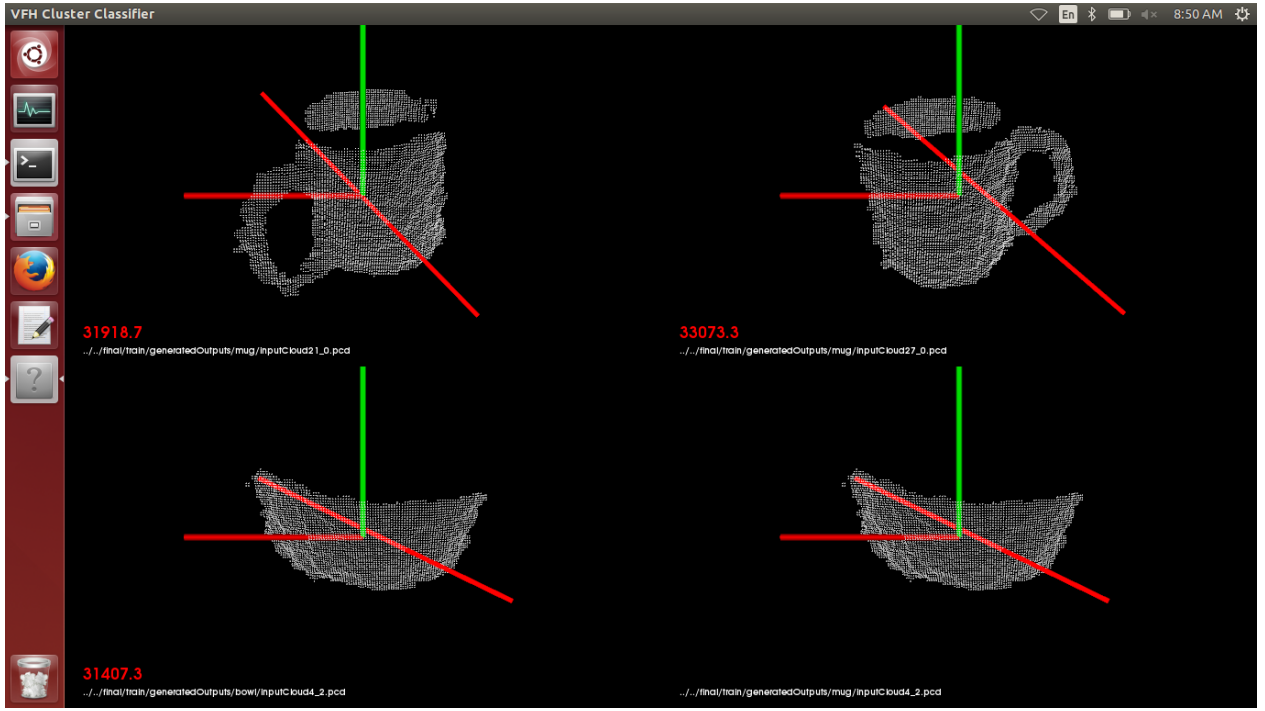
  - Compared to 2D datasets available online
- Kinect Data: Too noisy
- Need exact 3D models
- Need powerful segmentation
- One v/s all SVM wasn't good enough classifier
  - Only polynomial kernel provided good results

Results: False positives

- Objects with similar shapes were wrongly classified
- Example: Bowl and Coffee Mug



Future Work

- Use exemplar-SVM for classification as it has been proven
- Use better 3D dataset
- Use texture(color) information
- Use a sliding bounding box(as proposed by Song)
- Perform correspondence grouping
    - To fit best available model available

Thank you!