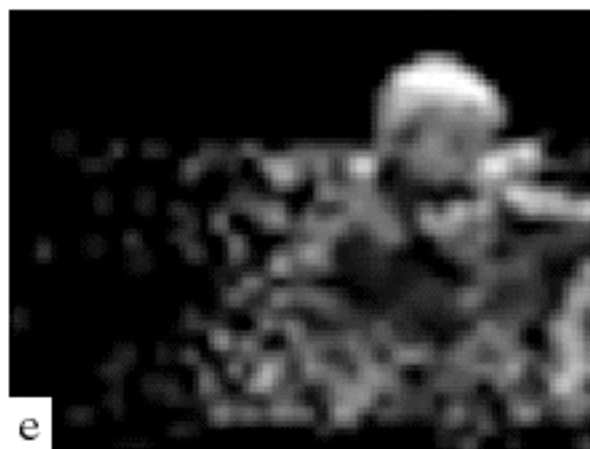
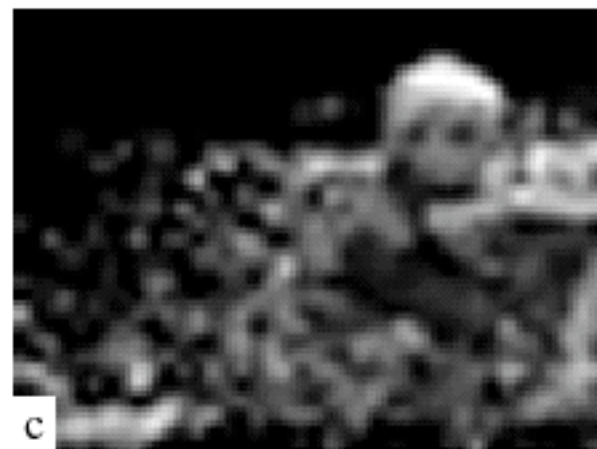
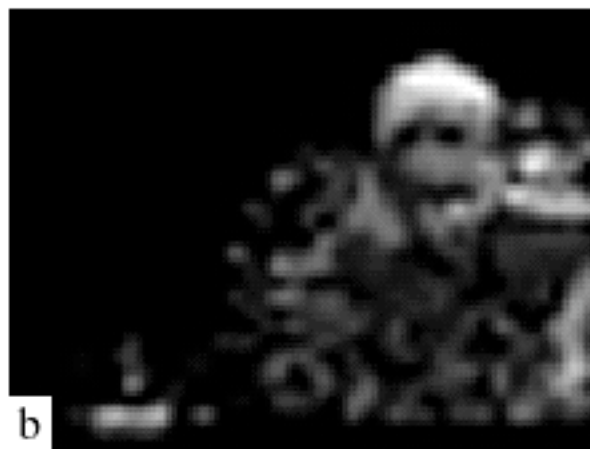
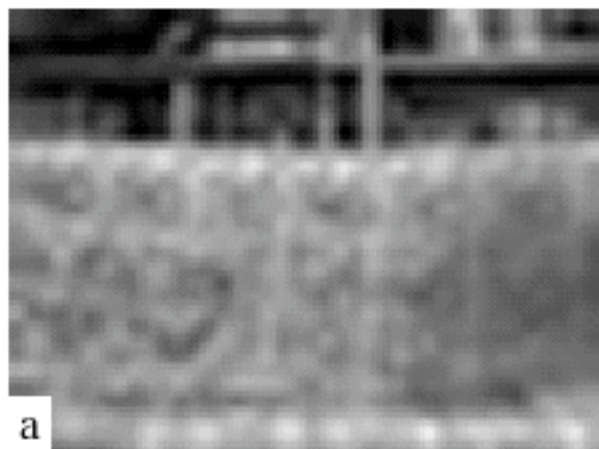
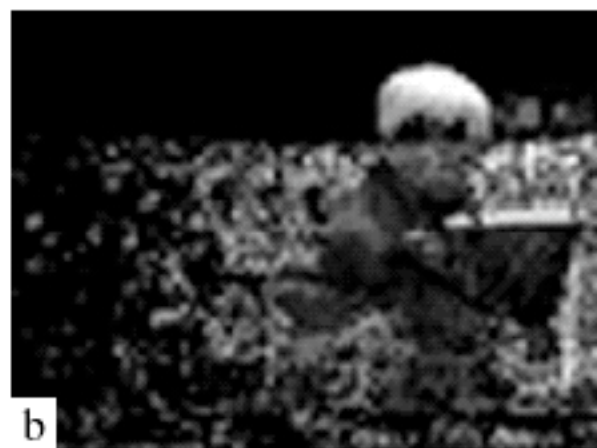


# Technique: Background Subtraction

- If we know what the background looks like, it is easy to identify “interesting bits”
- Applications
  - Person in an office
  - Tracking cars on a road
  - Surveillance
- Approach:
  - Use a moving average to estimate background image
  - Subtract from current frame
  - Large absolute values are interesting pixels
    - trick: use morphological operations to clean up pixels (remove “holes”)





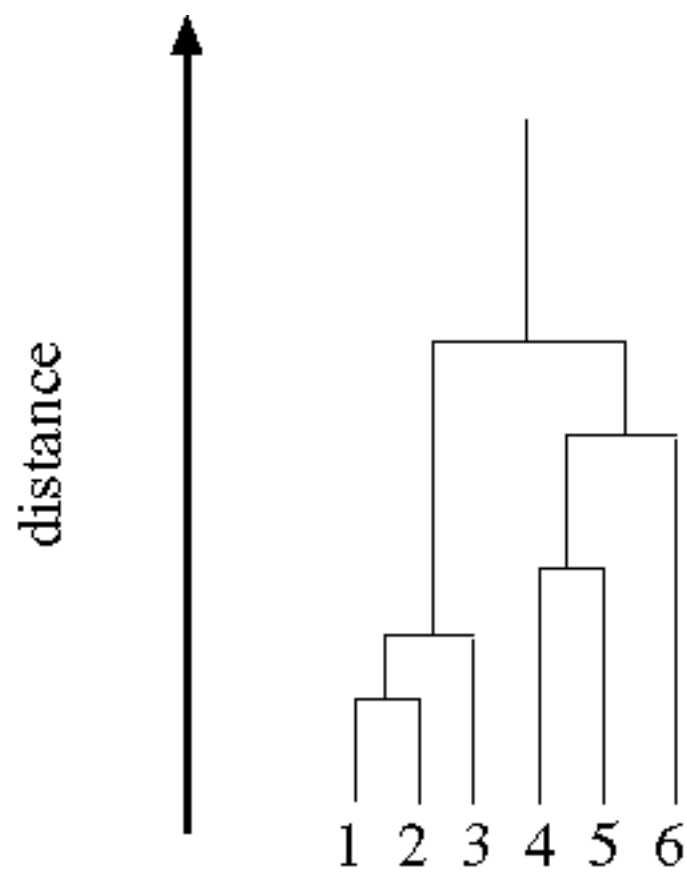
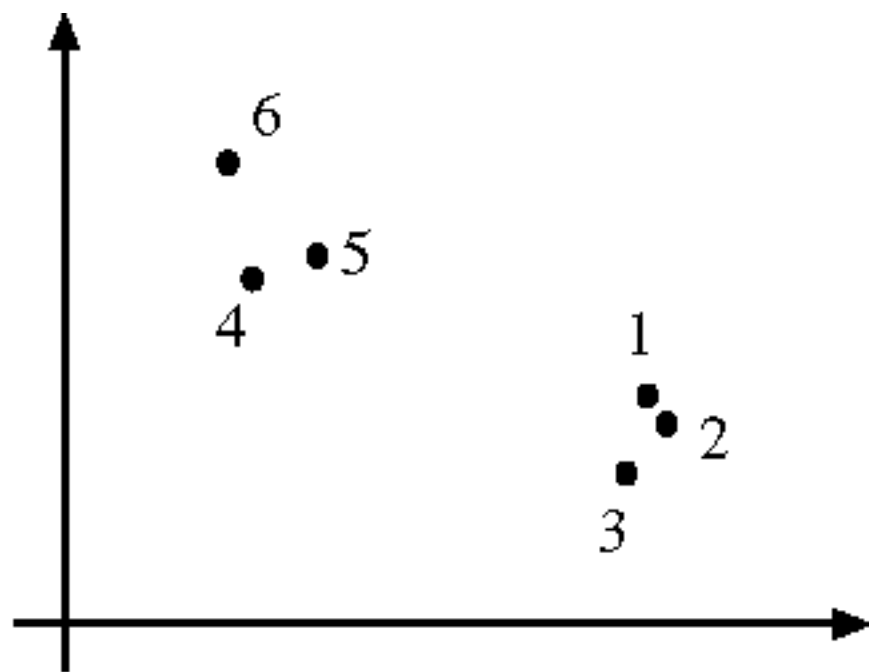


# Segmentation as clustering

- Cluster together (pixels, tokens, etc.) that belong together
- Agglomerative clustering
  - initialize: every token is a cluster
  - attach closest to cluster it is closest to
  - repeat
- Divisive clustering
  - split cluster along best boundary
  - repeat
- When to stop? (The million dollar question==how many clusters?)

# Segmentation as clustering

- Point-Cluster or Cluster-Cluster distance
  - single-link clustering (minimum distance from point to points in clusters or among pairs of points, one from each cluster)
  - complete-link clustering (maximum)
  - group-average clustering (average)
  - (terms are not important, but concepts are worth thinking about)
- Dendrograms
  - classic picture of output as clustering process continues



# K-Means

- Choose a fixed number of clusters
- Choose cluster centers and point-cluster allocations to minimize error

$$\sum_{i=1}^K \sum_{j \in \text{elements of } i\text{'th cluster}} \|x_j - \mu_i\|^2$$



# K-Means

$$\|x_j - \mu_i\|^2$$

$i$  clusters  $j$  elements of  $i$ 'th cluster

- Cannot do this optimization by search, because there are too many possible allocations.
- Standard difficulty which we handle with an iterative process
- Algorithm
  - fix cluster centers; allocate points to closest cluster
  - fix allocation; compute best cluster centers
- $x$  could be any set of features for which we can compute a distance (careful about scaling/normalization)