

# Hand Pose Estimation

Matthew Krenik

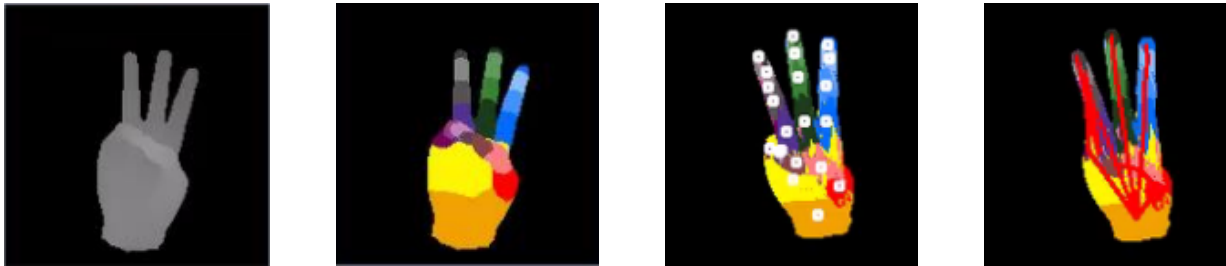
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# Agenda

- What is Hand Pose Estimation?
- Why does it matter?
- How does it work?
- What has been done?

# What is Hand Pose Estimation?

- Estimate full Degree of Freedom (DOF) of a hand from depth images

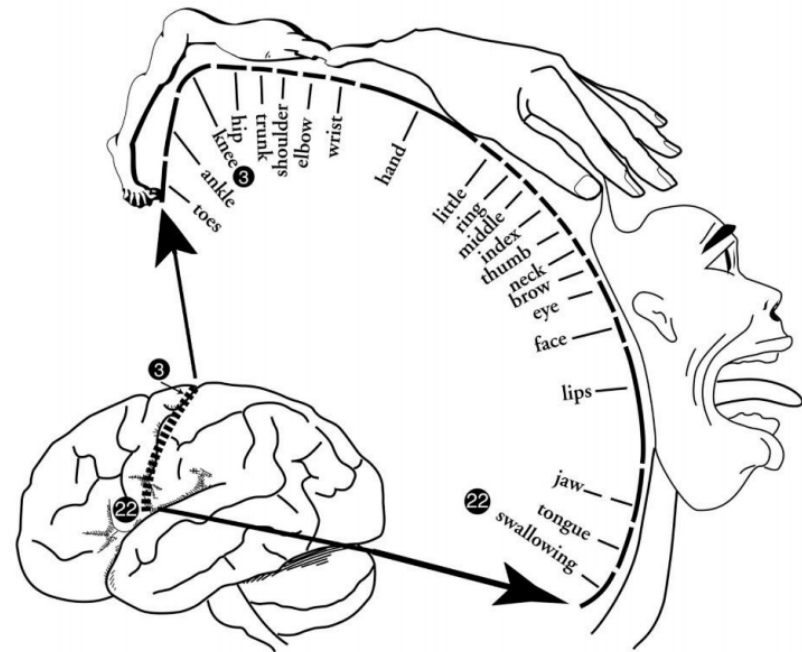


- This is a tough problem, especially to perform in real time!
- Not to be confused with “hand shape estimation”



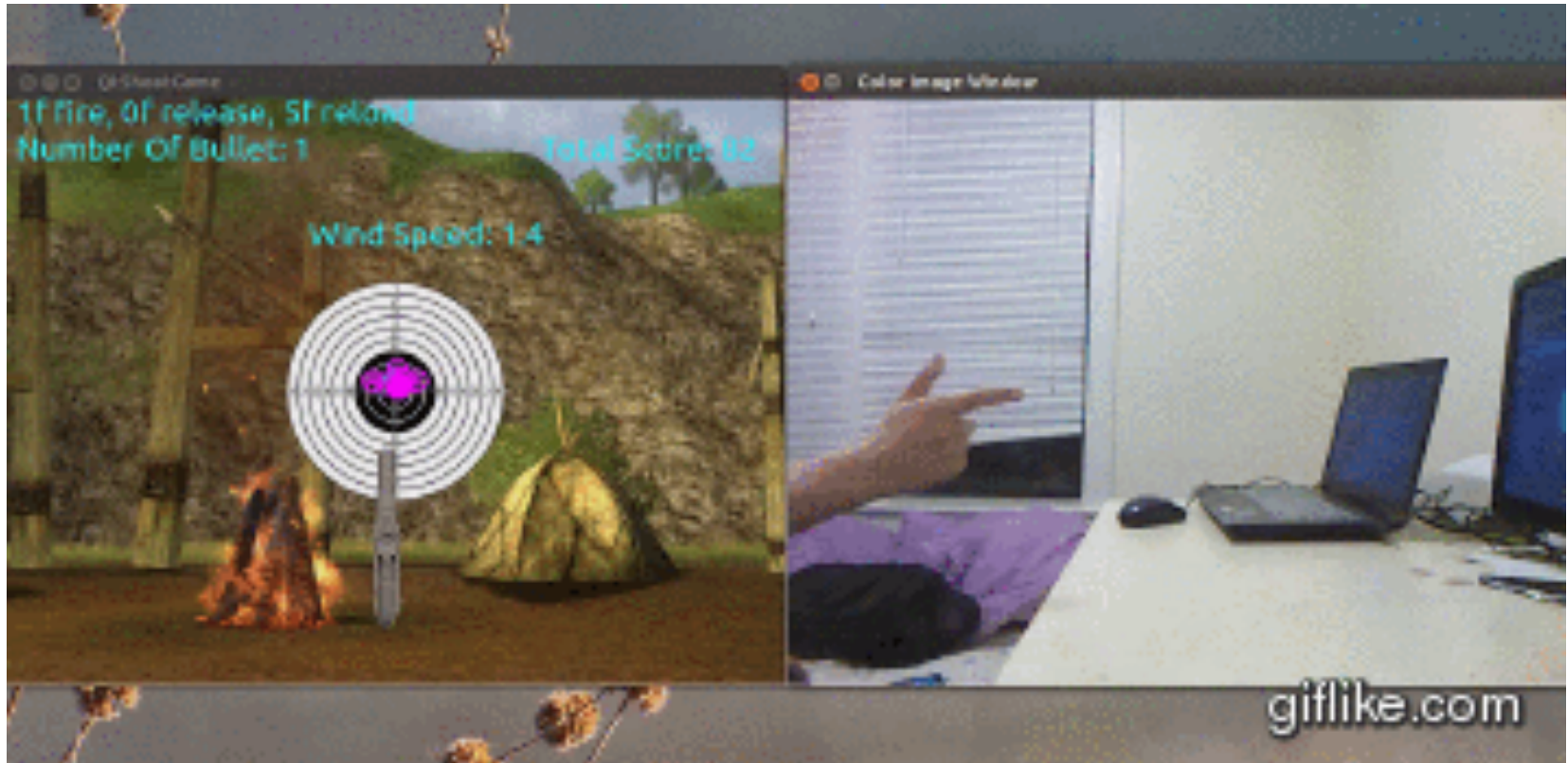
# Why Does it Matter?

- More than just gestures
- Ideal for continuous input applications
- Links your hand dexterity into a computer model
- Will it redefine how we interact with computers??





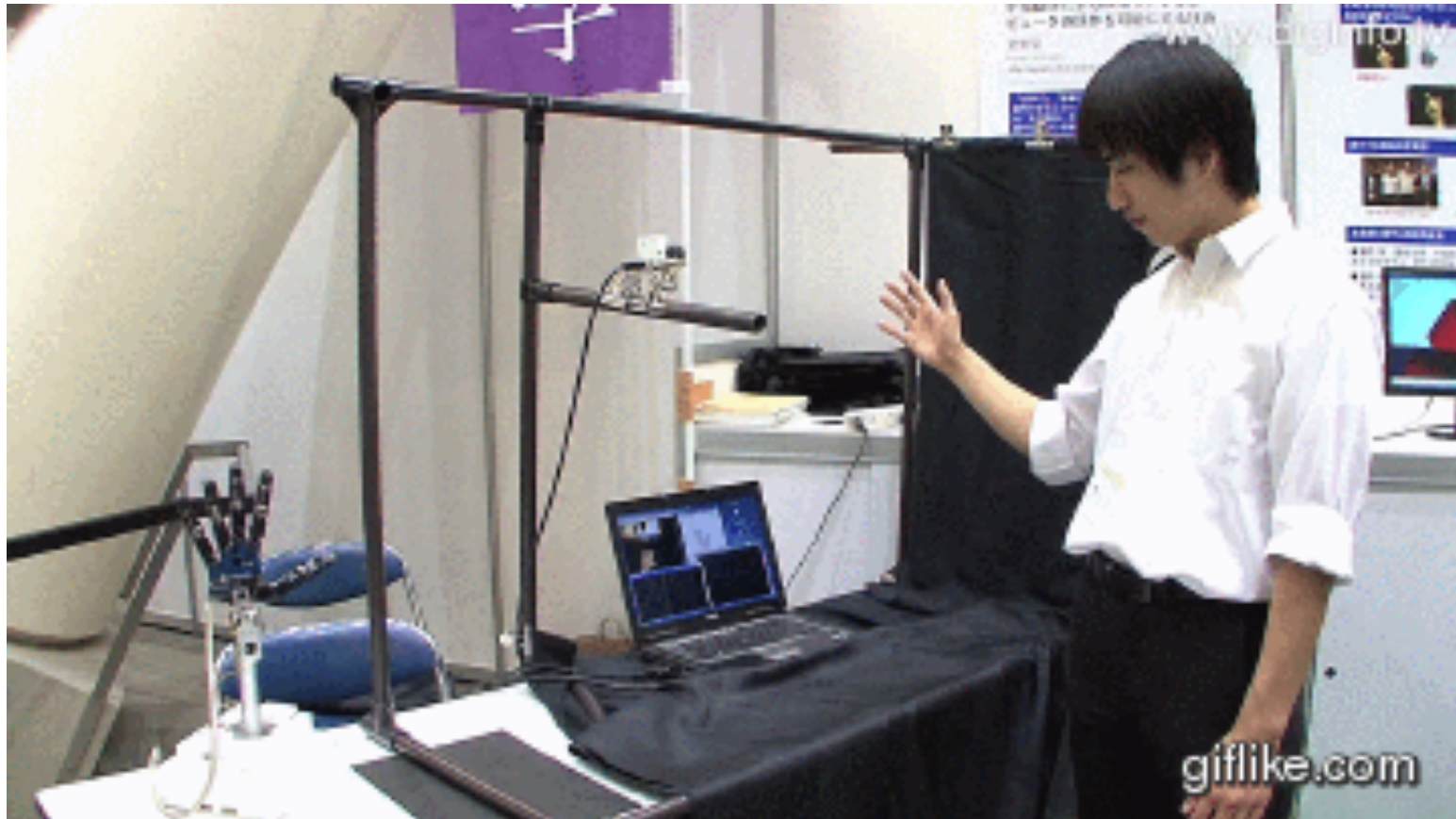
# Gaming



# Design / Engineering

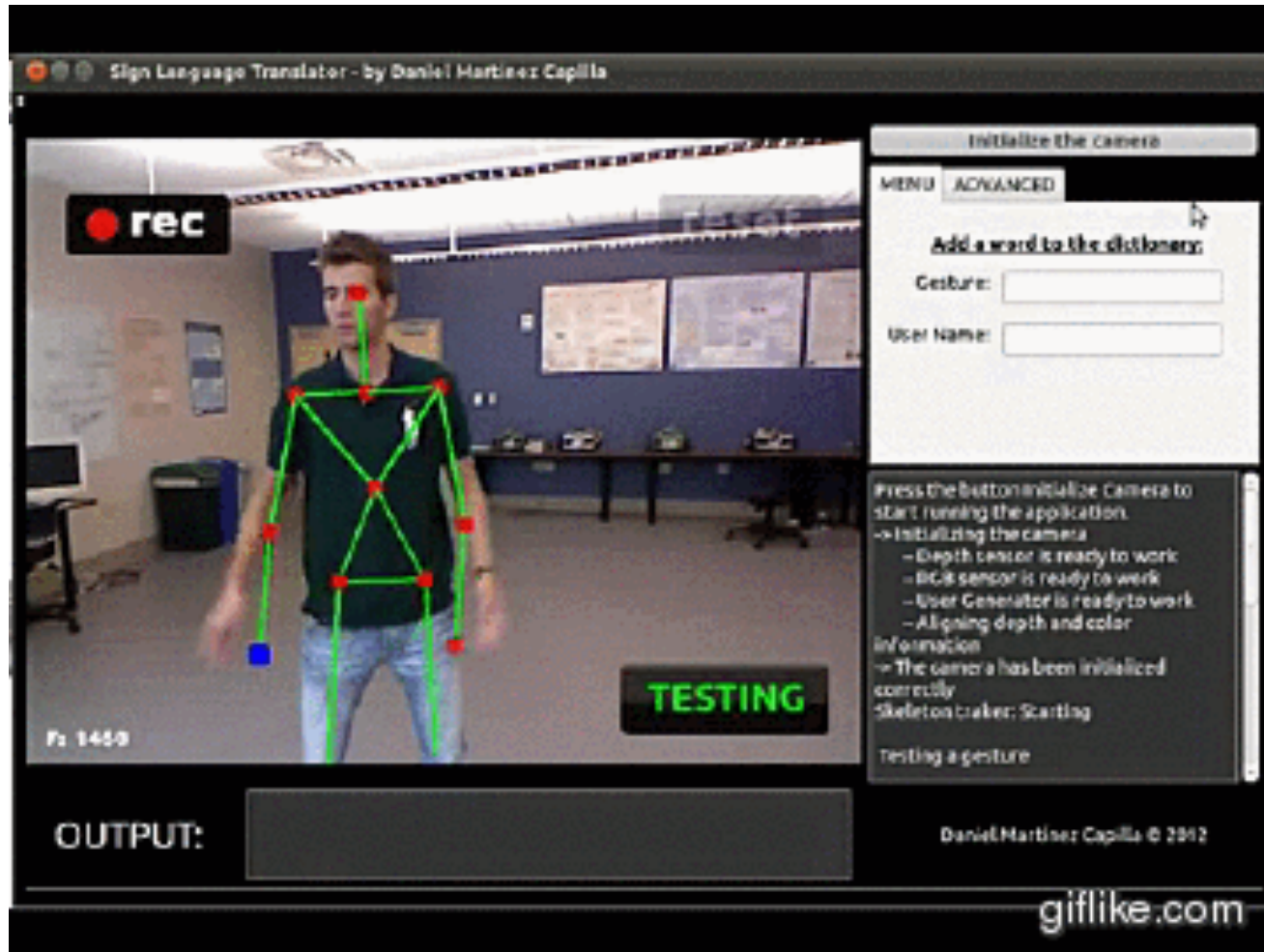


# Robot Hand Control– Surgery? Industry?



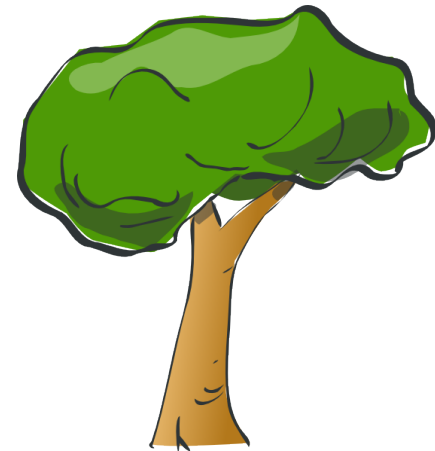


# Communication – Sign Language



# How Does it Work?

- Its going to take some time to explain
- Starting from the ground up!
  - Decision trees
  - Ensemble techniques
  - Random forests
  - Body Pose estimation
  - Hand Pose Estimation
- Assumption is that everyone has a very basic idea of what machine learning is and does



# Machine Learning

- Goal:
  - Given training data  $T$  with entries  $(x, y)$
  - Find a model that estimates  $y$  for unseen  $x$
  - This is called prediction
- Quality Measurement:
  - Minimize the probability of model prediction errors on future data
- What are some models?
  - Linear Regression
  - Support Vector Machines
  - Decision Trees!

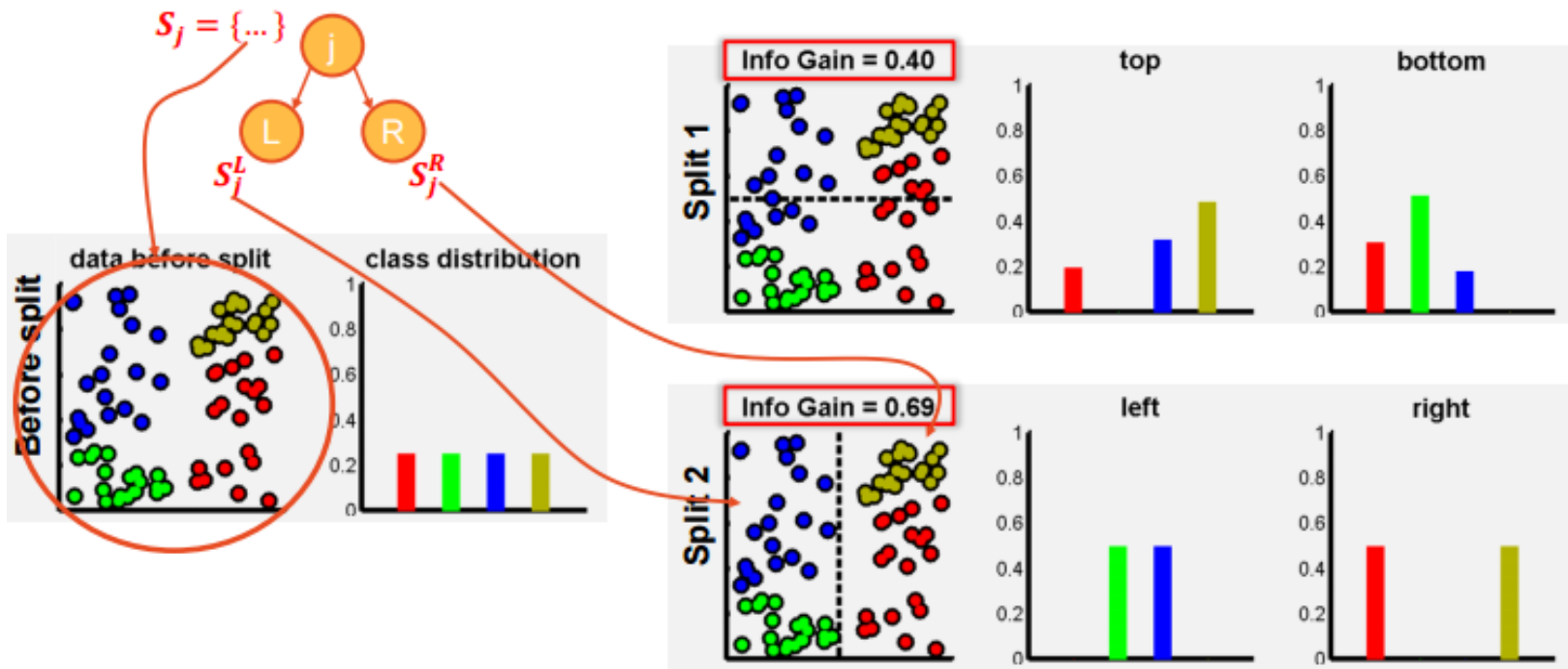




# How to grow a tree from data?

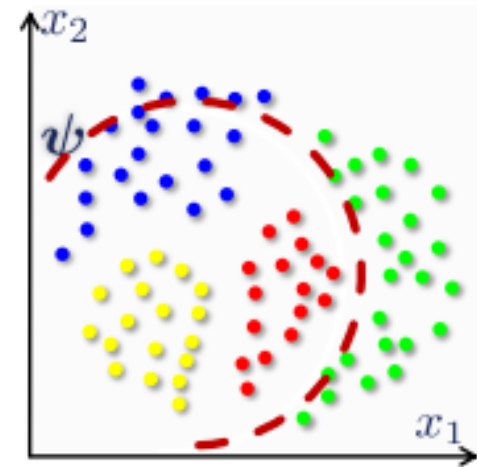
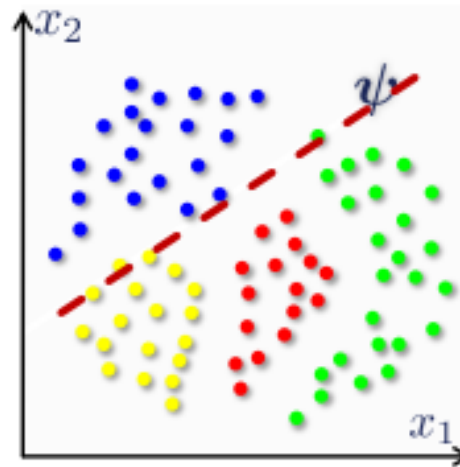
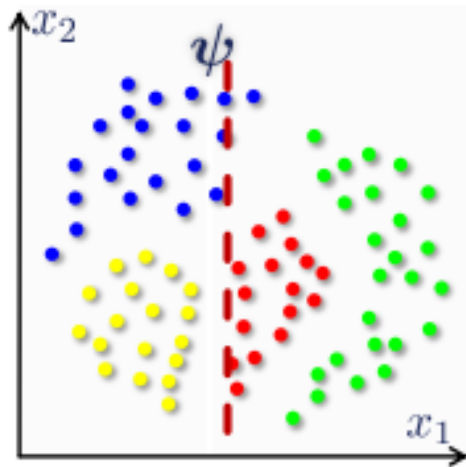
- In what order do we ask the questions (test features)?
  - Each possible tree has an amount of entropy
  - Test out all possible questions for a node, and choose the one that reduces the entropy the most (largest information gain)
- How do nodes make decisions based on the features?
  - Same way!
  - Choose a decision boundary that gives the largest information gain

# How to grow a tree from data?



# Decision Trees: A Pretty Good Model!

Examples of weak learners



# Ensemble Learning

- Two competing methodologies:
  - Traditional: Build one really good model
  - Ensemble: Build many models and average the results
- Build a ton of “pretty good” models
- Combine them into one “pretty awesome” prediction!
- Important for individual models to not be correlated, otherwise there is a strong tendency to overfit
- So we add randomness!



# Ensemble Techniques

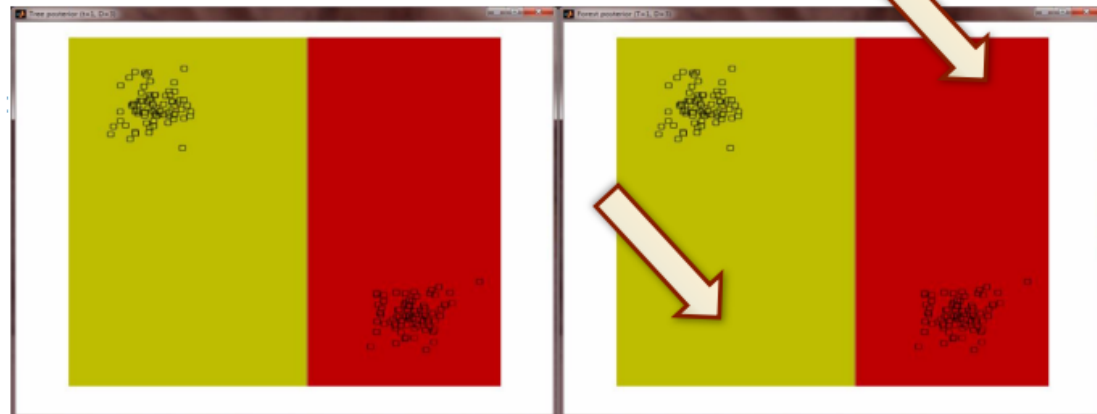
- Bootstrap Aggregation (Bagging)
  - Take a random subsample from the training set  $T$ , with replacement
  - Train each model on a different subsample
  - Classification is the majority vote; Regression is the average
  
- Random Forests: Multiple, randomized decision trees
  1. Bagging
  2. Randomized Node Optimization: choose random set of questions
    - Number of questions affects the correlation of the trees
  3. Decision boundary of the decision trees: conic, linear, etc.
  4. Depth of the component decision trees
    - More depth means there will be more overfitting

# Example: Different Trees

Training different trees in the forest

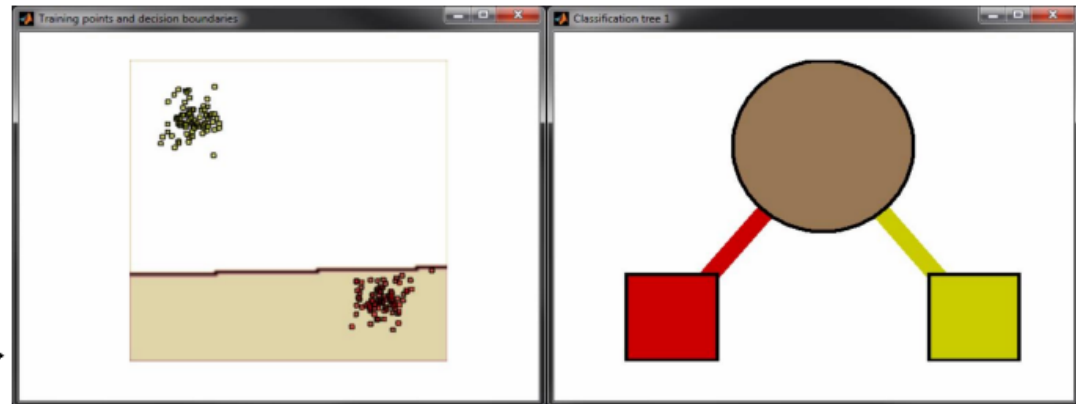
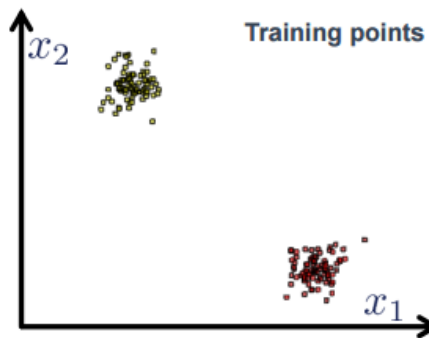


Testing different trees in the forest

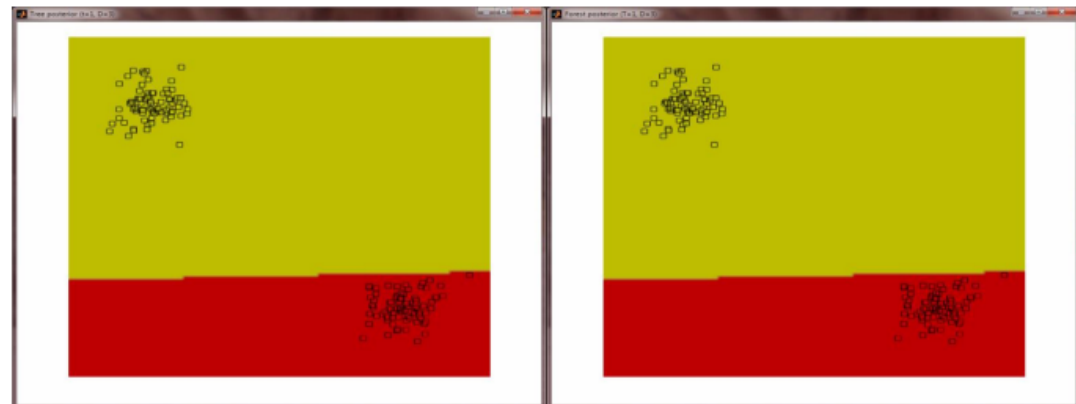


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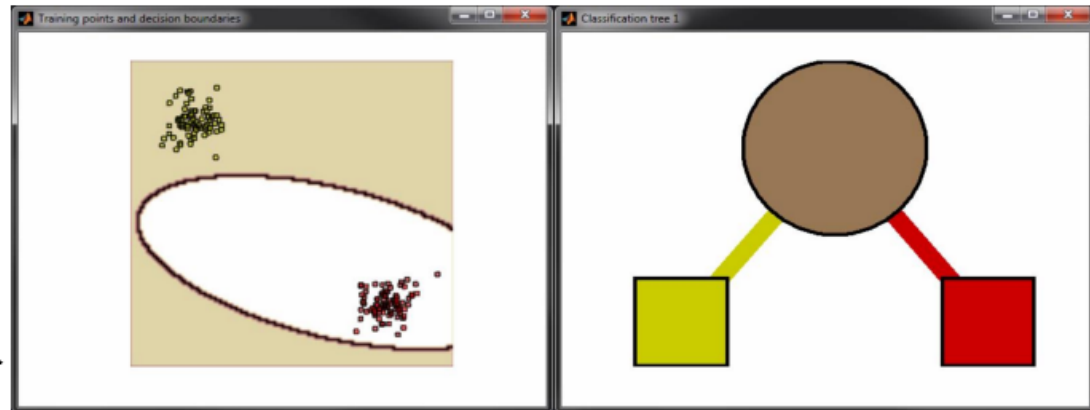
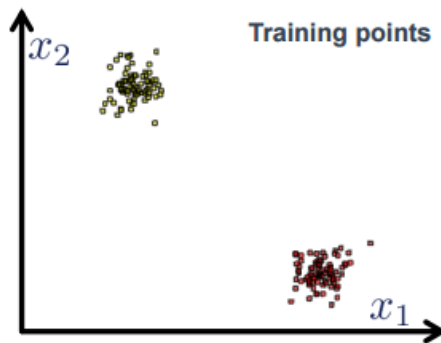


Testing different trees in the forest

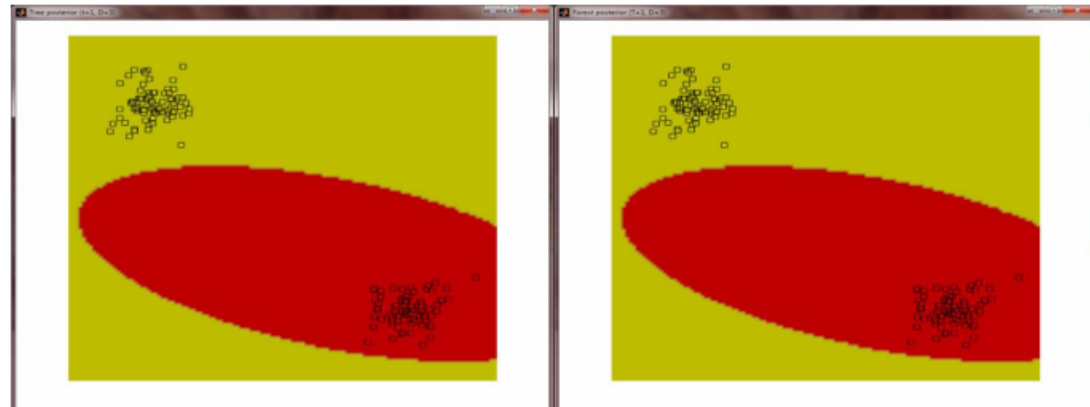


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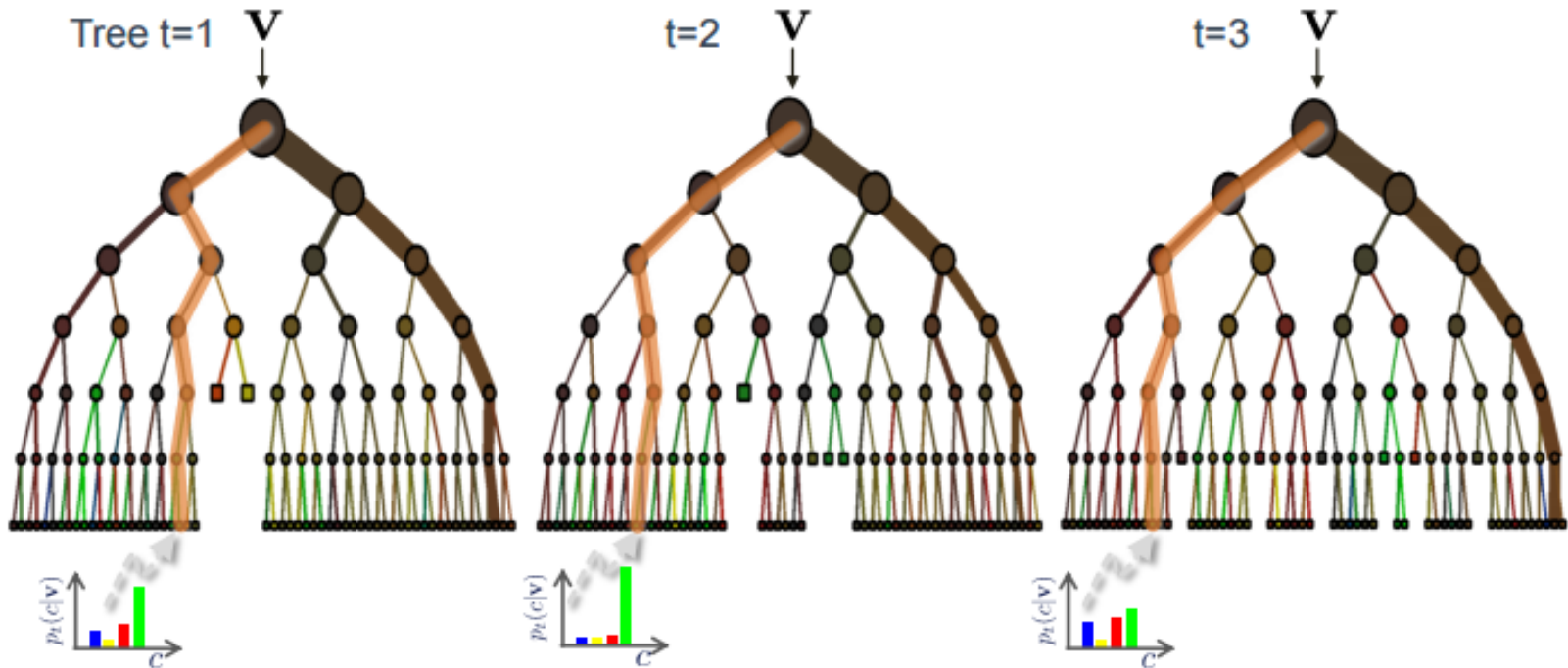


Testing different trees in the forest

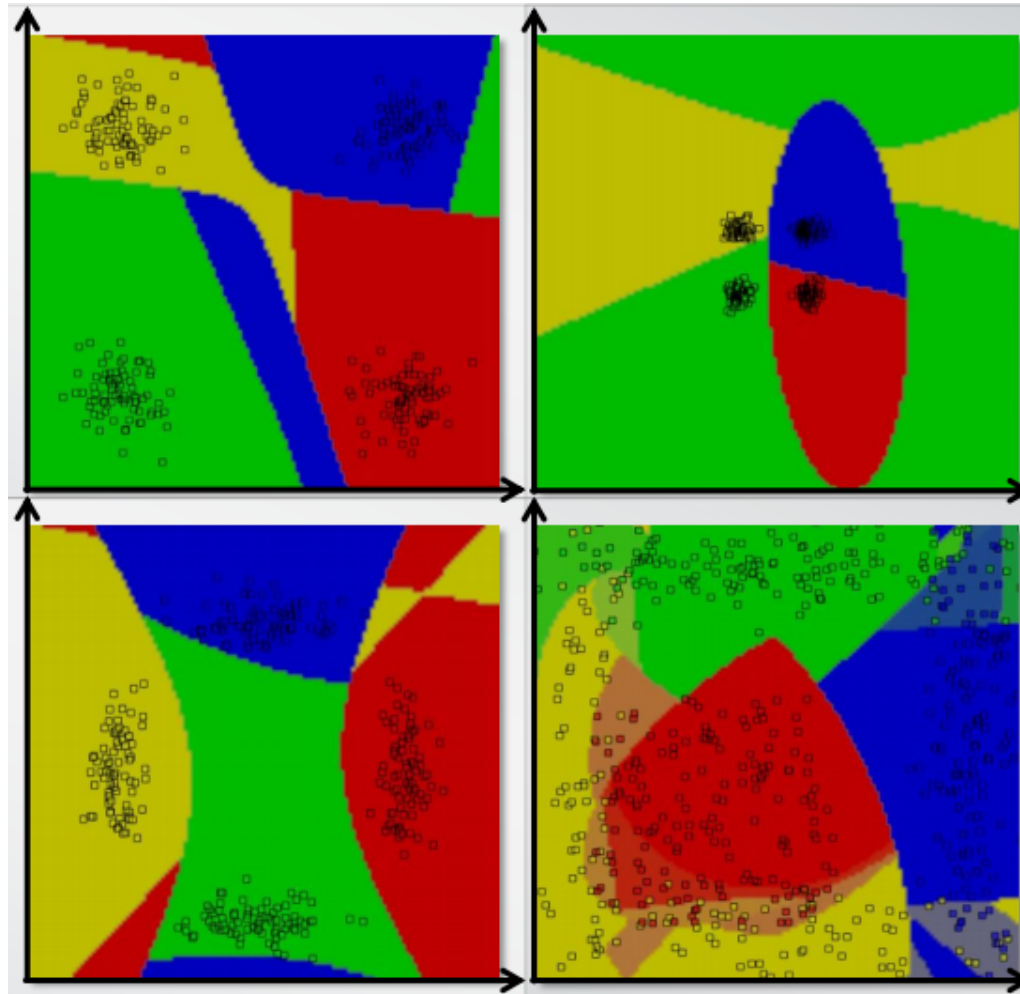




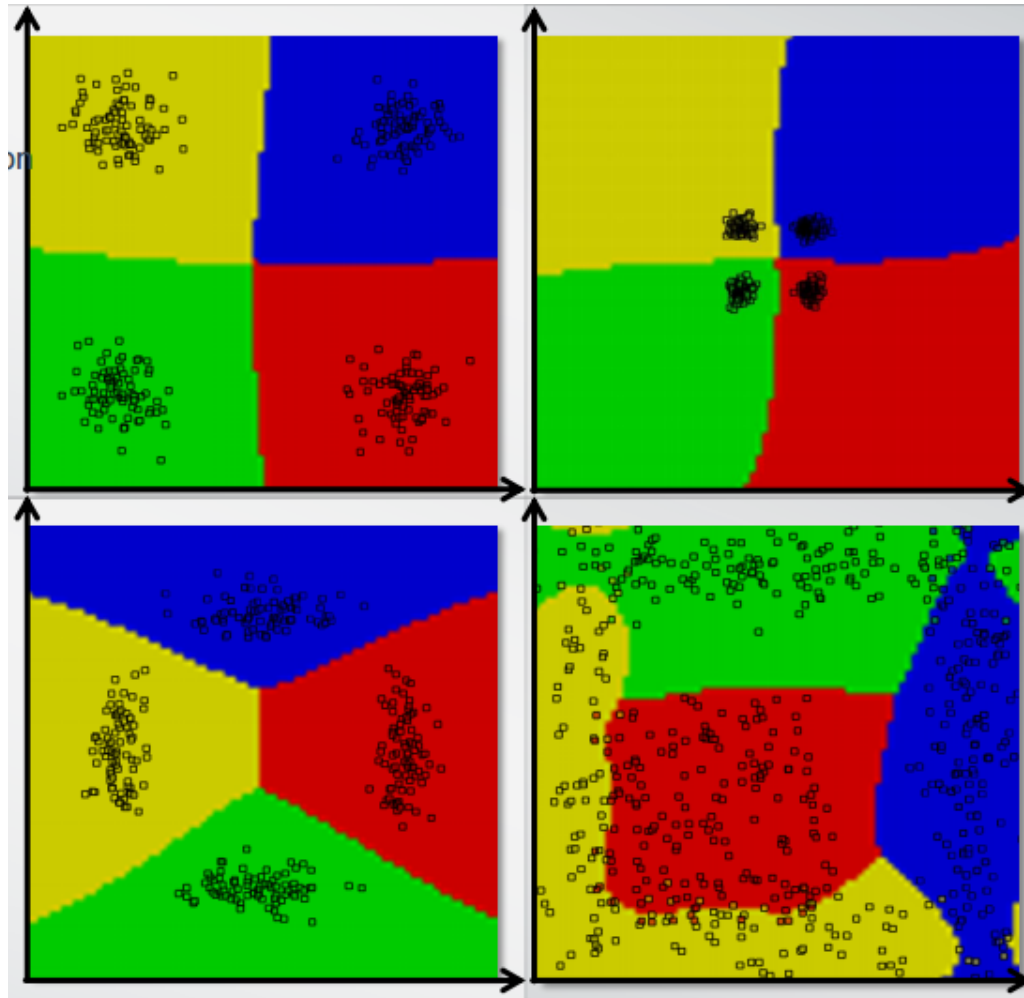
# Example: Random Decision Forest



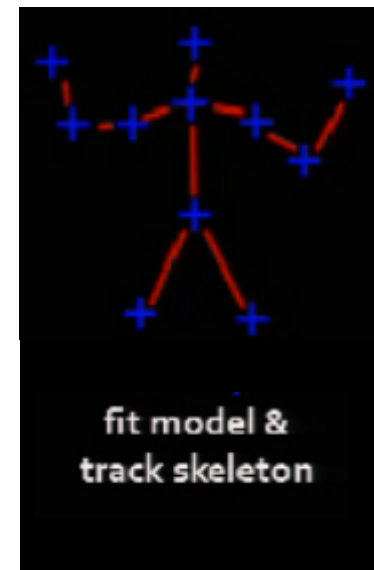
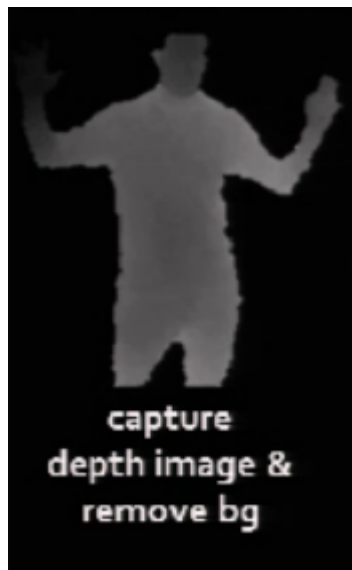
# Example: Multi-class Decision Trees



# Example: Comparison to SVM Model

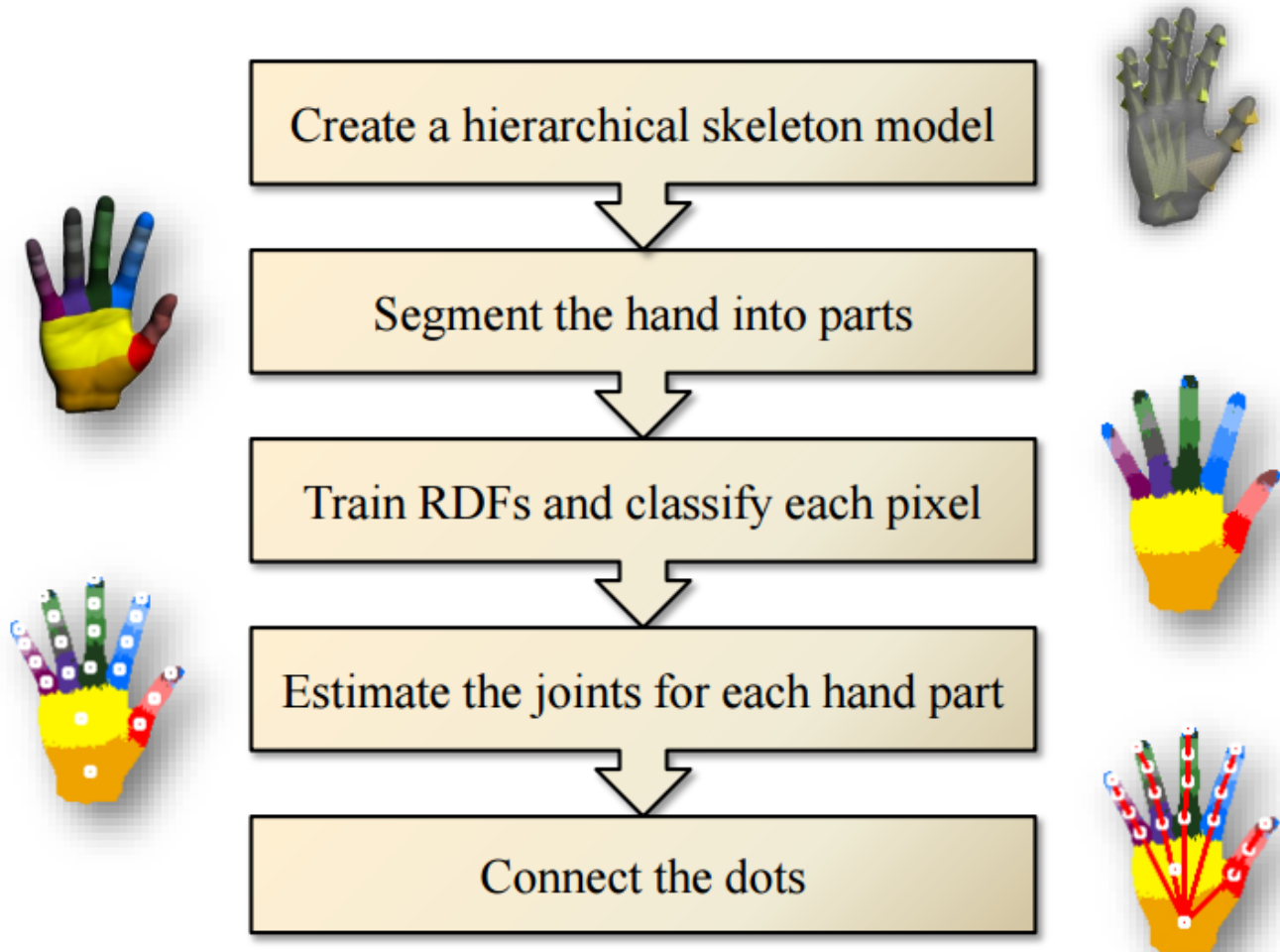


# A quick look at body pose estimation



- Body Pose Estimation Pipeline
- Technology found in consumer devices, like the Kinect
- Very similar to hand pose estimation

# Hand Pose Estimation Pipeline



# What makes Hand Pose tough?

- Hand is much smaller than the body, but still has 22 DOF
- Self occlusion is very common and severe
- Can be rotated in any direction (body is always upright)
- Real depth data can be difficult to label



# Some ideas..

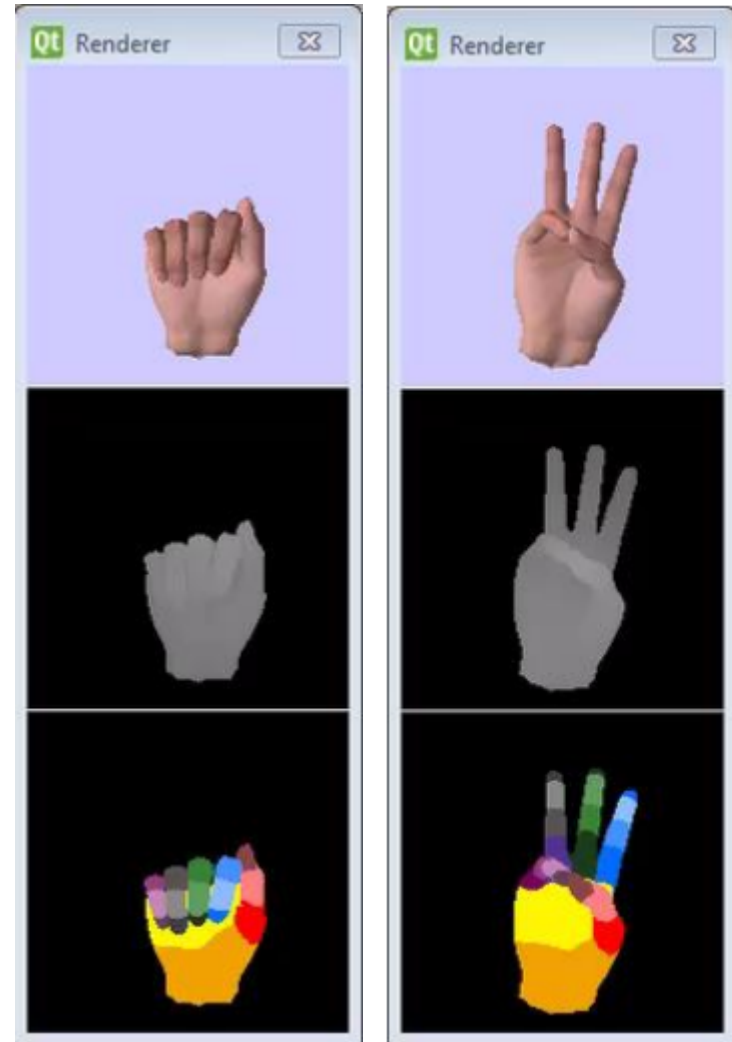
- Restrict the viewing area of the hand
- One Advantage: Hands are fairly invariant among humans
- Train with synthetic data, rendered from 3D models



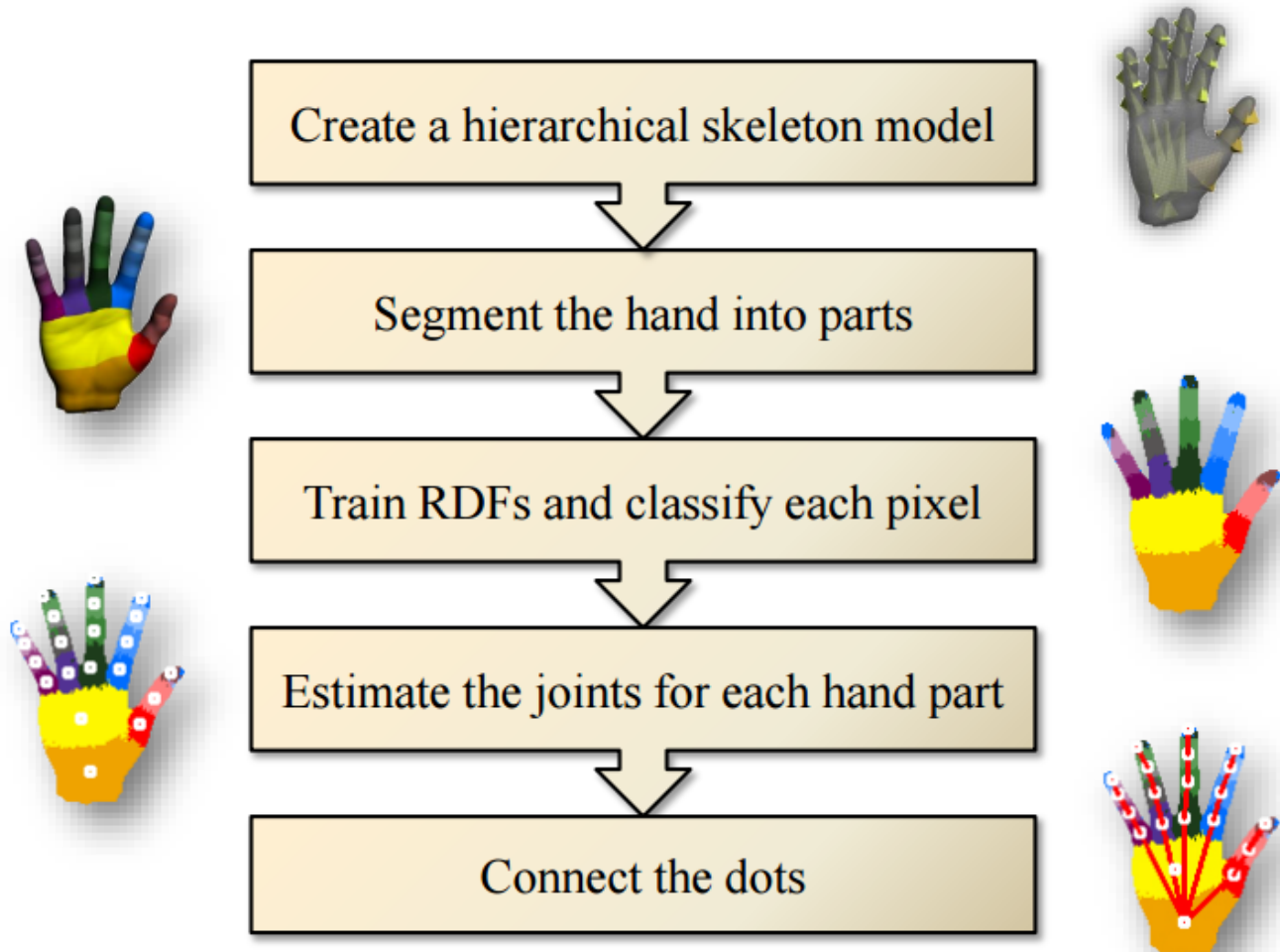


# Train based on Synthetic Data

- Use 3D hand models to generate data
- Train the Random Decision Forests using this data



# Hand Pose Estimation Pipeline



# Pixel Classification



One Tree



Two Trees

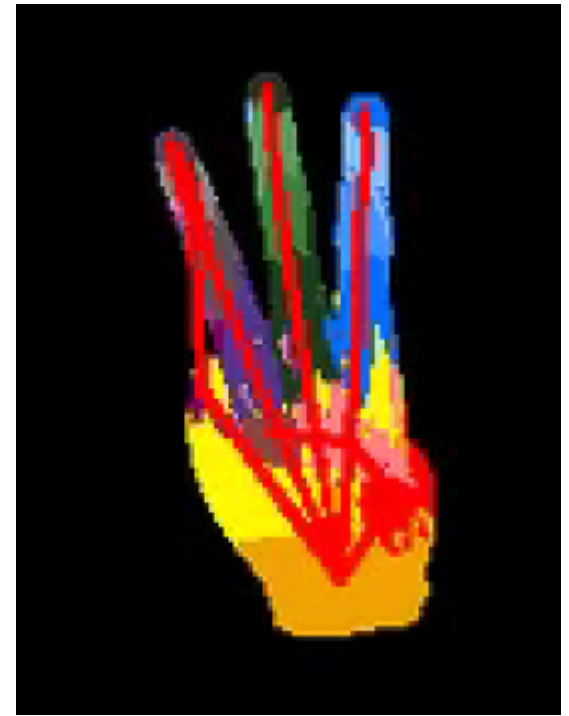
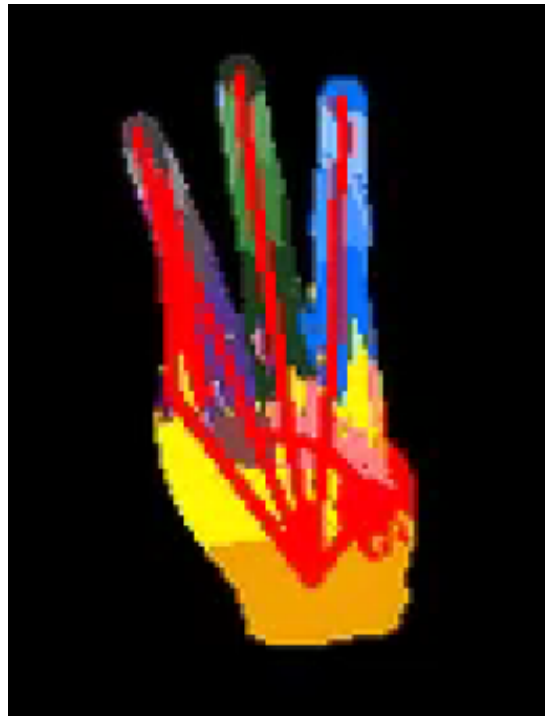
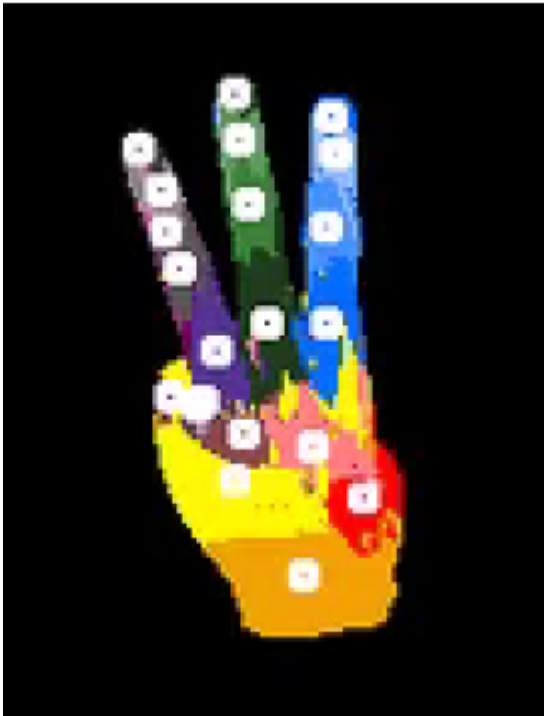


Three Trees

# Mean shift local mode finding

- Algorithm used to determine where the joints are
- Each pixel is given a weighted Gaussian kernel
- Weight is determined by class probability times depth
- Gradient ascent from many points finds the local maxima
- Highest local maxima determines the joint
- Threshold the scores to filter out non-visible joints

# Joint Determination



# Hand Pose Estimation Algorithm

## Strengths

- Very fast
- Robust to fast movements and noise
- No initialization needed
- Can run on a GPU for interface applications or games

## Issues

- Training must be done offline
- Number of images ~1-10M, takes 25-250 GB of data
- Number of operations is huge even with simple algorithm

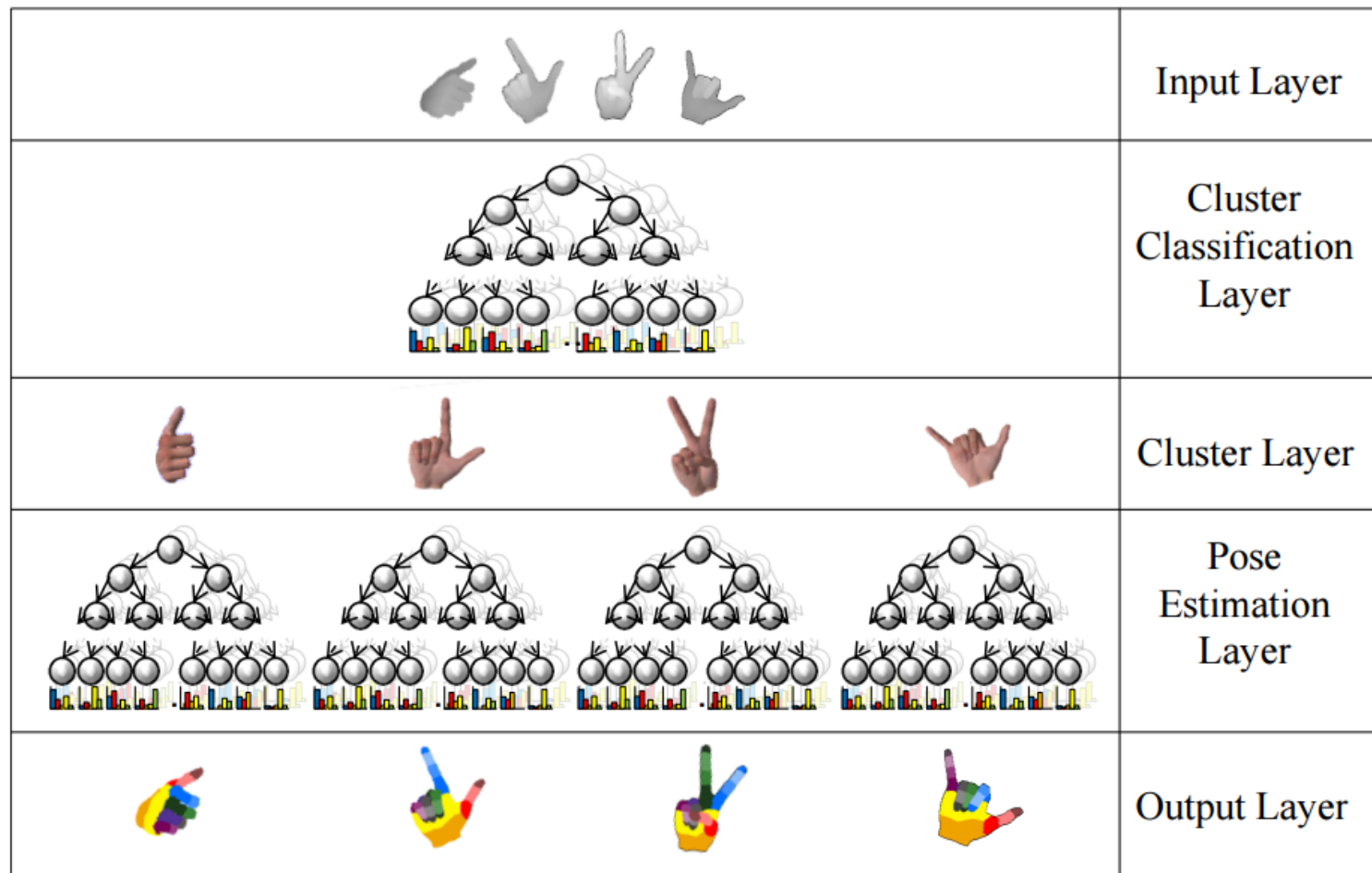
# Limitations of Single Layer RDF

- Difficult to generate every possible hand pose
- Dataset size is huge!
- Hard to capture the variation in the data set
- More variation → deeper trees → more RAM/memory
  
- Solution: Divide into sub problems and solve with separate RDFs
- Lower variation → lower complexity → less RAM/memory





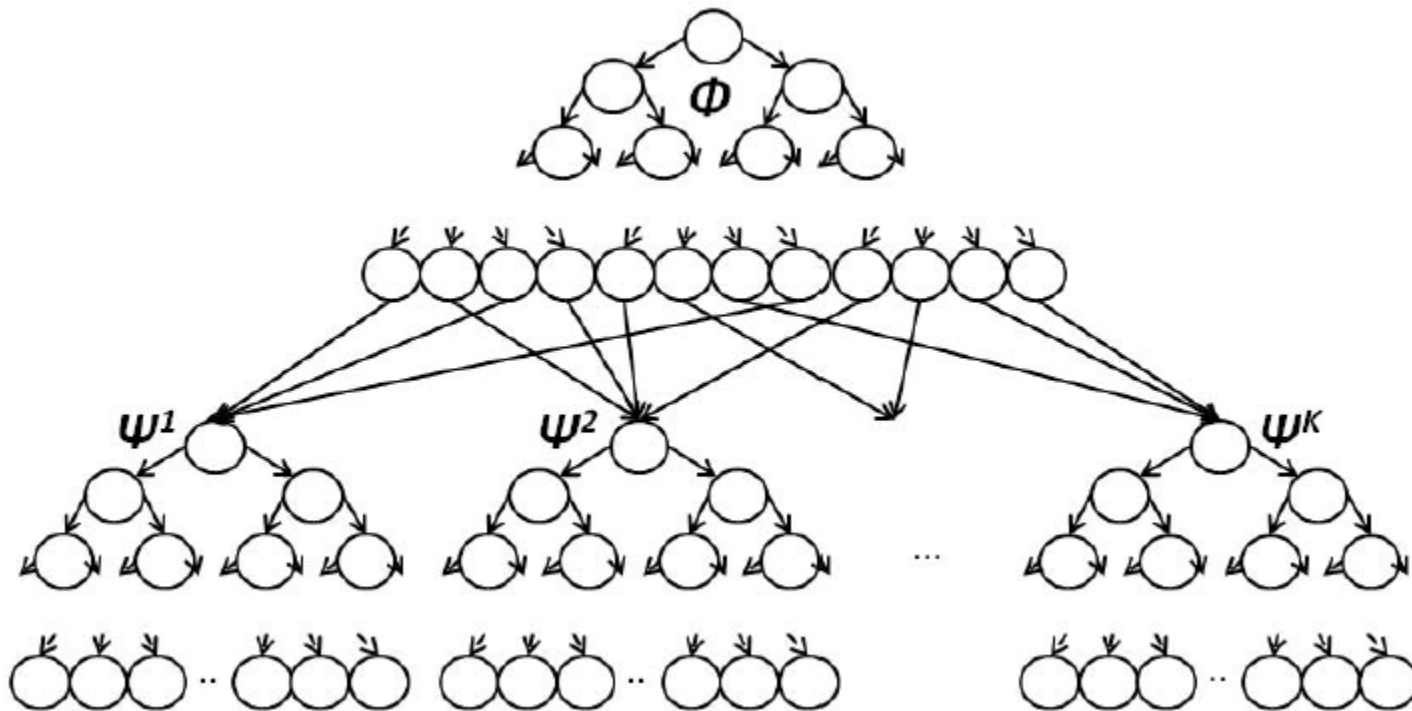
# Multi-layered RDFs for Hand Pose



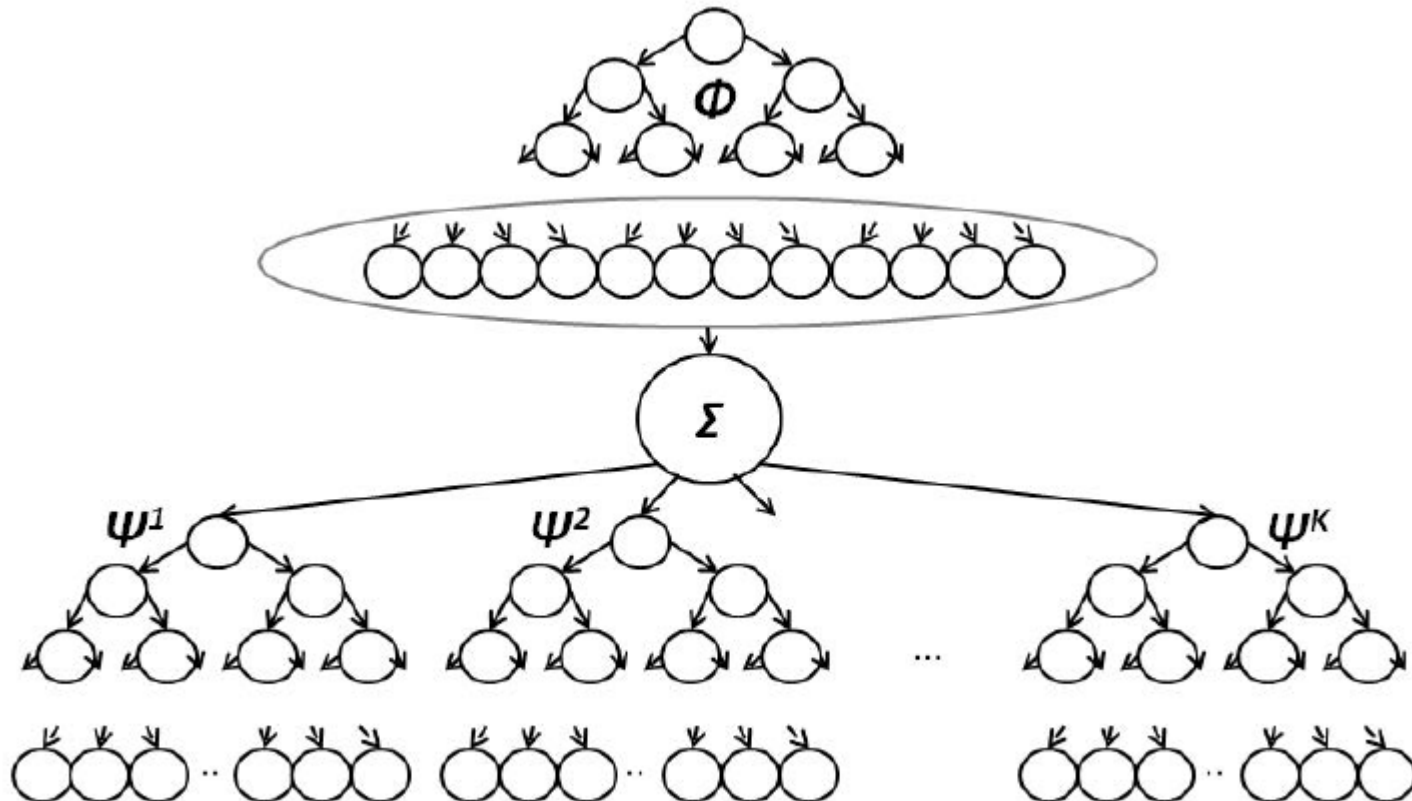
# Two Structures of Multi-layer RDFs

- Local Expert Network
  - Hand Shape Classification gives each pixel a label
  - Train local expert forests for each pixel label
  - Expert forest depends on pixel label; each pixel is classified
- Global Expert Network
  - Hand Shape Classification gives each pixel a label
  - The hand shape is determined by pixel voting
  - Train global expert forests for each pixel label
  - Expert forest depends on hand shape label; each pixel is classified

# Local Expert Network



# Global Expert Network



# Training a Multi-layer RDF

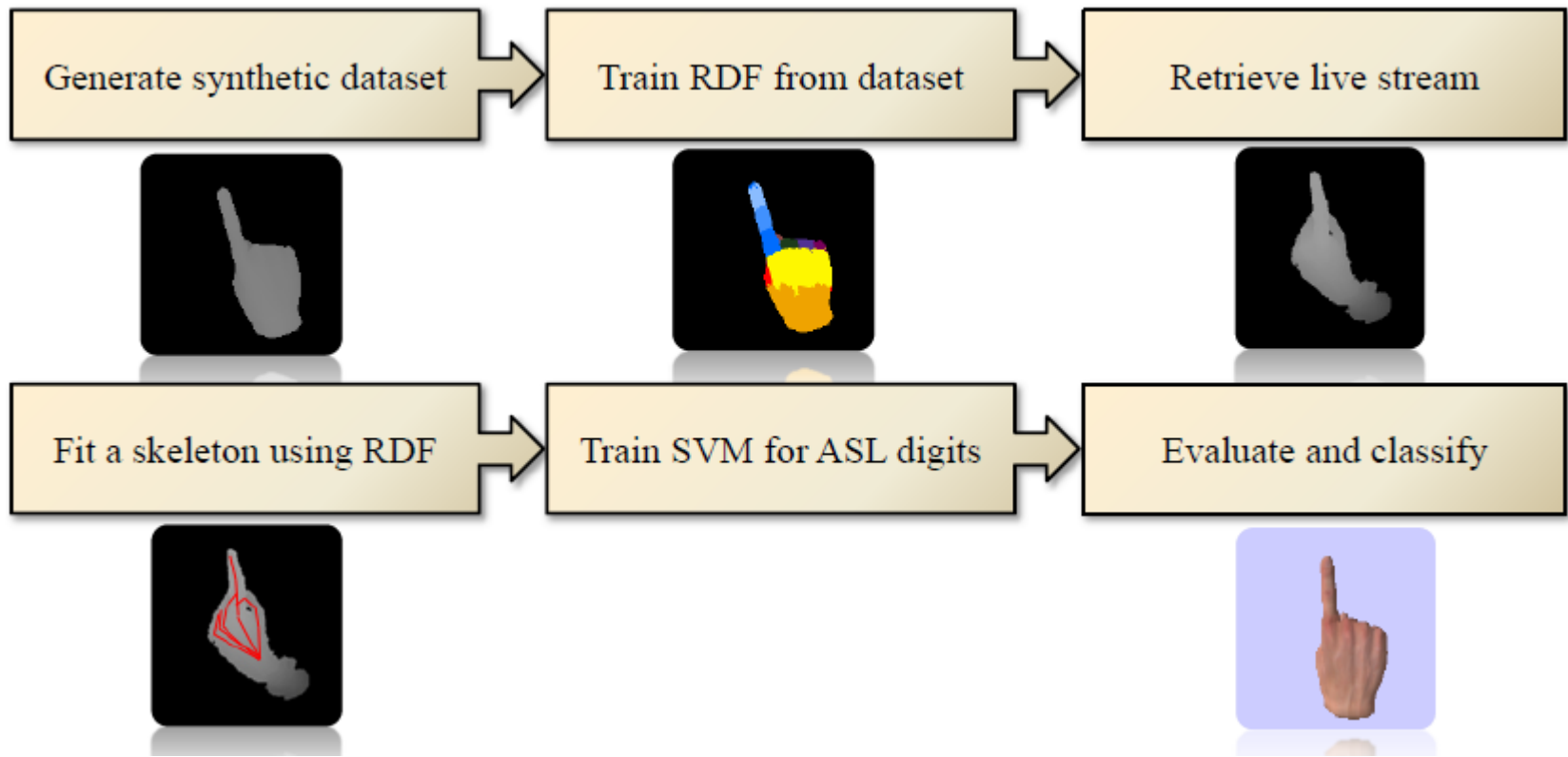
- Given the same data as before (hand shape not given)
  1. Cluster the data
  2. Train Hand Shape Classifier based on all clusters
  3. Train each Pixel Classifier based on a specific cluster

# Which is better? GEN or LEN

- Global Expert Networks average class distributions →  
More robust to noise
- Local Expert Networks use info from each pixel →  
Better at generalizing unseen data



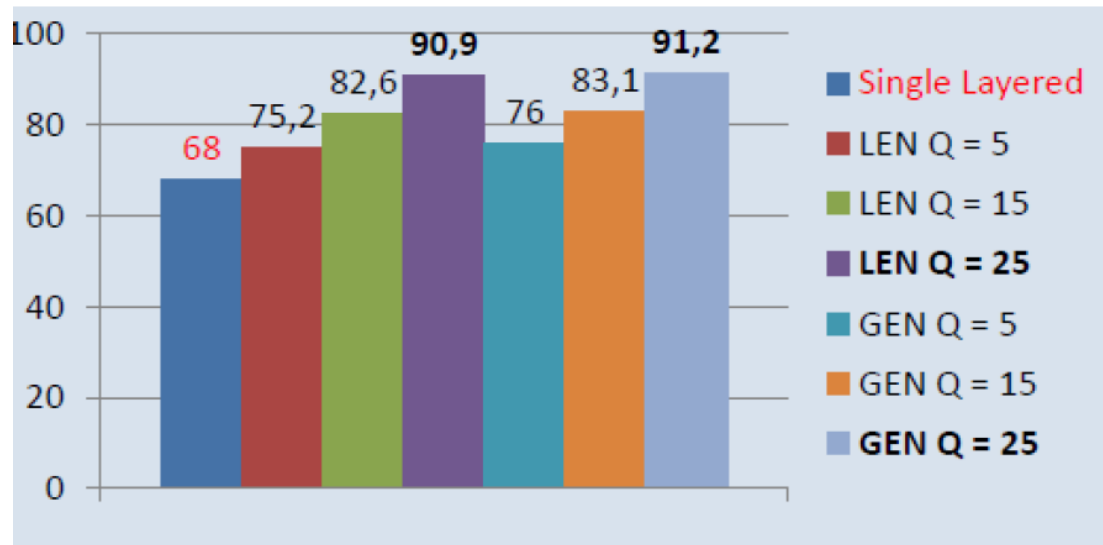
# Test: American Sign Language



# Results

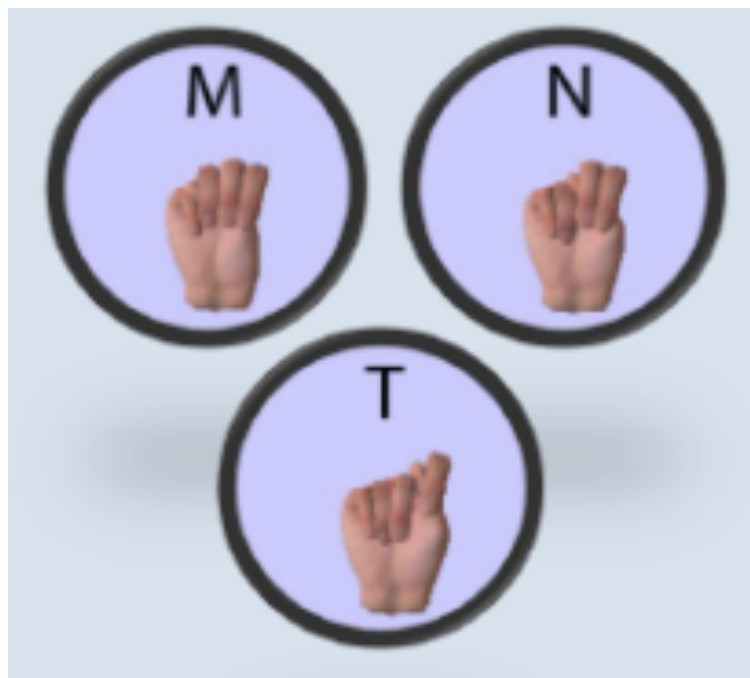
- Huge improvement over single-layer RDFs

Method	Single-layered RDF	GEN	LEN
Per Pixel	68.0%	91.2%	90.9%



# Results

- Remaining errors are concentrated on very similar poses



# Summary

- What is Hand Pose Estimation?

Determine the joint positions to fix all DOFs of the hand

- Why does it matter?

Continuous Input Applications

- How does it work?

Randomized Decision Forests

- What has been done?

Add multiple layers for increased performance.

# References

- [1] Keskin- Hand Pose Estimation and Hand Shape Classification Using Multi-layered Randomized Decision Forests
- [2] Thompson-Real Time Continuous Pose Recovery of Human Hands Using Convolutional Networks
- [3] Qian- Realtime and Robust Hand Tracking from Depth
- [4] Tang- Latent Regression Forest: Structured Estimation of 3D Articulated Hand Posture
- [5] Oikonomidis - Evolutionary Quasi-random Search for Hand Articulations Tracking
- [6] Wang - 6D Hands: Markerless Hand Tracking for Computer Aided Design
- [7] Hilliges - Advanced topics in Gesture Recognition Part II

**Questions?**

## Appendix: Getting Hand Shape from Hand Pose

- Hand shape is just shape information “fist”, “flat”, etc.
- Hand pose is specific joint angles for every DOF
- With hand pose, can use SVM to determine hand shape very robustly