

# Object Recognition + Gesture Recognition

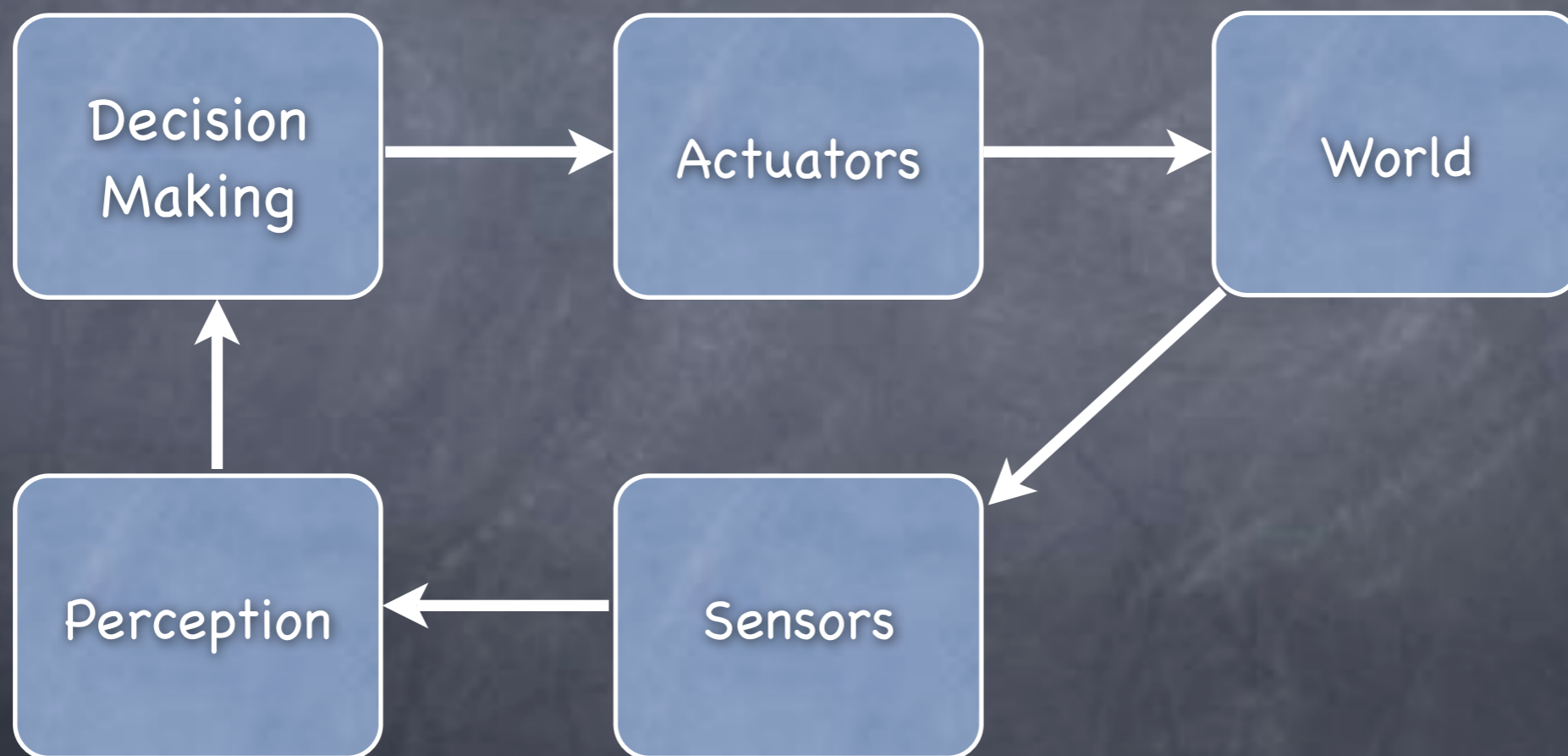
Matt Loper  
CS148

Nov 1st, 2007



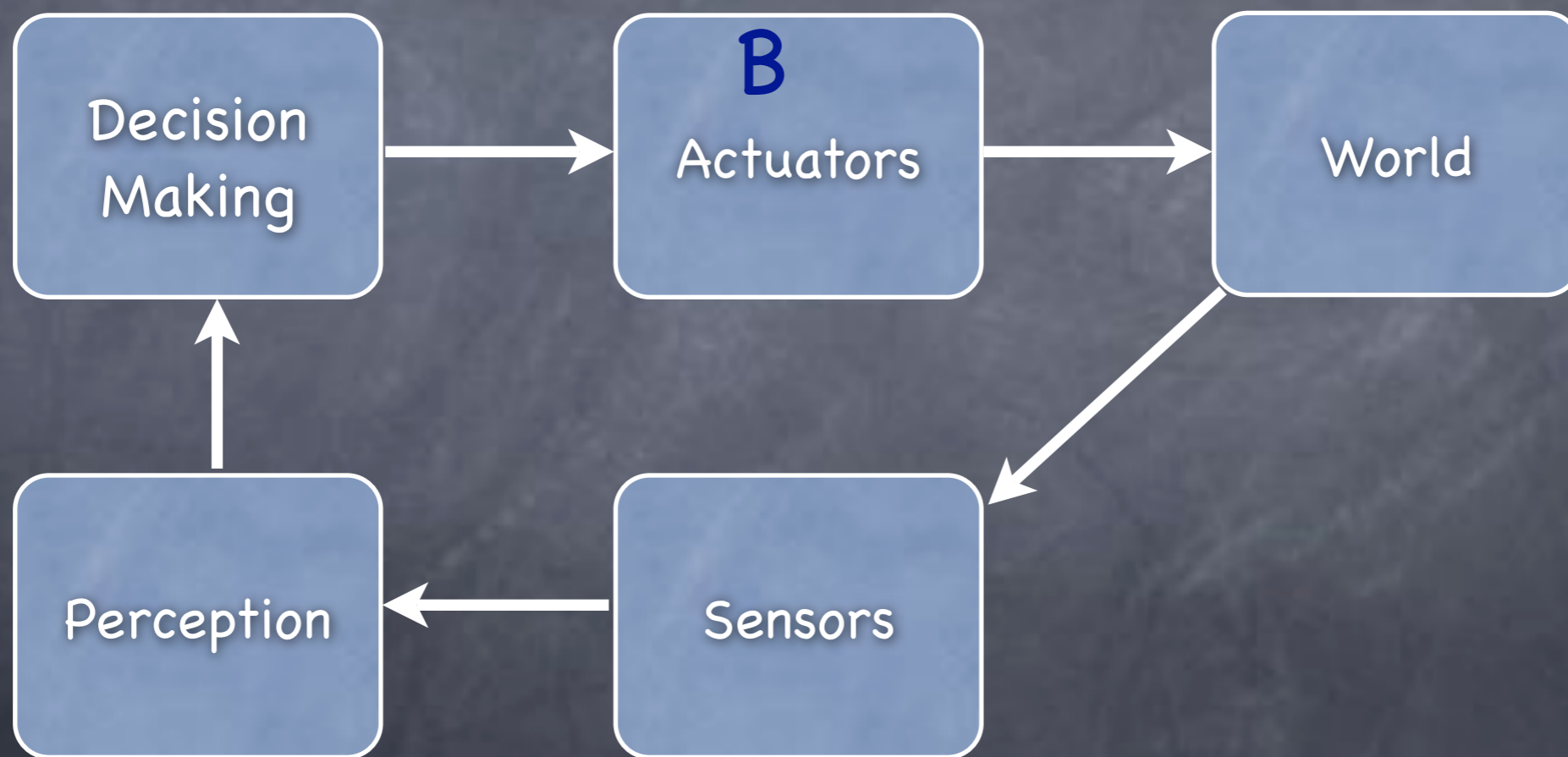
# Motivation

- Consider the robot control loop
- Compare it to a human



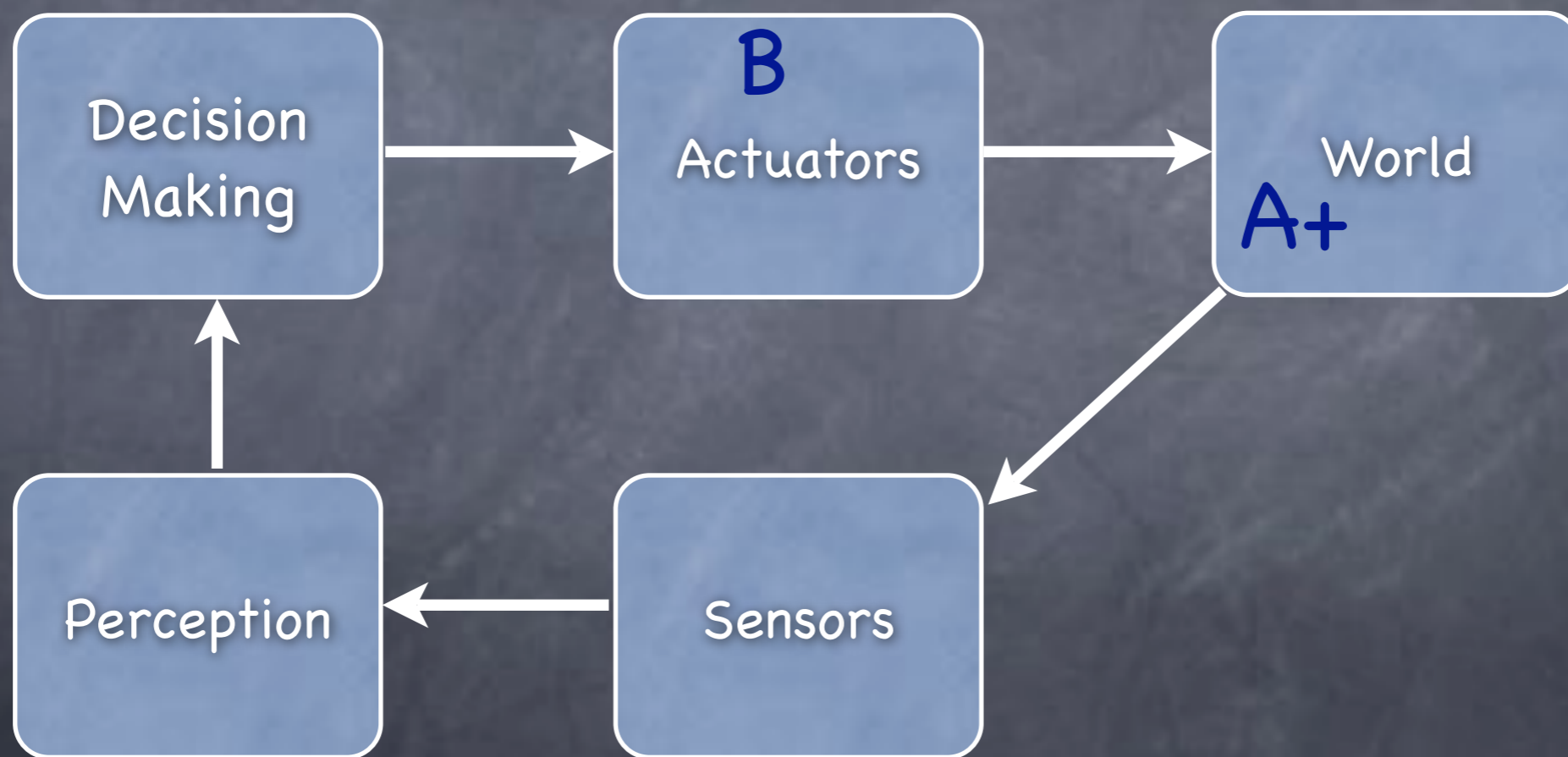
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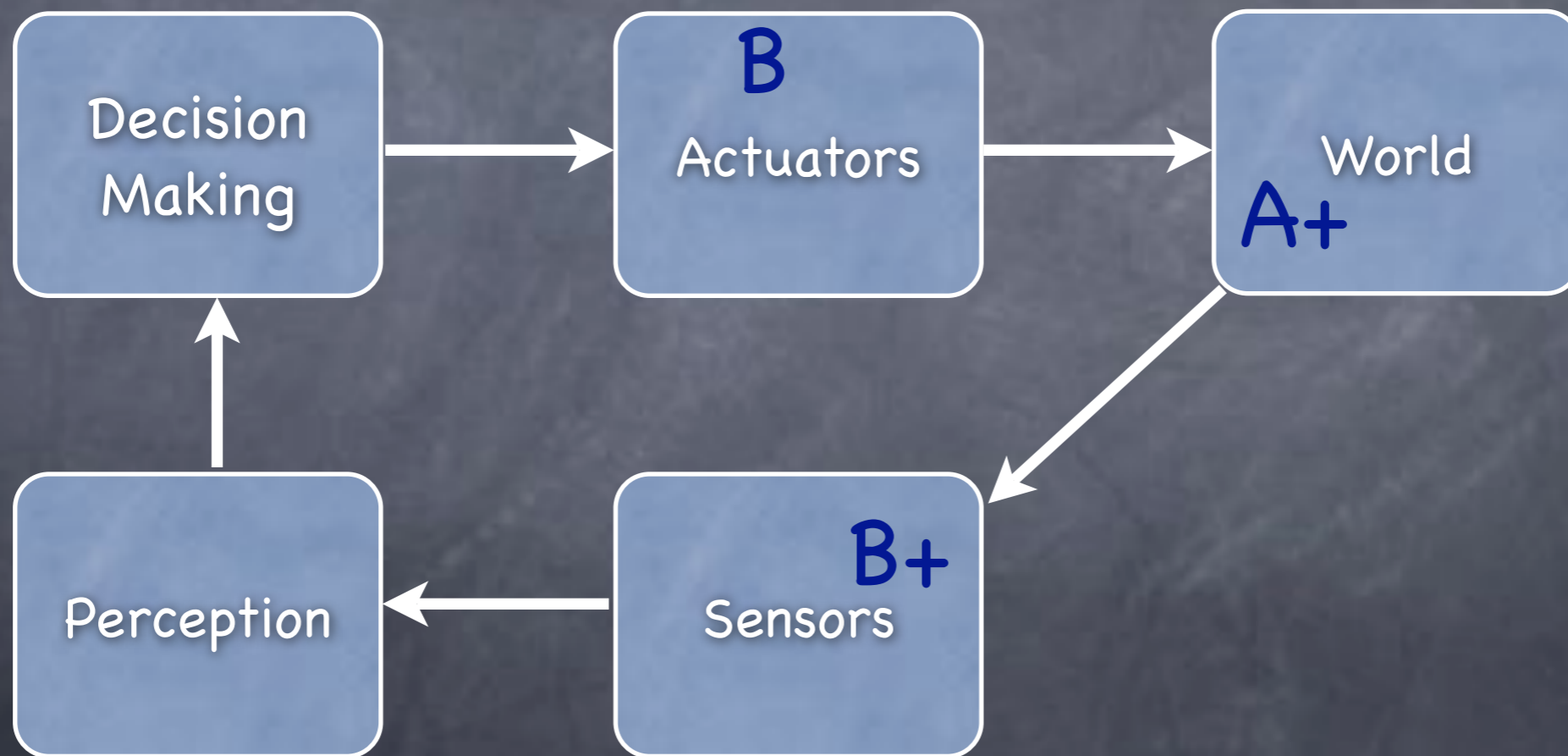
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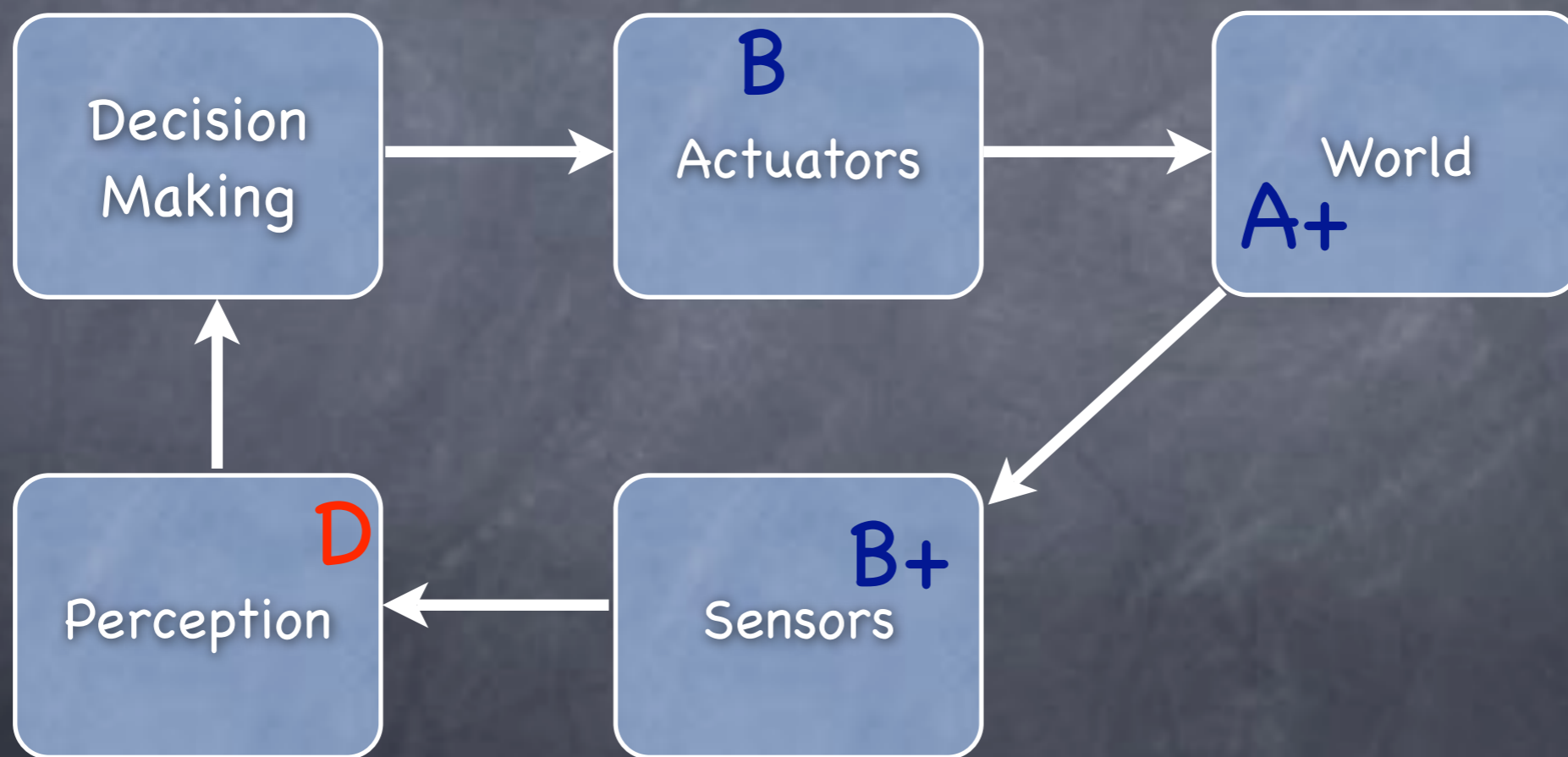
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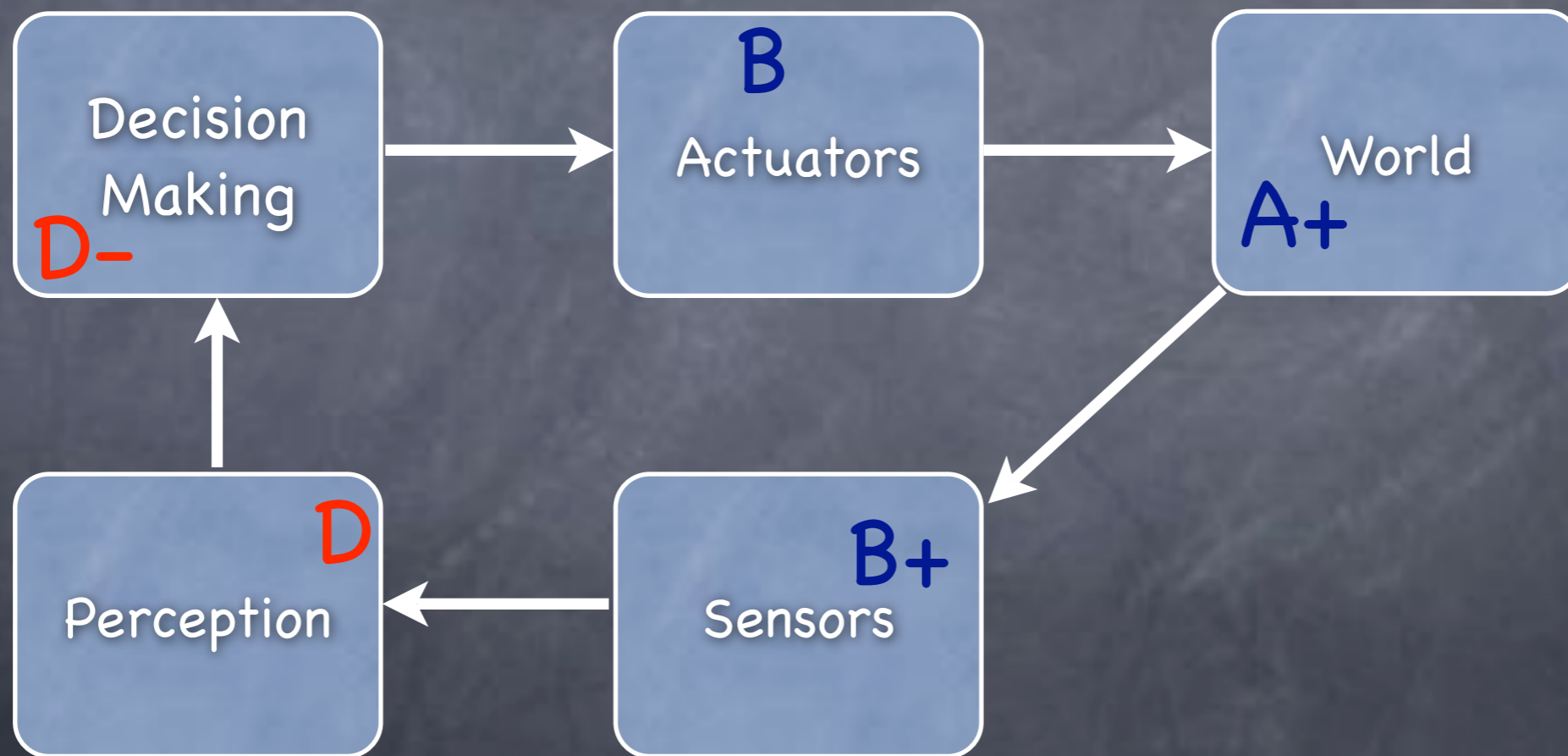
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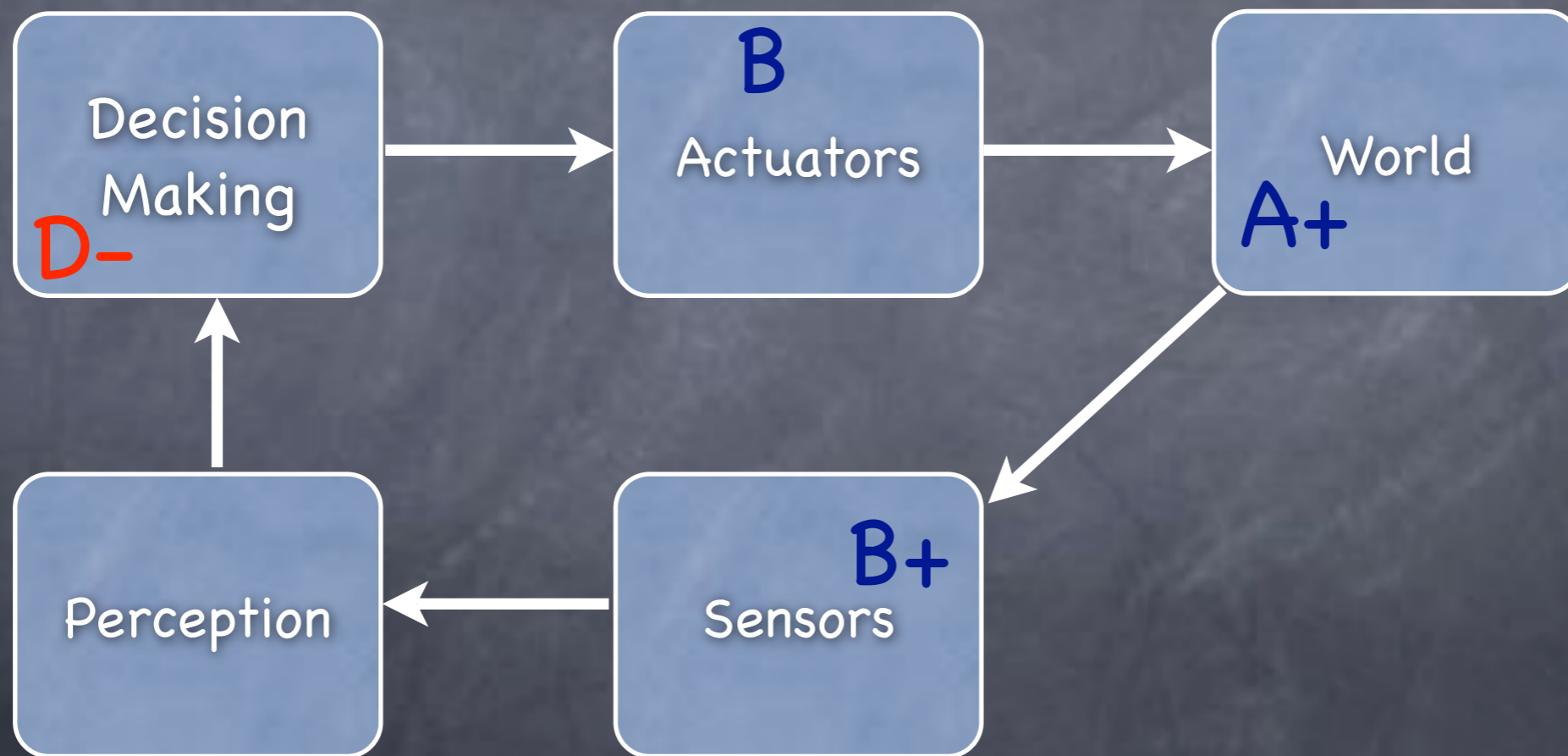
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- Compare it to a human

## Perception

Localization

People Detection

Object Recognition

Action Recognition

Others...

# Motivation

- Consider the robot control loop
- Compare it to a human

## Perception

Localization

People Detection

**Object Recognition**

**Action Recognition**

Others...

# Object Recognition

## What is object recognition?



# Two philosophies

Model based  
Object Centric  
Top Down

Template based  
View Centric  
Bottom up

# Object Recognition

## Two philosophies

Goal: Find the horse in the picture



Model based  
Object Centric  
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# Object Recognition

## Two philosophies

Goal: Find the horse in the picture



Model based  
Object Centric  
Top Down

"I have a geometric  
model of the  
horse."

Template based  
View Centric  
Bottom up

"I have pictures of  
parts (hooves etc) of  
the horse."

# Object Recognition

## Two philosophies

Goal: Find the horse in the picture



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# Object Recognition

## Two philosophies

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# Object Recognition

## Two steps to O.R.

- In theory, only two things to do:
  1. Collect features
  2. Perform classification, using those features

# Object Recognition

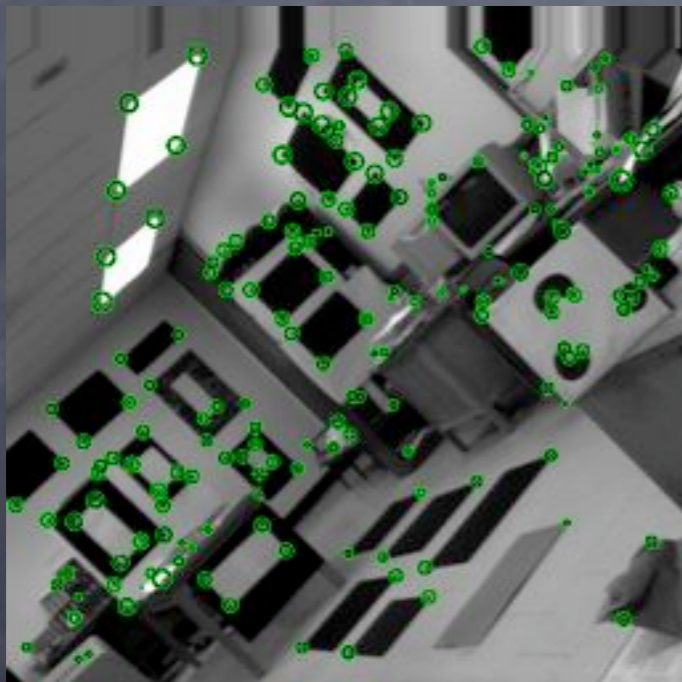
## Two steps to O.R.

- In theory, only two things to do:
  1. Collect features
    - Tool: image processing
  2. Perform classification, using those features
    - Tool: machine learning approach

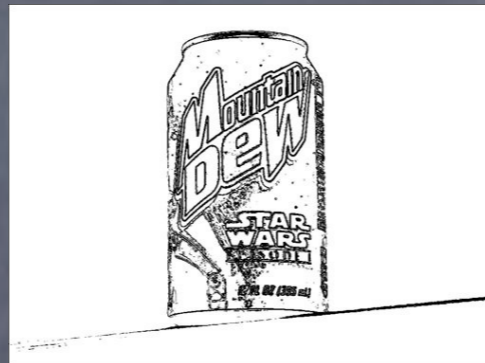
## Feature Collection

- Image processing brings us closer...

### Corners



### Edges



### Blobs

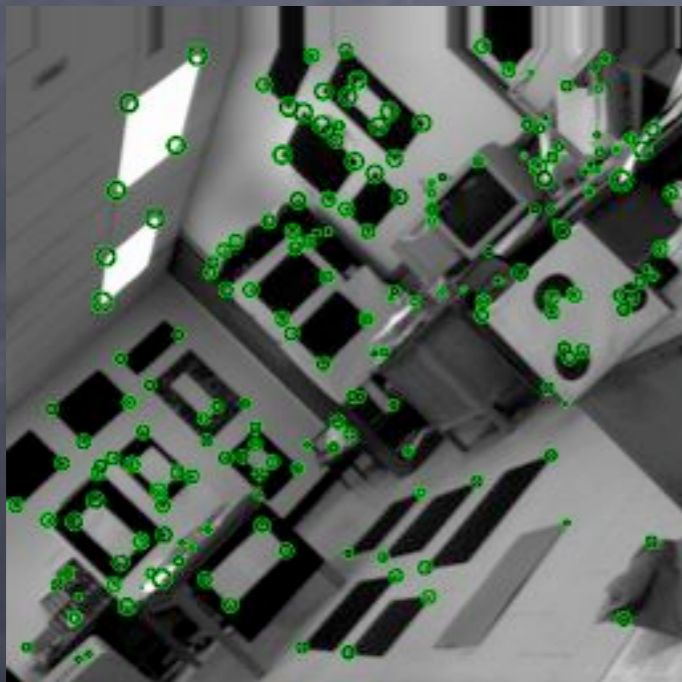


- But now we must formalize these into features

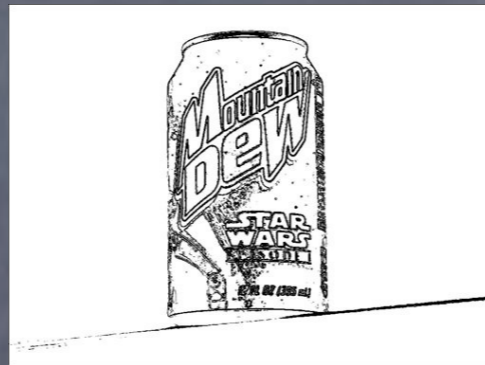
# Object Recognition

## Feature Collection

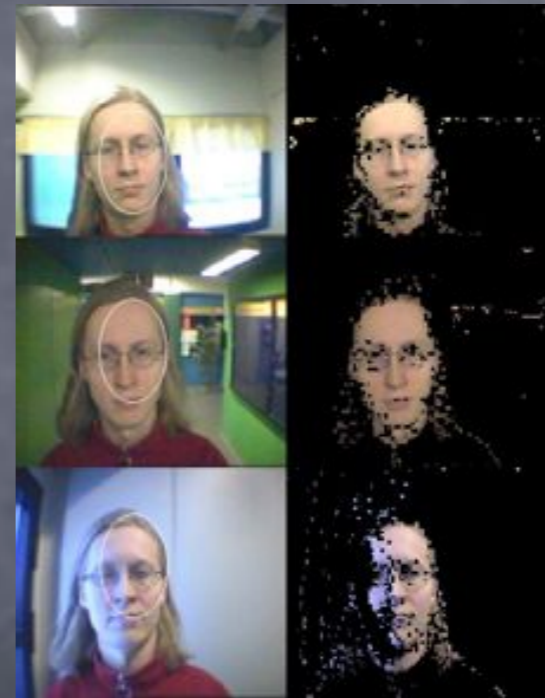
Corners



Edges

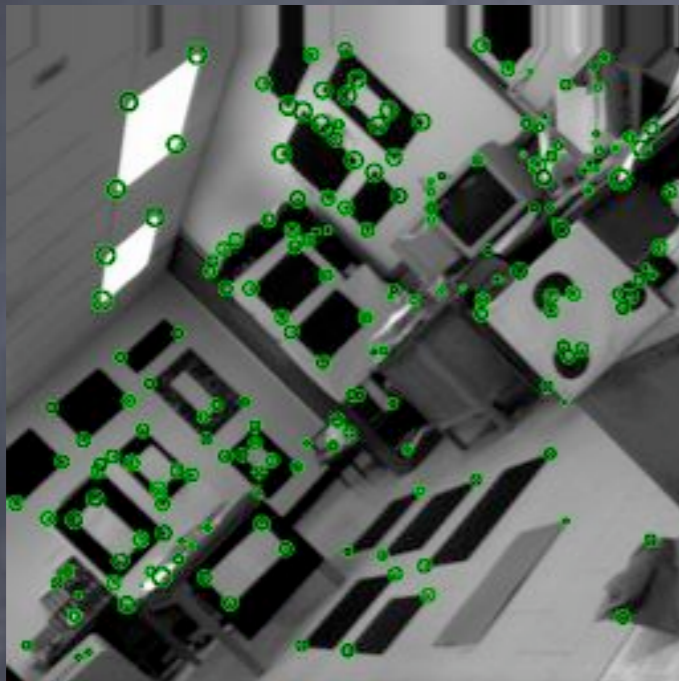


Blobs



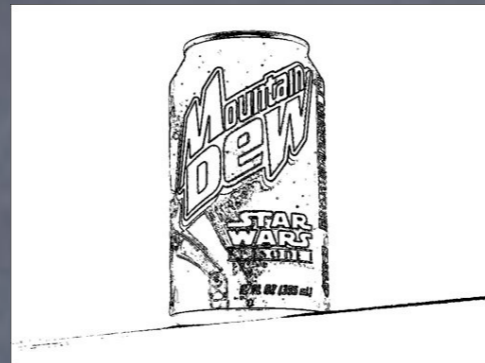
## Feature Collection

### Corners



x  
y  
local brightness

### Edges



begin x,y  
end x,y  
curve polynomial

### Blobs



mean blob x,y  
color distribution

## Feature Limitations

- General limitations
  - Rotational invariance
  - Scale invariance
- Specific feature limitations
  - Corners: Many objects are soft
  - Edges: Aperture problem
  - Blobs: subject to lighting changes, surface reflectance

## SIFT



- Introduced in 1999 by David Lowe
- (S)cale (I)nvariant (F)eature (T)ransform
- Galvanized the field
- Three attributes
  1. Scale invariance
  2. Rotation invariance
  3. Corner detection

# Scale Invariance

- How do you look for a variable sized object?
- Looking for a needle in a haystack...

Needle



Haystack



# Scale Invariance

- How do you look for a variable sized object?
- Looking for a needle in a haystack...

Needle



Match!



Haystack



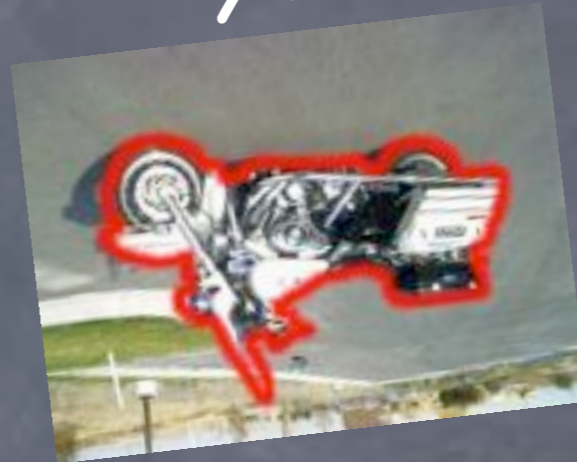
# Rotation Invariance

- What if the object is rotated?

Needle



Haystack



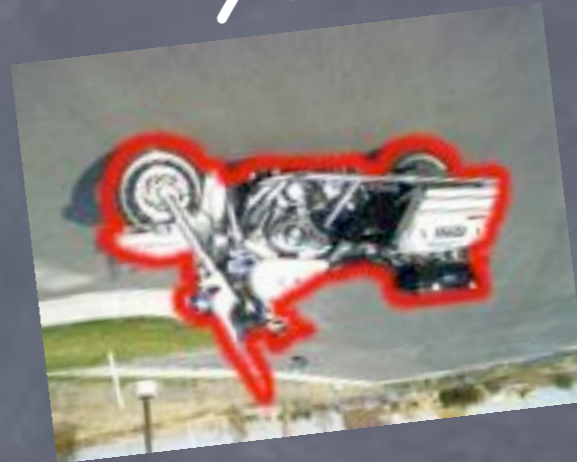
# Rotation Invariance

- What if the object is rotated?

Needle



Haystack



- Rotate to canonical orientation before comparison...



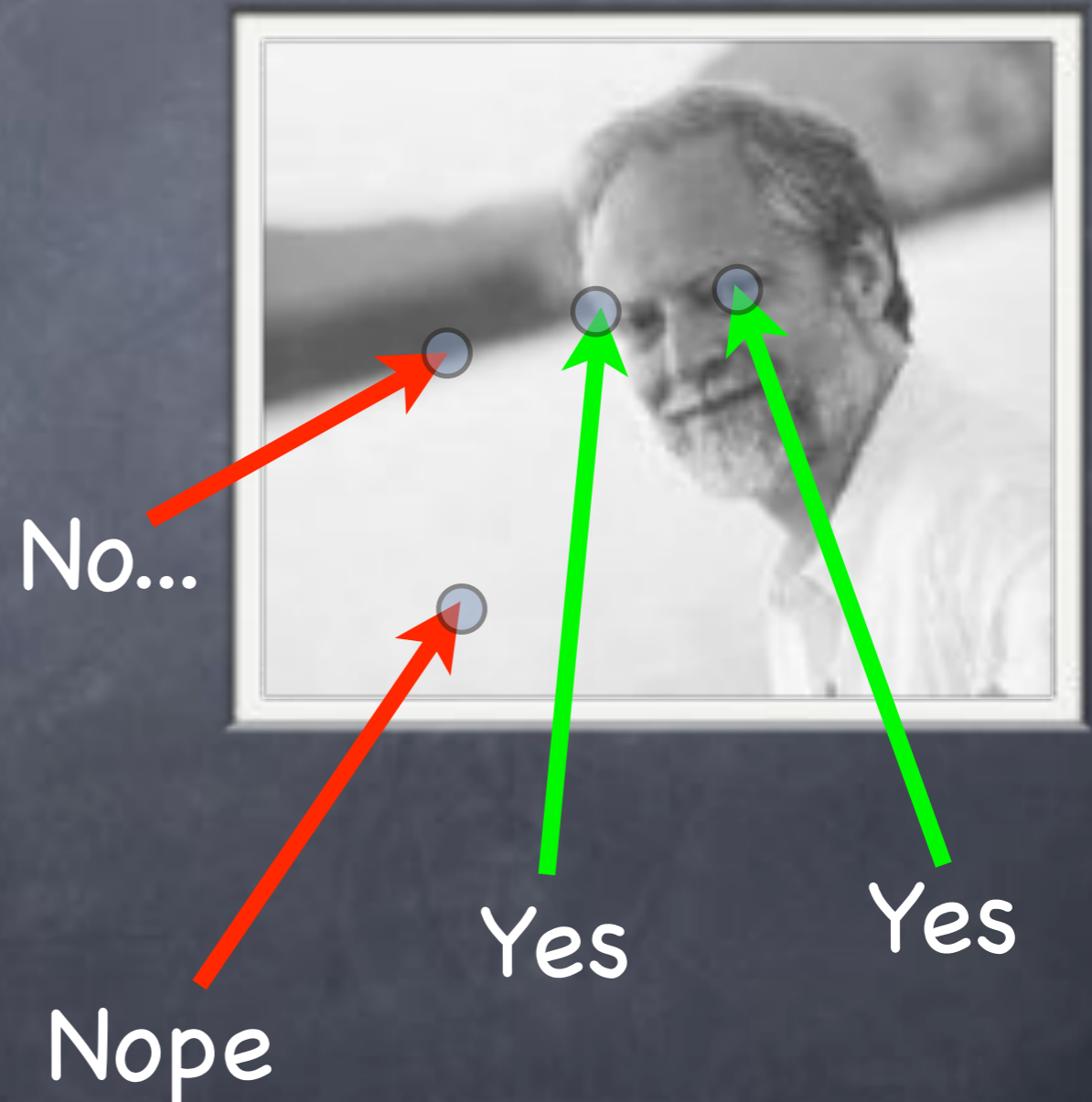
# Corner detection

- Corner detection: misnomer
- Finds locally unique regions
- What is NOT a corner?



# Corner detection

- Corner detection: misnomer
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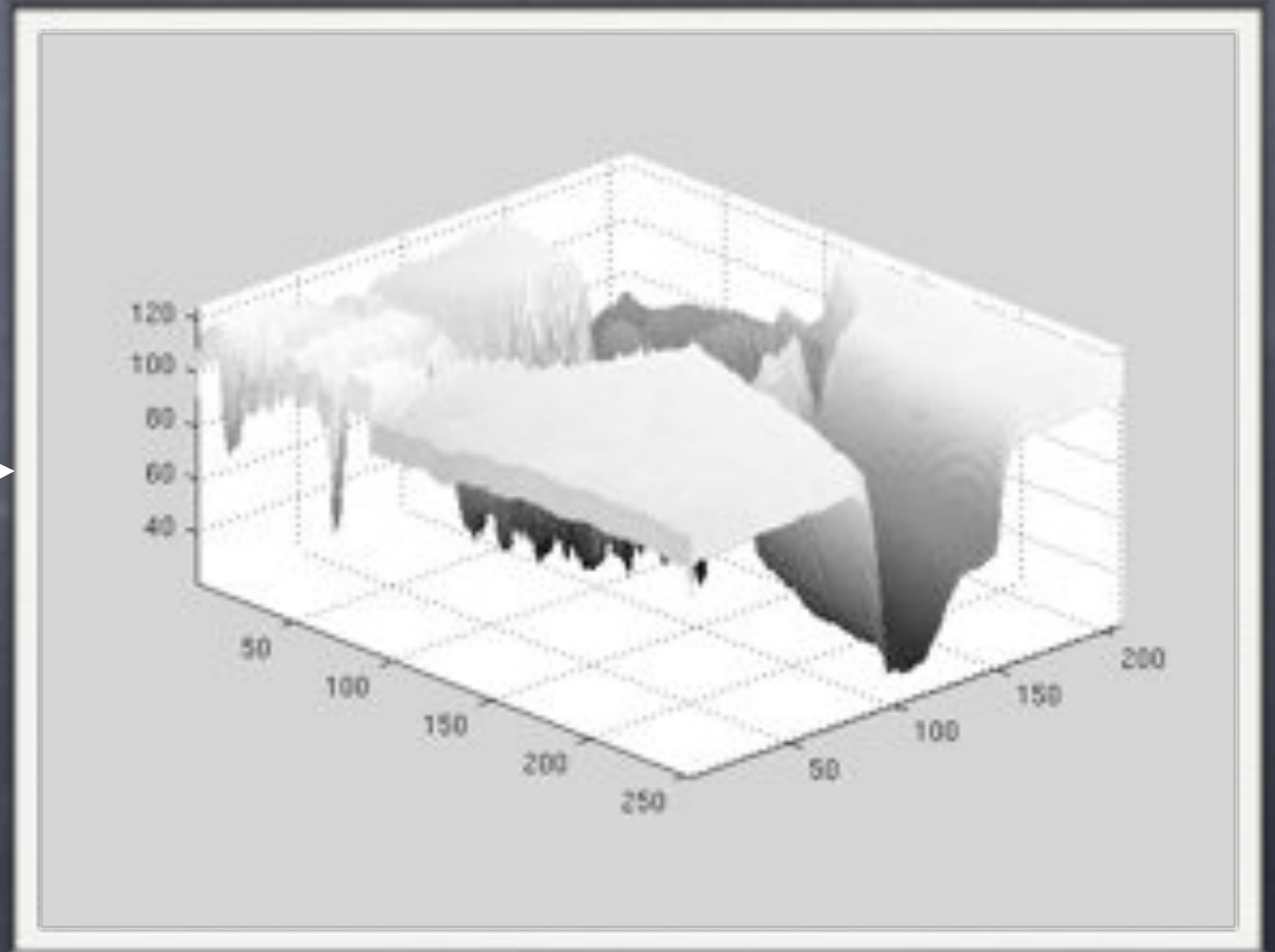


# Background: corner detection

- Think of an image as a mountainous landscape
- White is high, black is low

# Visualizing gradients

- Images can be seen as heightmaps
- Where are corners?

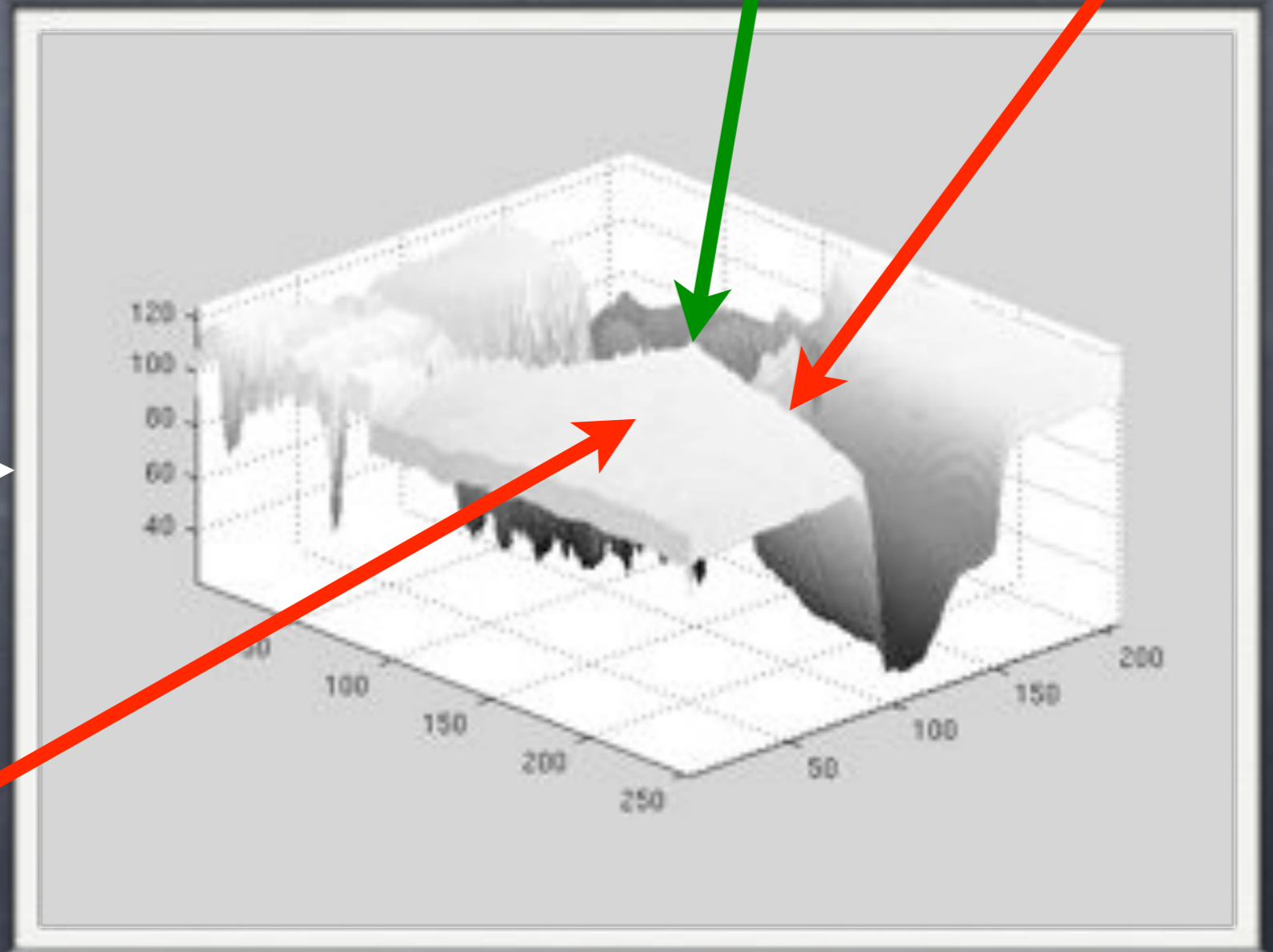


# Visualizing gradients

- Images can be seen as heightmaps
- Where are corners?

Yes

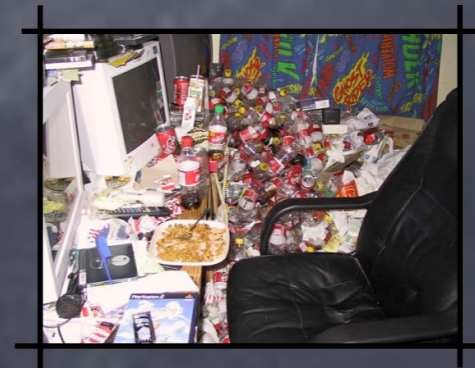
No...



No...

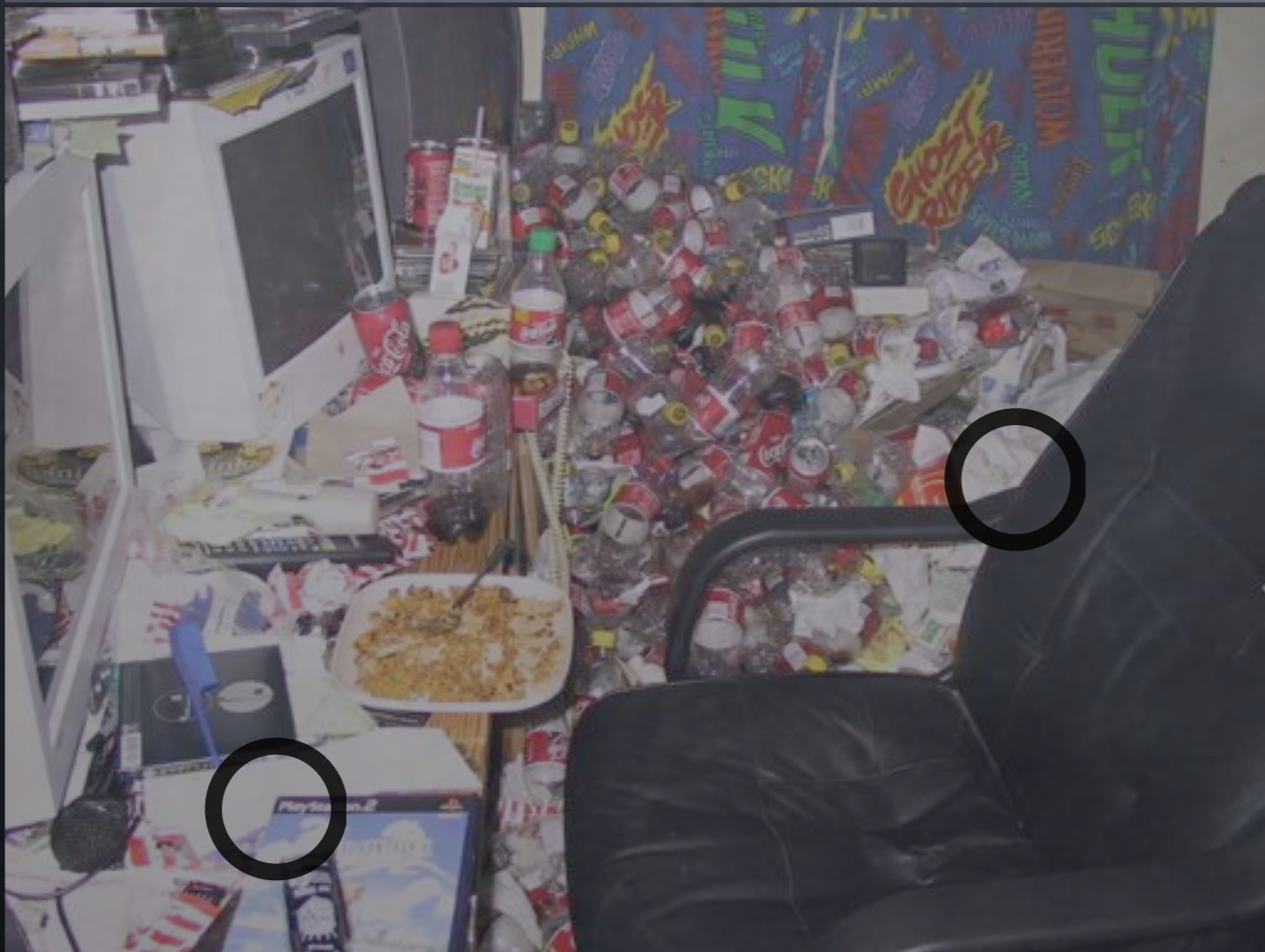
# Multiscale corners

- Different corners at different scales



# Multiscale corners

- Different corners at different scales



# Step 1 of 3: Get features

- In training image (needle)
  - Find corners in different scales
  - For each corner...
    - Find local image patch
    - Rotate it to canonical orientation
- In testing image (haystack)
  - Do the same thing!!

# Step 2 of 3: match features

- What do we have now?
  - Corner features in training
  - Corner features in testing
- Now we just have to match them up
  - We have  $M \times N$  comparisons
  - $M$  is # training corners,  $N$  is # testing corners
  - Compare image regions

# Step 3 of 3: match objects

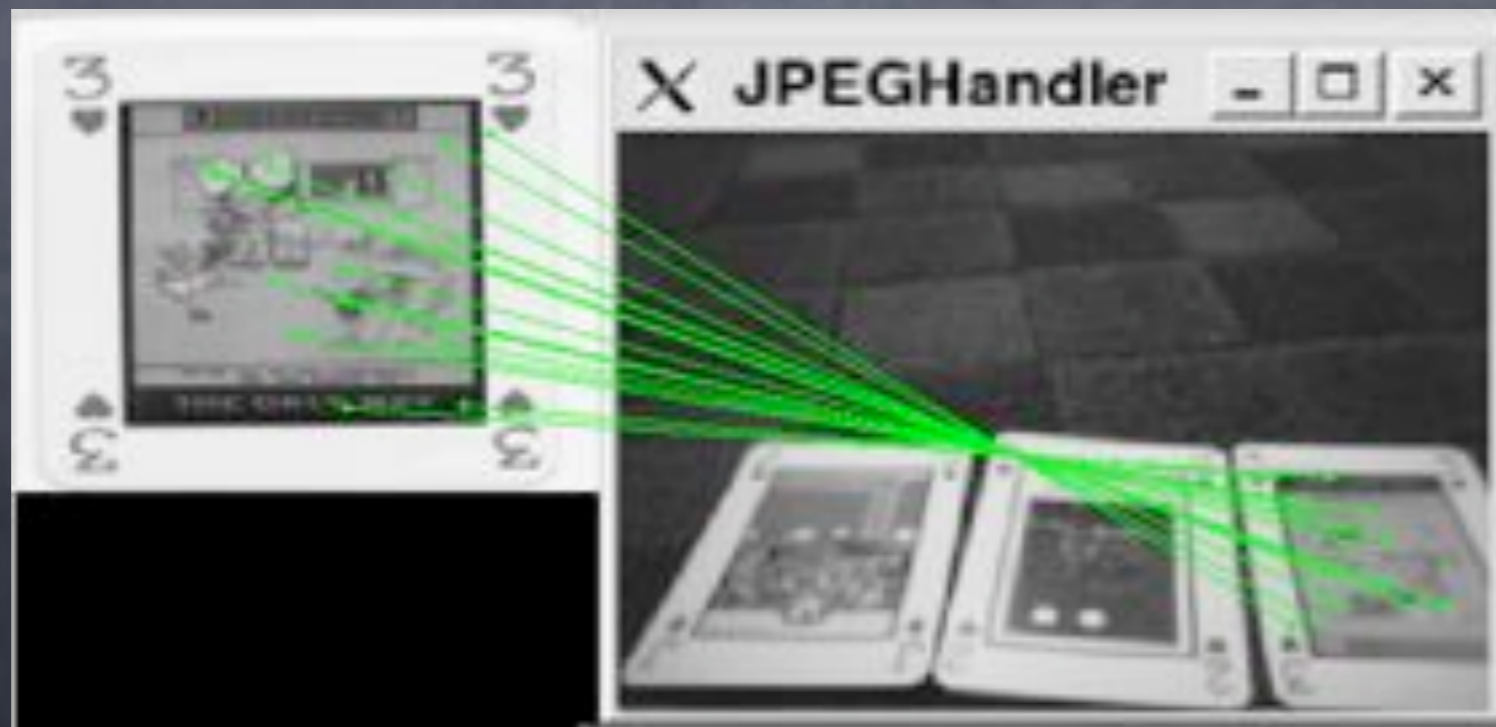
- Find collections of matches that make sense
- Training images show spatial relationships
- Testing images should retain those for objects found

# SIFT corners found



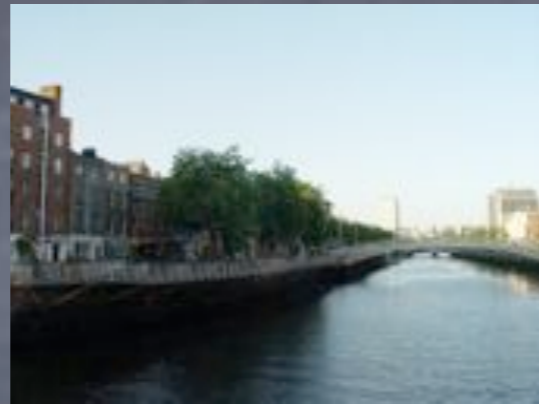
# Applications: Blackjack

- Train dog on each card
- Look for features that match known spatial arrangement



# Applications: Panoramas

- AutoStitch (google it, it's fun and easy)



## SIFT at home

👁 <http://vision.ucla.edu/~vedaldi/code/sift/sift.html>

SIFT

11/01/2007 12:54 PM

Andrea Vedaldi UCLA Vision Lab

### SIFT

An open implementation of SIFT

Home

Research

Publications

Code

VLFeat

Bag of features

MDoc

Autorights

VLPOV

Anaview

SIFT++

SIFT

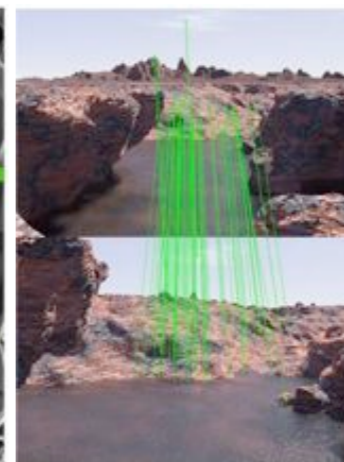
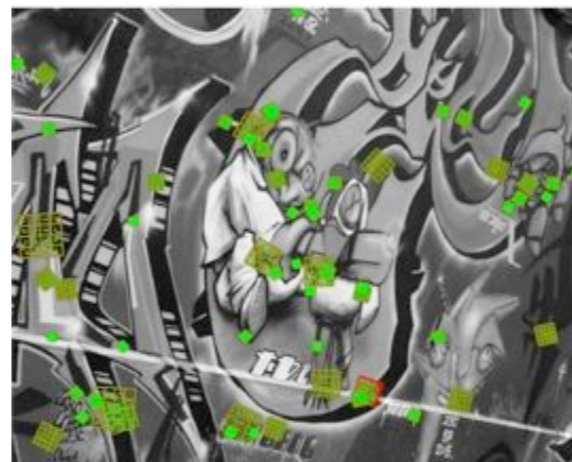
Custom keypoints

MSER

VLUtil

Code Snippets

Restricted



This is a MATLAB/C implementation of SIFT detector and descriptor. It is fairly customizable and features a decomposition of the algorithm in several reusable M and MEX files. This implementation produces interest points and descriptors which are very similar to [David Lowe's implementation](#).

**Remark.** This code is well suited to study, understand and modify SIFT, but it is not particularly fast. If you need to compute lots of features, you might be interested in [this](#) lightweight C++ version, which does not require MATLAB and comes with a flexible command line interface.

### Copyright

This software program is Copyright © 2006 The Regents of the University of California and can be freely used for academic purposes (see the included license file for details). Although this implementation is original (in particular, it is *not* derived from [Lowe's implementation](#)), the SIFT algorithm has been issued a patent. Thus you should note that:

# SIFT Drawbacks

- Rotation
  - If object rotates around camera's z-axis, that's ok
  - But if object rotates around other axes, that's a potential problem
  - SIFT tolerates only 15% to 20% rotation
  - Can be worked around by generating features at other rotations
- Floppy objects don't generate reproducible features

# Object Recognition Summary

- Why: because current robot perception is not good
- What: feature selection+classification
- How: SIFT (or Viola & Jones, or color-based segmentation)

## Motivation

- Automation: for the 3 d's
  - dirty
  - dangerous
  - dull
- Great! What's done already?

# What's automated today?

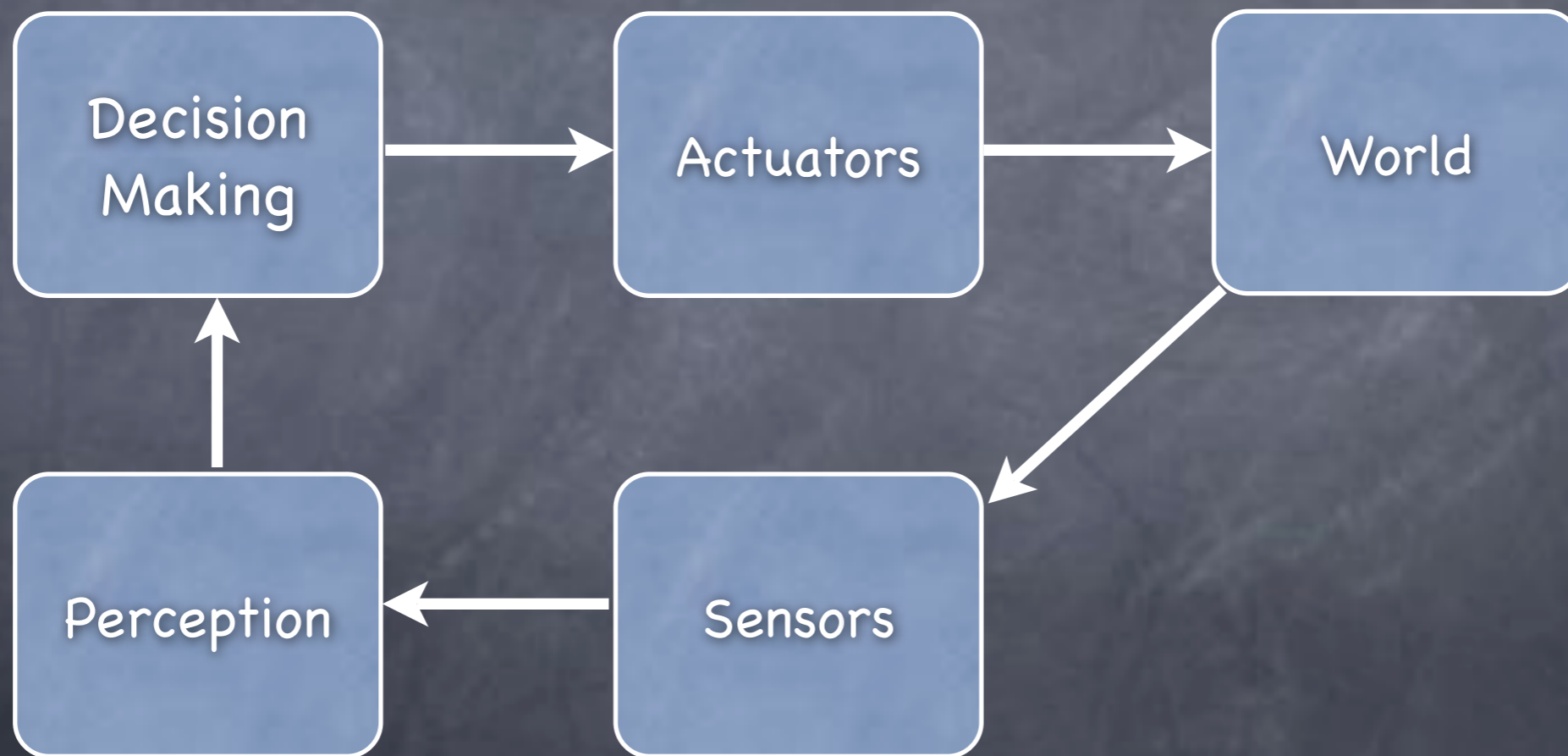
- Today's automation
  - ATM's
  - Automatic/assisted assembly
    - cars
    - electronics
    - packaging
  - Vending
- What is in common?

# Motivation

- Today's automation: ATM's, assembly, vending, automated phone assistance
- What's in common?
  - They are **immobile**
  - Communicating with them is **unnatural**
- Many dull, dangerous tasks need mobility!
- ...and can benefit from natural communication!

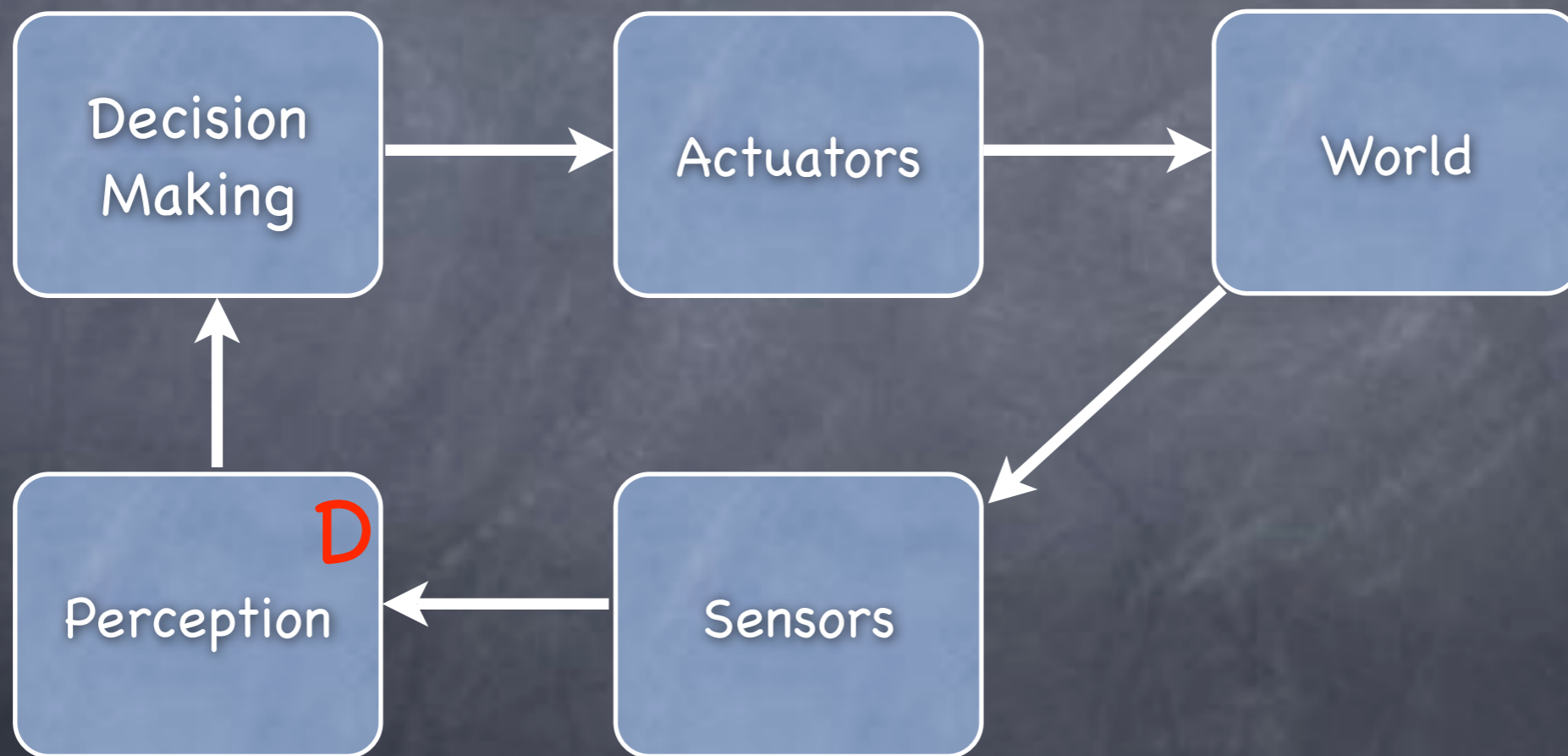
# Immobility: why?

- Why don't robots truck around on thayer?



# Immobility: why?

- Why don't robots truck around on thayer?



# Immobility: why?

- Danger to us, and/or themselves
- Can't "see" things or people



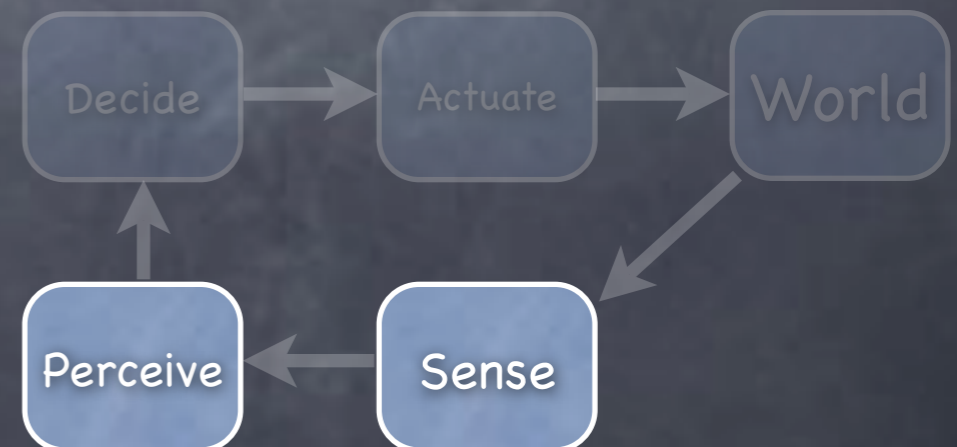
# Natural communication

- Hard to communicate when you can't "see" people
- Speech recognition works alright when trained on one person, or on simple words
  - Hard to hear when it's noisy, different accents are being used, etc
- I will focus on Action Recog.

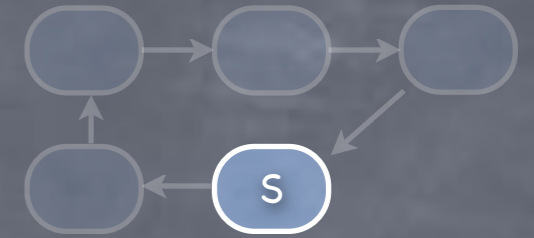
## Goals

- Goals
  - Person detection
  - Gesture-based communication
  - A 3d view of the world
- Means

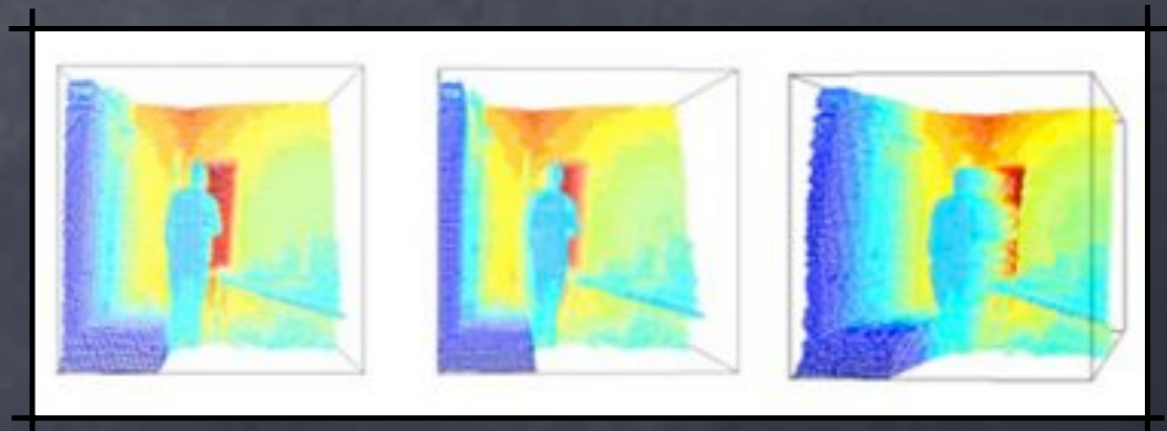
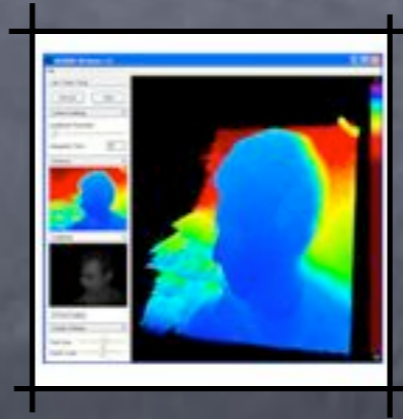
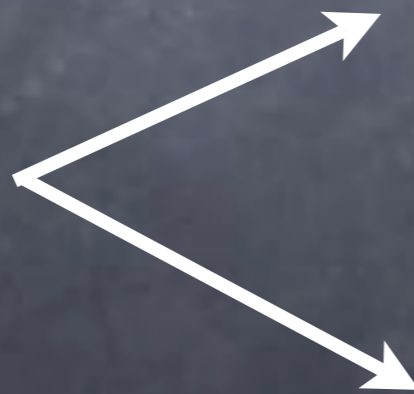
- Improve sensors
- Improve perception



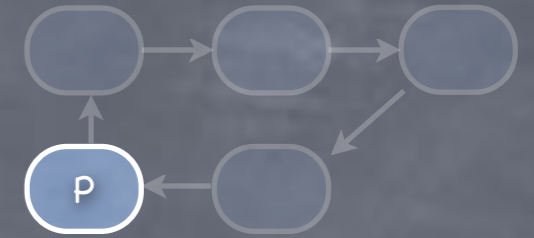
## Sensors



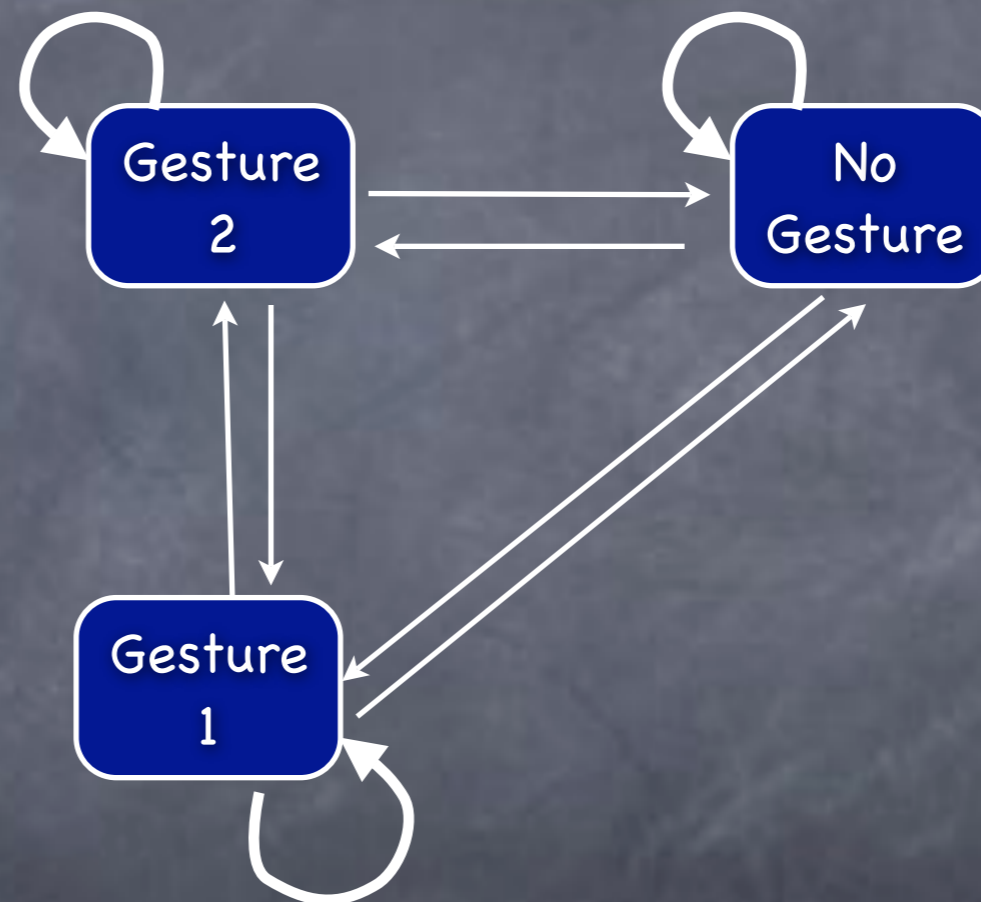
- CSEM SwissRanger
- Emits nonvisible light
- Recovers a depth image
- Expensive



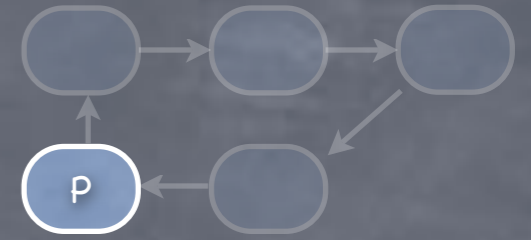
# Perception



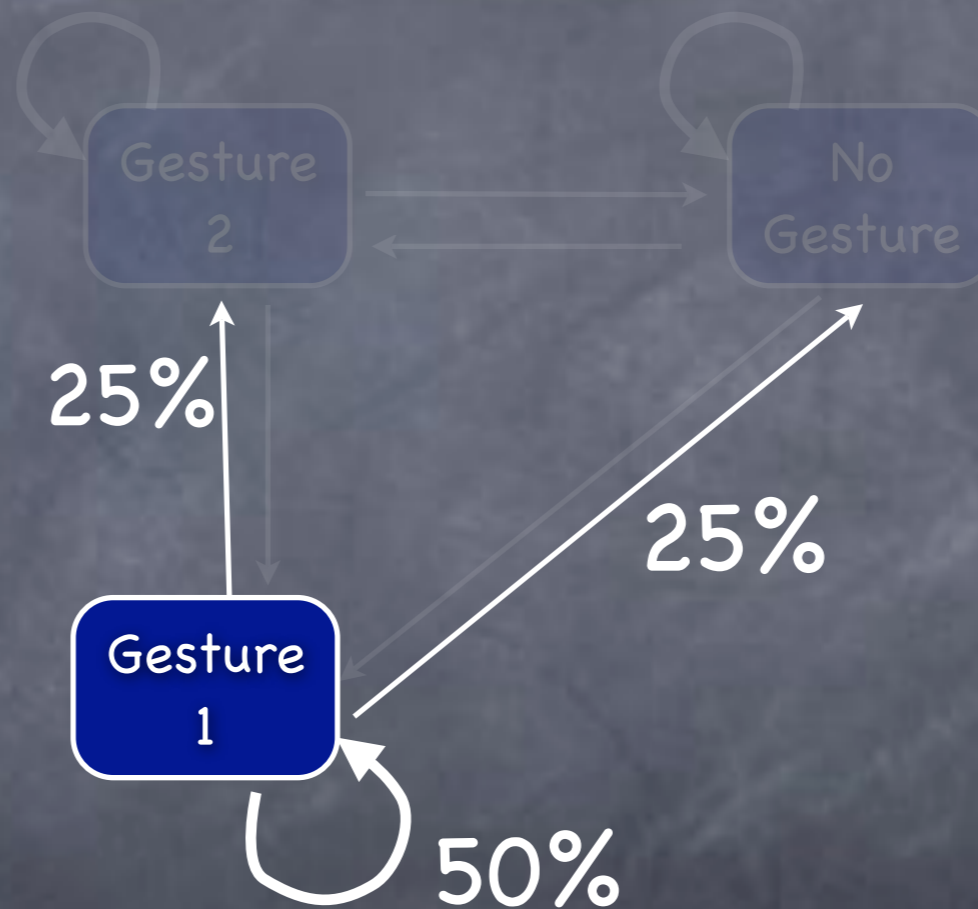
- Hidden Markov Model



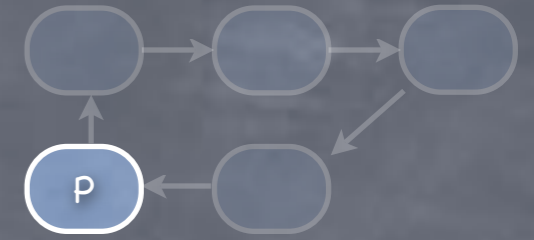
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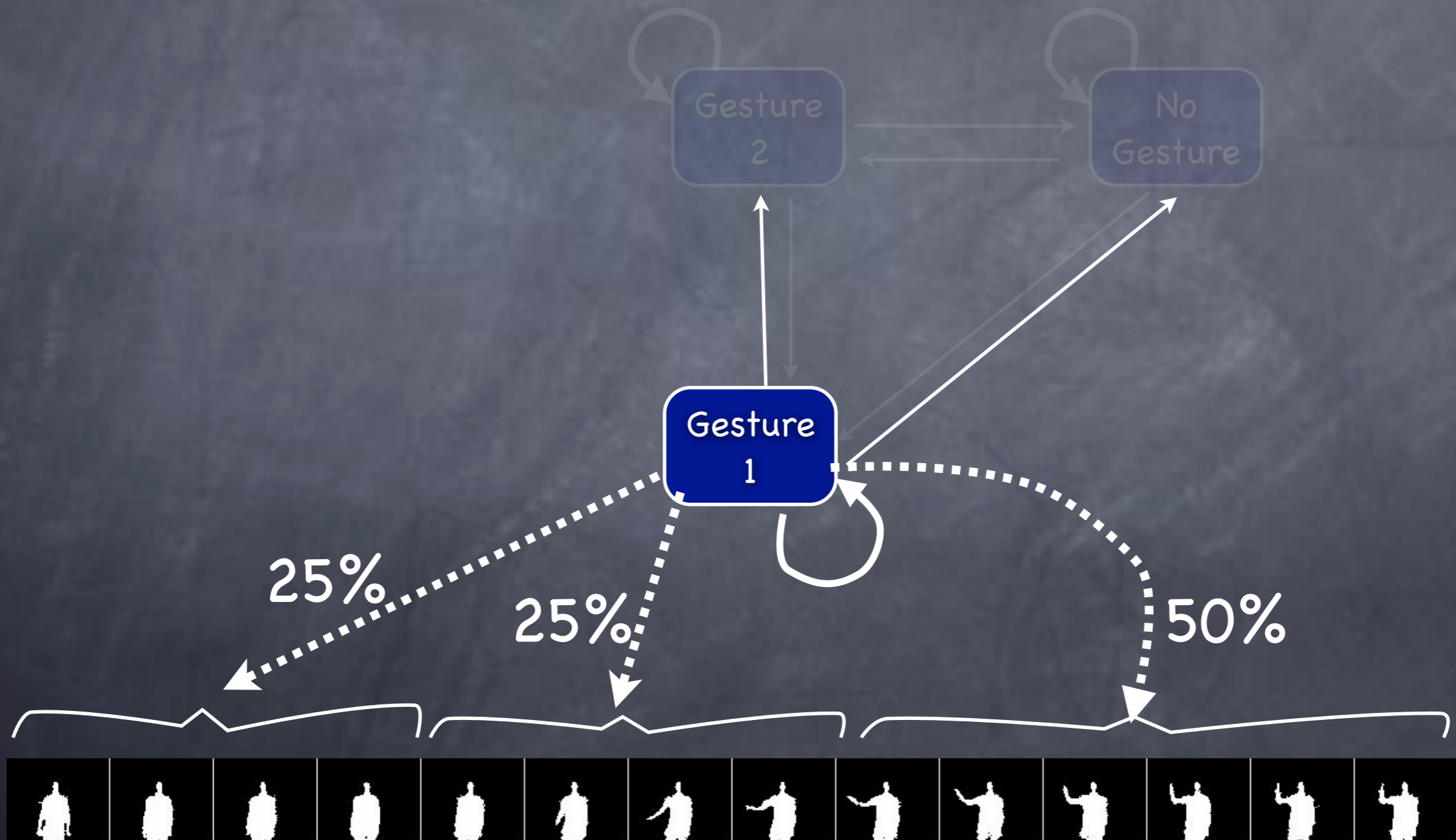
- Hidden Markov Model



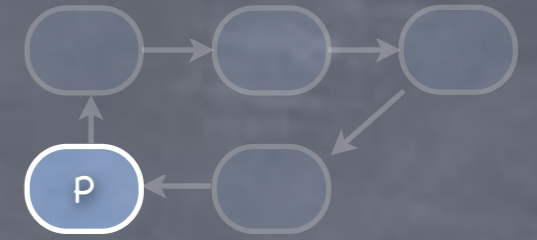
# Perception



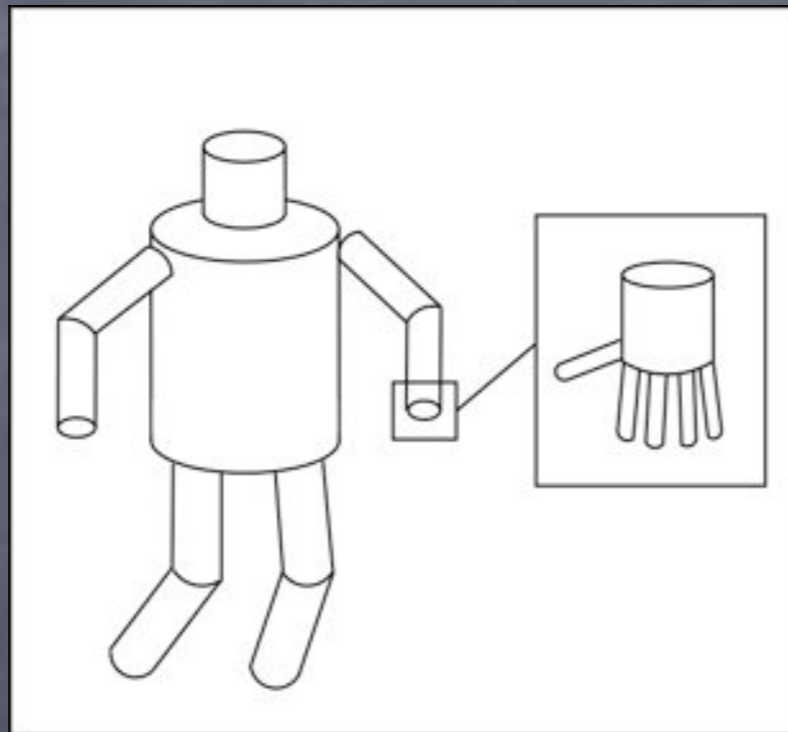
- Hidden Markov Model



# Getting features



- I use a cylindrical body model (ok, not this one)



- And I use "guess and check", aka Bayesian reasoning
- Gives me poses, which give me features

# Mobile Action Recognition > Tactical Teams

## Demo

