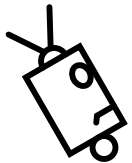


Teaching an Old Robot New Tricks: Learning via Interaction with People and Things

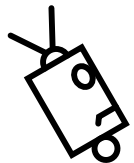
Matthew J. Marjanovic
MIT AI Lab



Embodied AI



Lots of structure *built-in*... What about *building structures*?



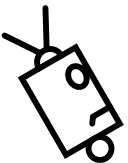
Overview

Three contributions to Embodied AI:

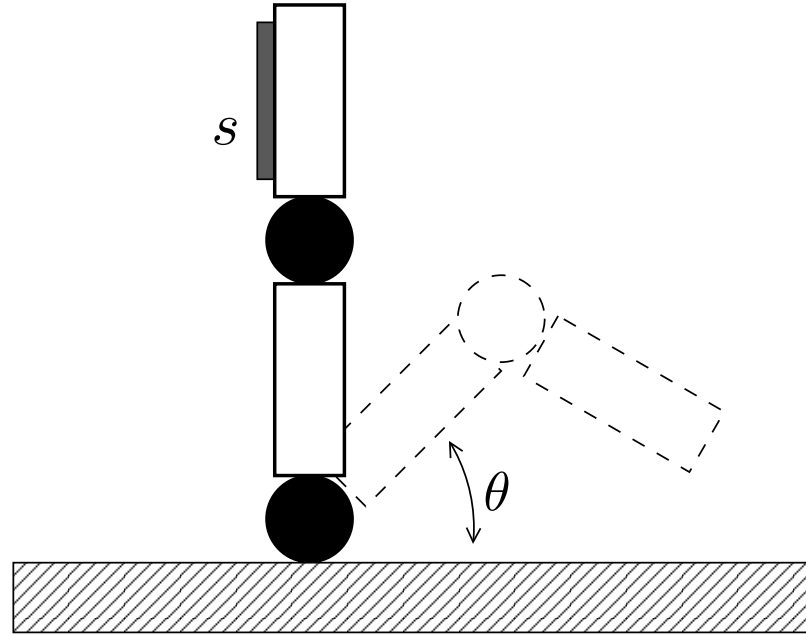
- *sok*: Environment for behavior-based programming.
- *meso*: A biologically-motivated motor-control system (*virtual muscles*).
- *pamet*: A modular system for learning from interaction with the environment and people, with enough modules to learn some simple behaviors.

What you will see:

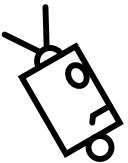
- Cog is taught to perform some simple motor tasks.



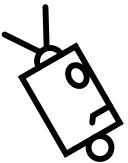
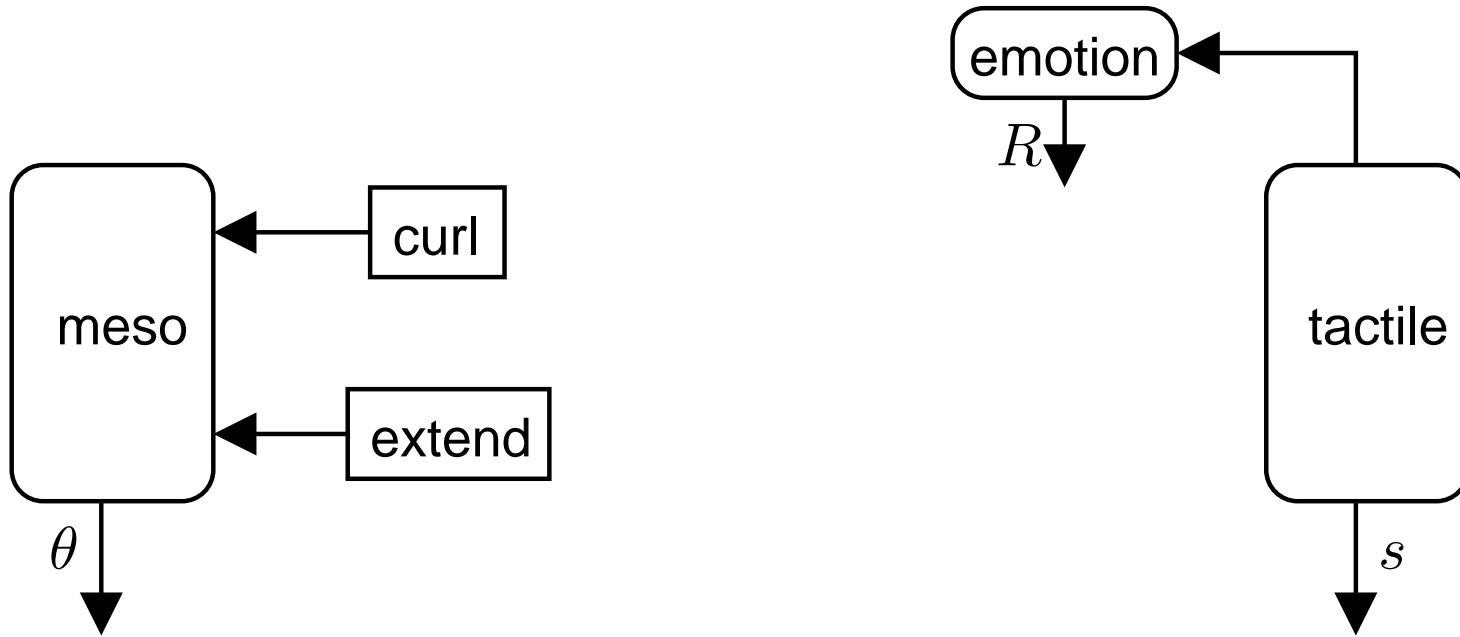
An Example: The FingerBot



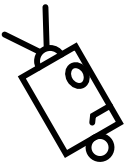
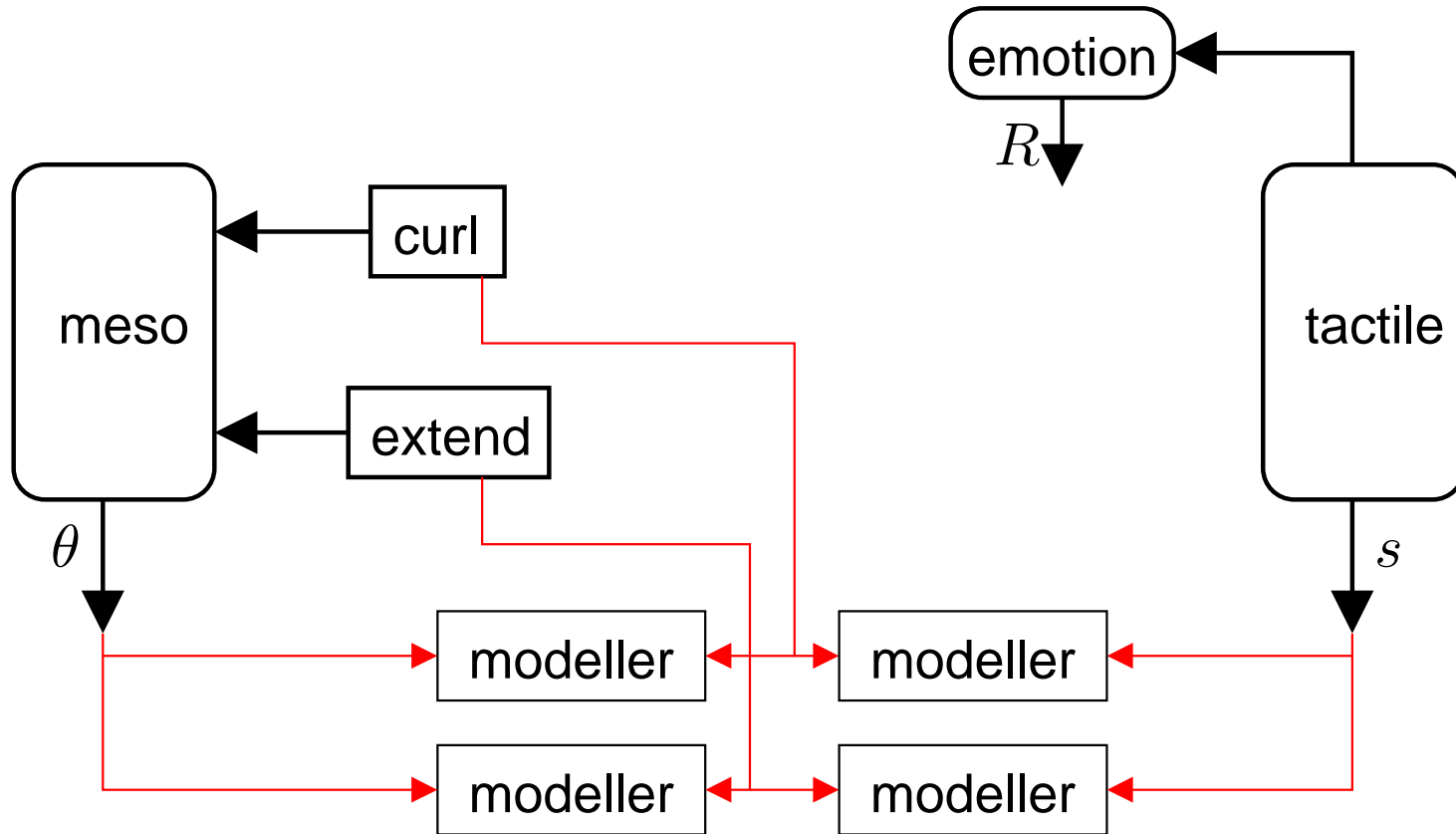
- One degree-of-freedom motion; single tactile sensor.
- Our goal: teach FingerBot to *point in response to touch*.



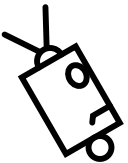
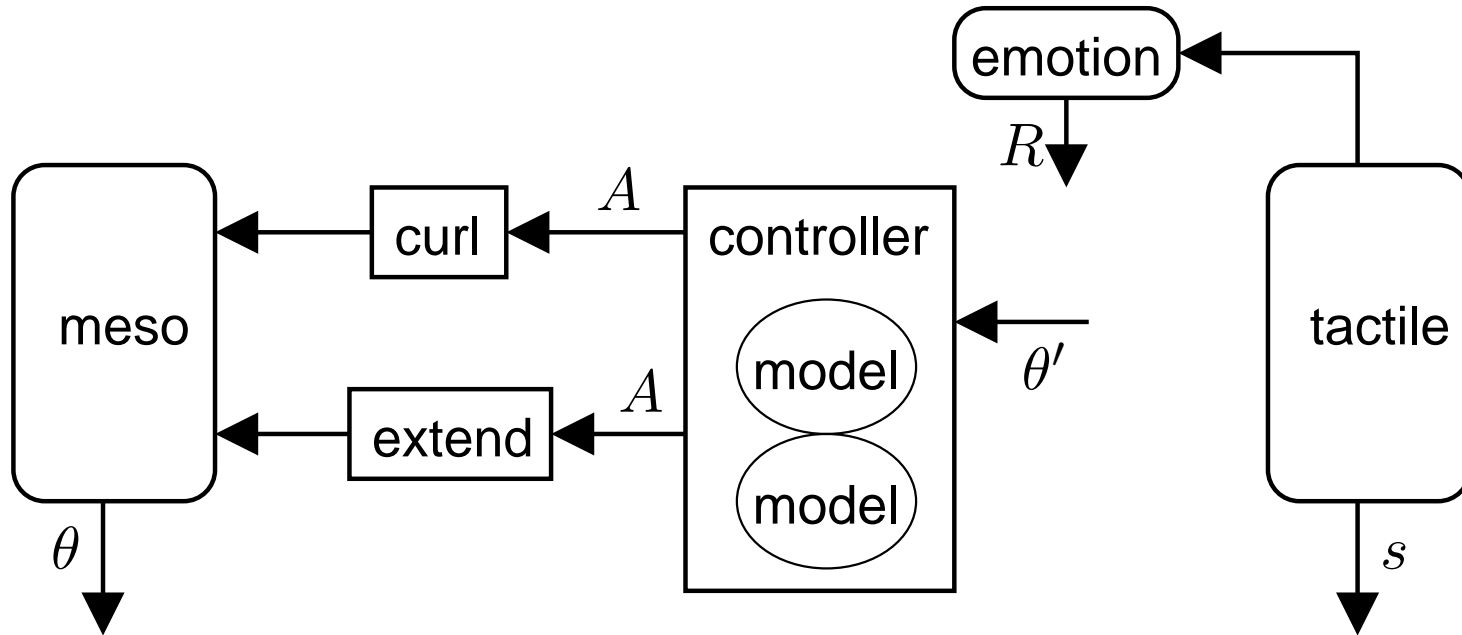
FingerBot initial state



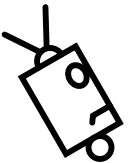
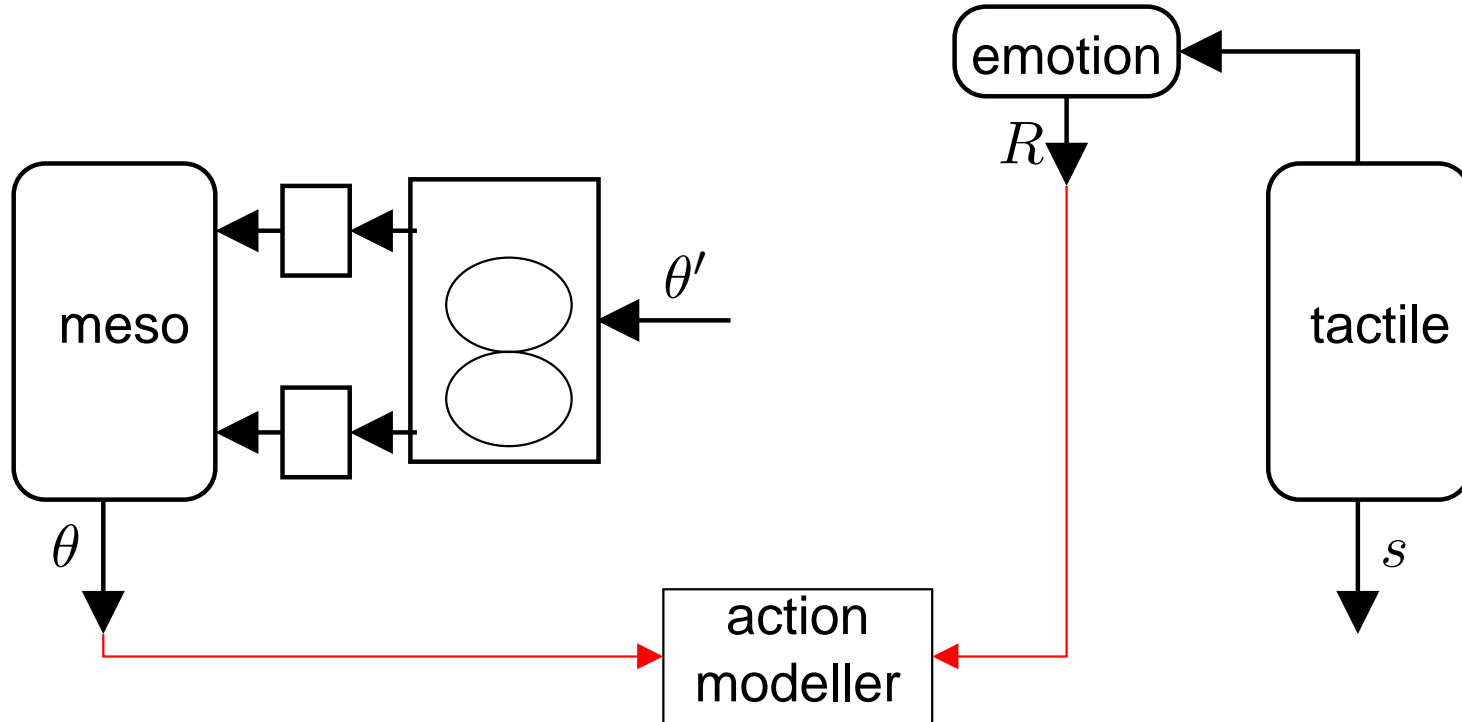
FingerBot learns to move



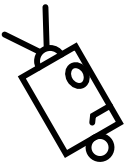
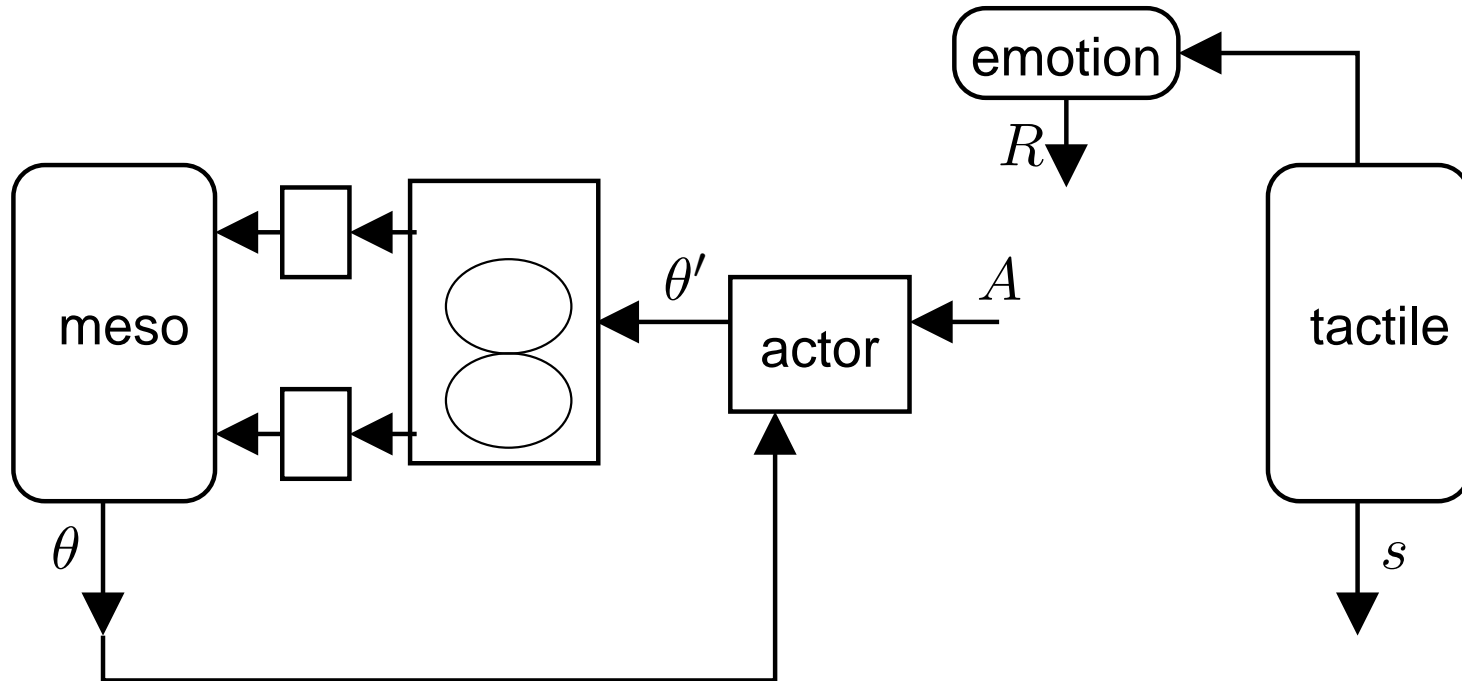
FingerBot controller



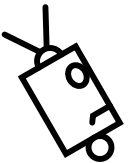
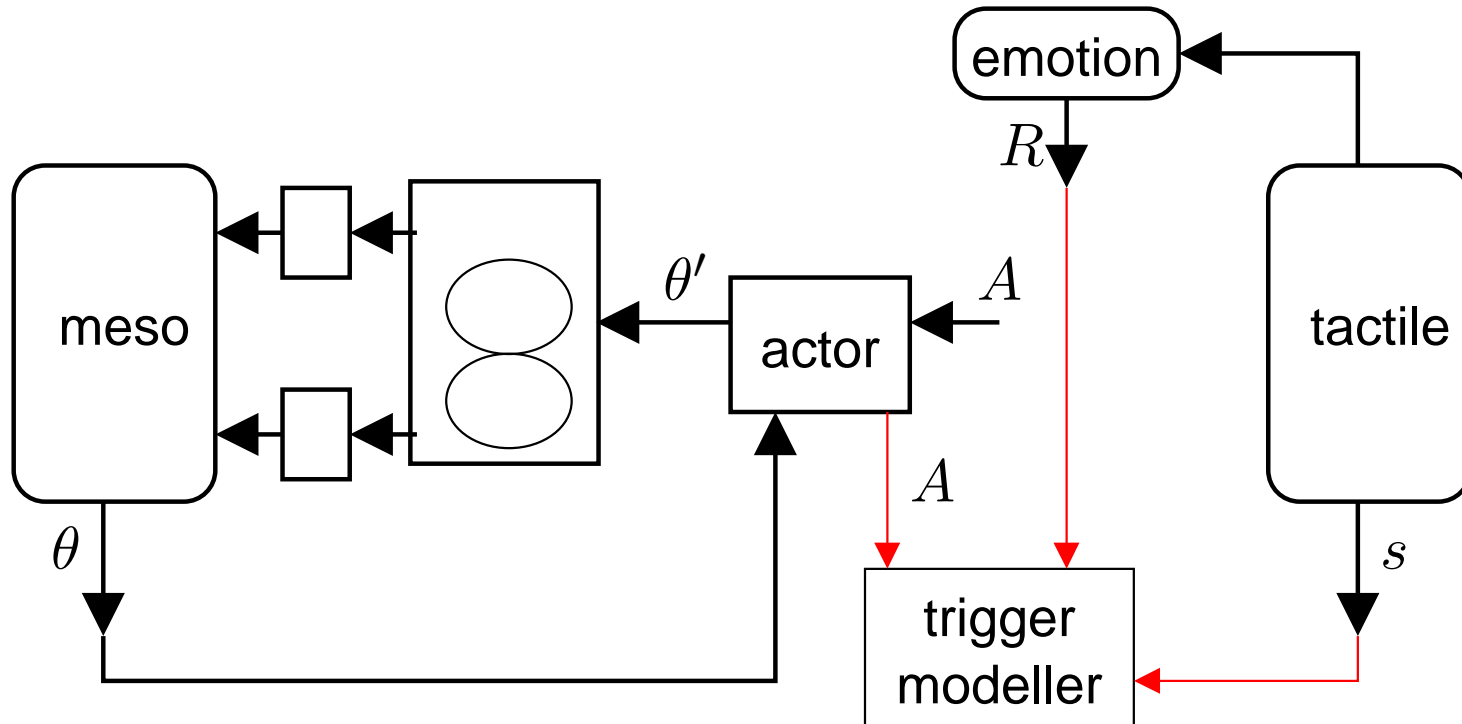
Teach FingerBot *how* to point



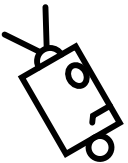
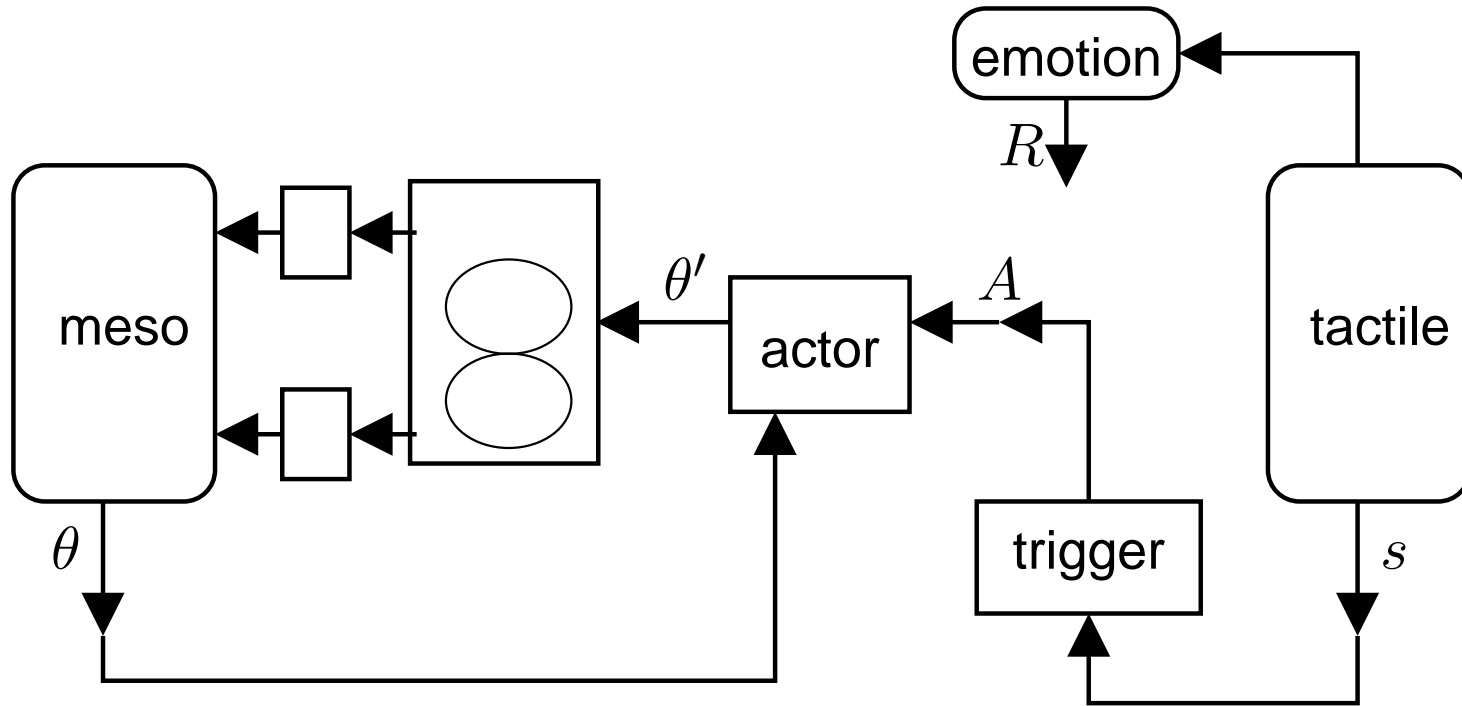
FingerBot points



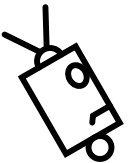
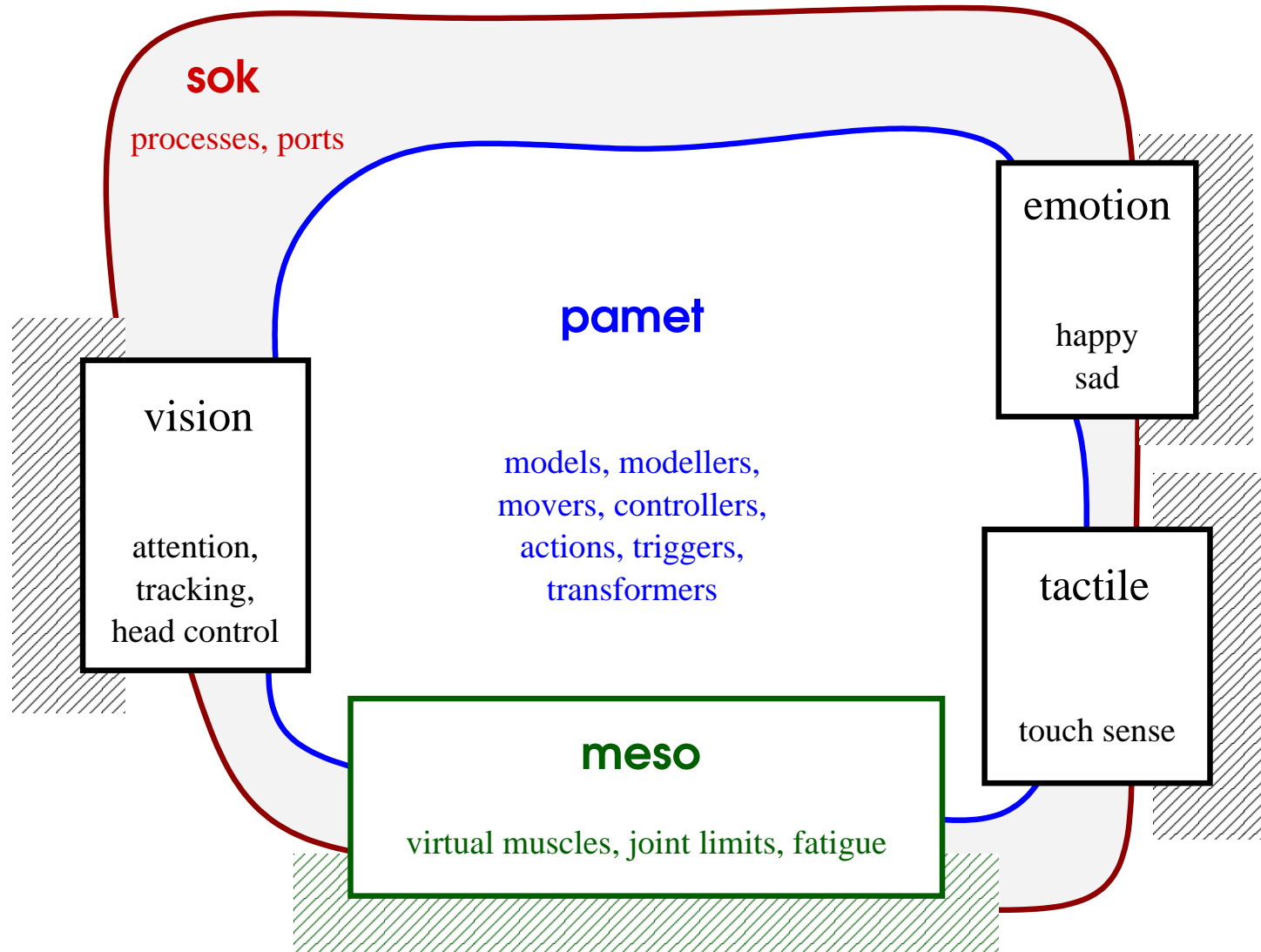
Teach FingerBot *when* to point



FingerBot points when touched



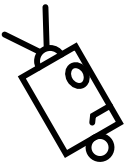
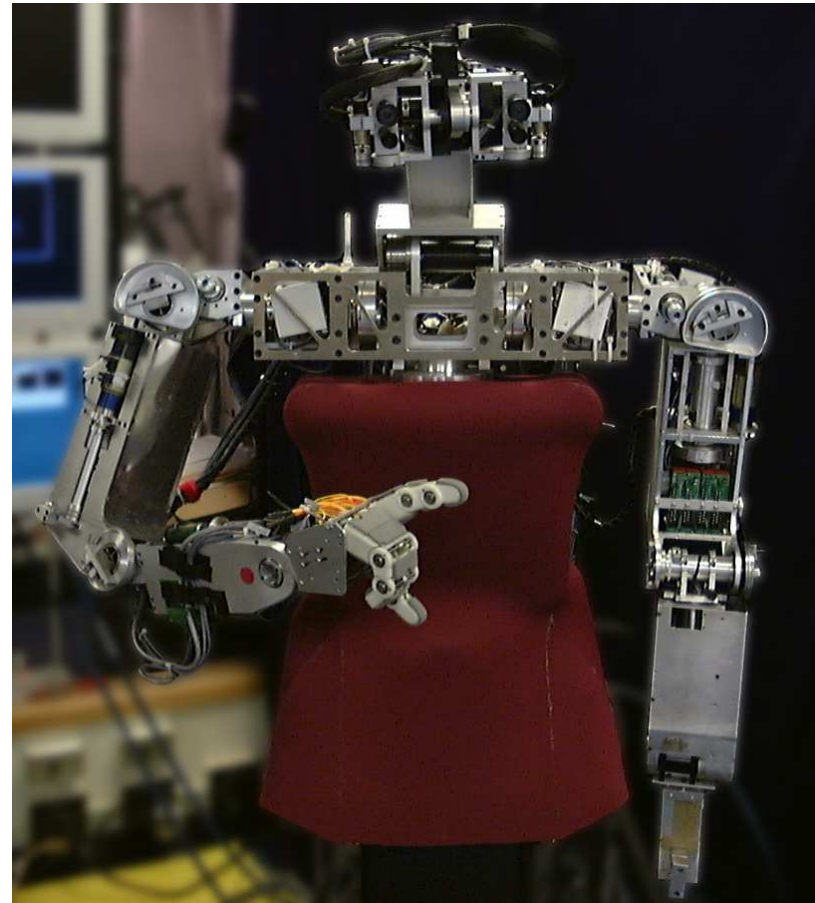
Overview



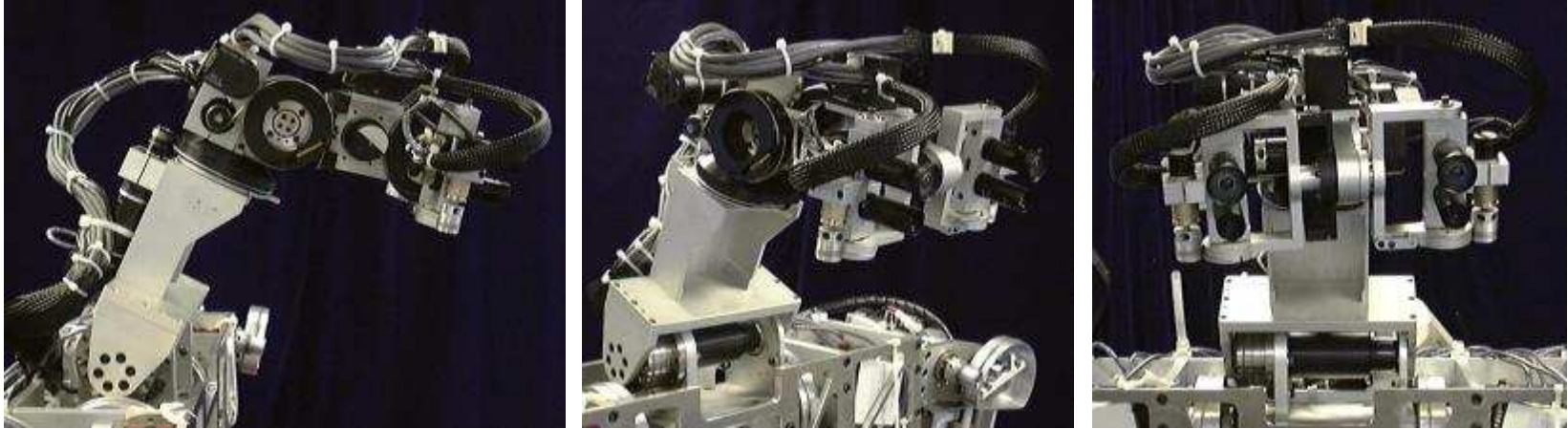
The Robot: Cog

Humanoid, anthropomorphic robot:

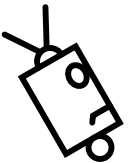
- 4-dof head, with 3-dof stereoscopic eyes
- two 6-dof torque-controlled arms
- 3-dof torque control in the torso
- off-board processing: ~28 off-the-shelf x86 PC's running QNX4



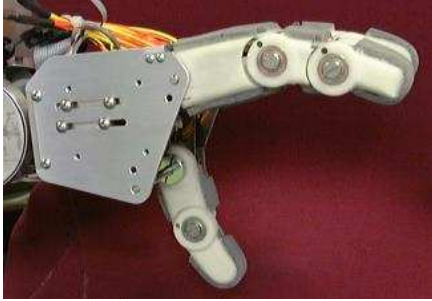
Cog's Head



- 4-dof in head: tilt, pan, roll, neck “lean”
- gyroscope: angular velocity, inclination
- 3-dof in two eyes: separate tilt, linked pan
 - dual cameras: wide-angle, narrow-angle “foveal”



Cog's Hand



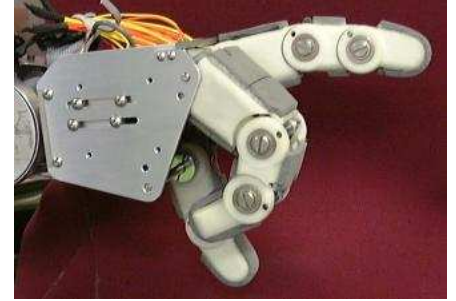
reach



grasp

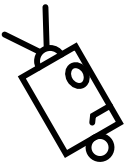


pinch



point

- 2-dof: linked finger/thumb, paddle
- Four recognizable gestures (sorry, no “thumbs up”)
- Six surfaces of tactile sensation



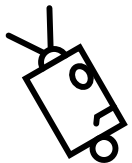
Why build a humanoid robot?

Assorted “practical” reasons:

- Create machines/tools which adapt to human environments.
- Test theories from cognitive science, neuroscience.

Grand philosophical reason:

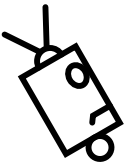
- We want to create a human-level machine intelligence.
- Intelligence is predicated on how an agent interacts with the world.



Metaphors We Live By

[Lakoff & Johnson, 1980]

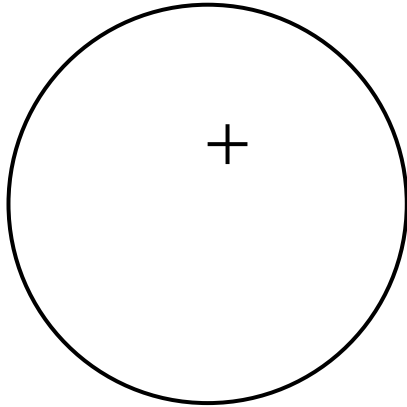
- Metaphors are not just linguistic constructs; we *think* in metaphors.
 - Happy is Up; Sad is Down.
 - Significant is Big.
 - Time is Money.
- No *literal* meaning; no reduction to discrete propositional forms or symbols.
- *Operational* meaning: represent consistent patterns of interaction.
- Grounded in experience.



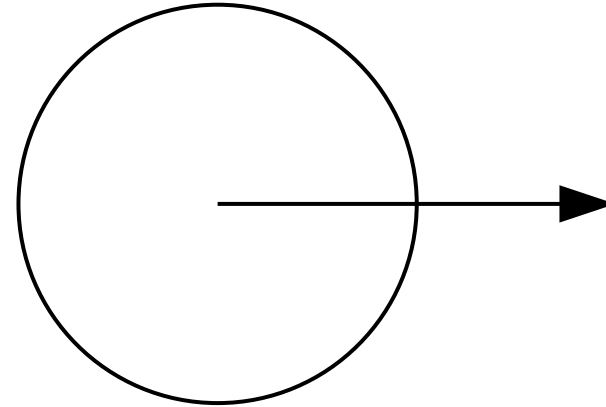
The Body in the Mind

[Johnson, 1987]

Some metaphors are cultural;
some arise from basic human physical interactions: *image schemata*.



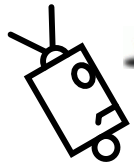
CONTAINER



IN-OUT

Simple relationships which appear at all levels of thought:

- Physical: “George put the toys in the box.”
- Abstract: “Donald left out some facts.”

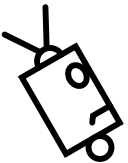


So, what does this mean?

If you want to build a *human-like* machine intelligence:

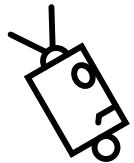
1. You need a system which can develop and manipulate metaphorical structures.
2. Those structures must be grounded in raw sensory and motor experiences.
3. Those experiences must be human-like.

(You need a humanoid robot.)



Cog is a humanoid robot.

- Much work on different aspects of humanoid-ness...
 - Matt Williamson: motor control via coupled non-linear oscillators (central pattern generators).
 - Robert Irie: auditory localization.
 - Cynthia Breazeal (Kismet): facial/vocal gestures, social interaction, emotional models.
 - Brian Scasselatti: visual animate/inanimate distinction, theory of body, imitation of simple motions.
 - Paul Fitzpatrick: visuomotor object understanding.
- Isolated parts, lacking direction/means for integration.
- Mostly learning parameters, not structures.

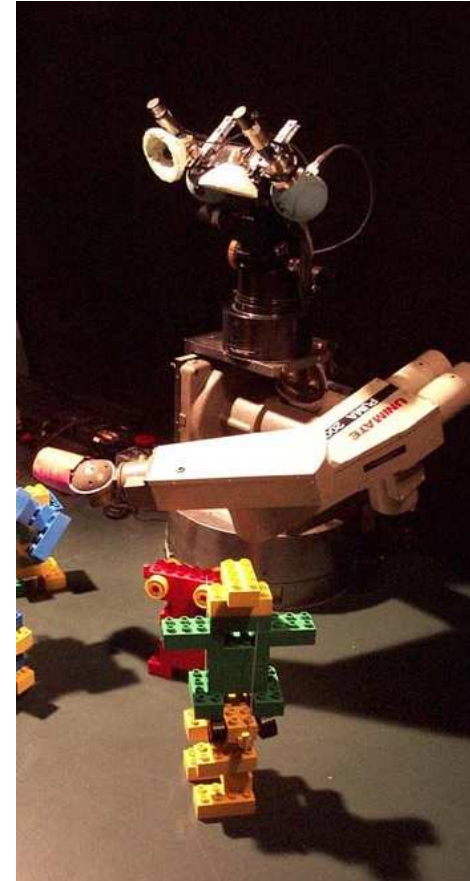
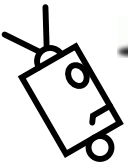


(Where are the metaphors gonna go?!)

Metta's Babybot

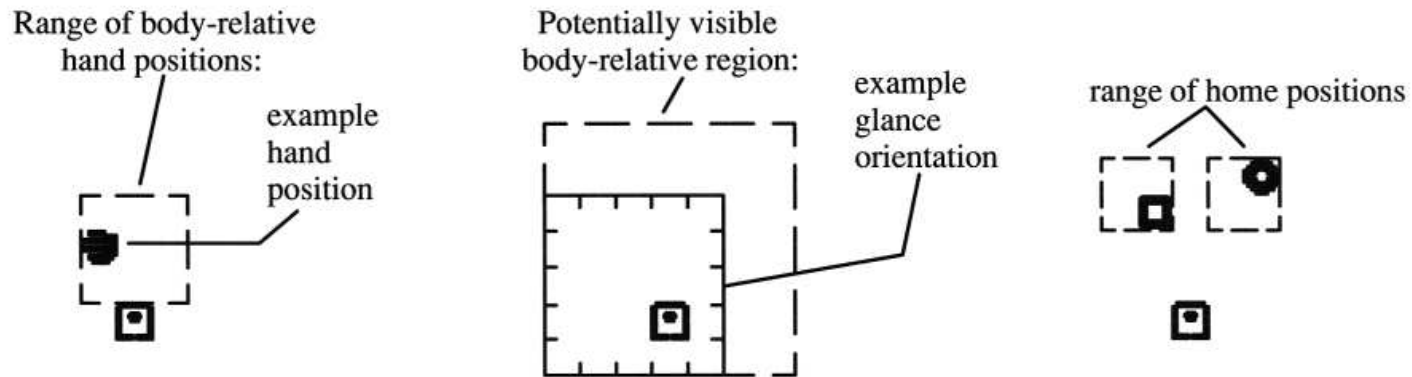
[Metta, 1999]

- 5-dof head with stereoscopic vision, gyroscope
- 6-dof torque-controlled arm
- Learns a developmental progression of sensorimotor coordination:
 - Saccades to visual targets via visual feedback (head motion rare).
 - Coordinated head and eye movement (random arm movement).
 - Controlling movement of arm, as a visual target.
- Culminates in reaching out toward moving visual stimuli.

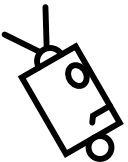


Drescher's Schema Mechanism

- Simulated robot learns progressively more abstract relations by interacting with its world. [Drescher, 1991]



- Mechanism has *items*, *actions*, *schemas*: predictors, CONTEXT + ACTION \Rightarrow RESULT
- Learning and abstraction:
 - New schemas for more specific context or result.
 - Composite actions and synthetic items.

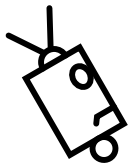


Schema Issues

Completely unrealistic simulation:

- 2-D grid-world with binary features.
- 10 discrete primitive actions.
- Total of 141 bits of primitive binary state.
- No physics, no noise.
- Serialized state-machine for action execution.

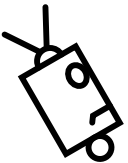
It's a symbolic AI engine for a symbolic universe.



A Design Philosophy

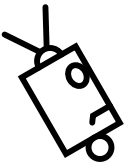
First and foremost, Real-World Constraints:

- Real robot, real physics.
- Real-time operation — human time-scales.
- Distributed computation — expandable, scalable.
- Noise — because separating signal from noise is what it's all about!

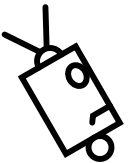
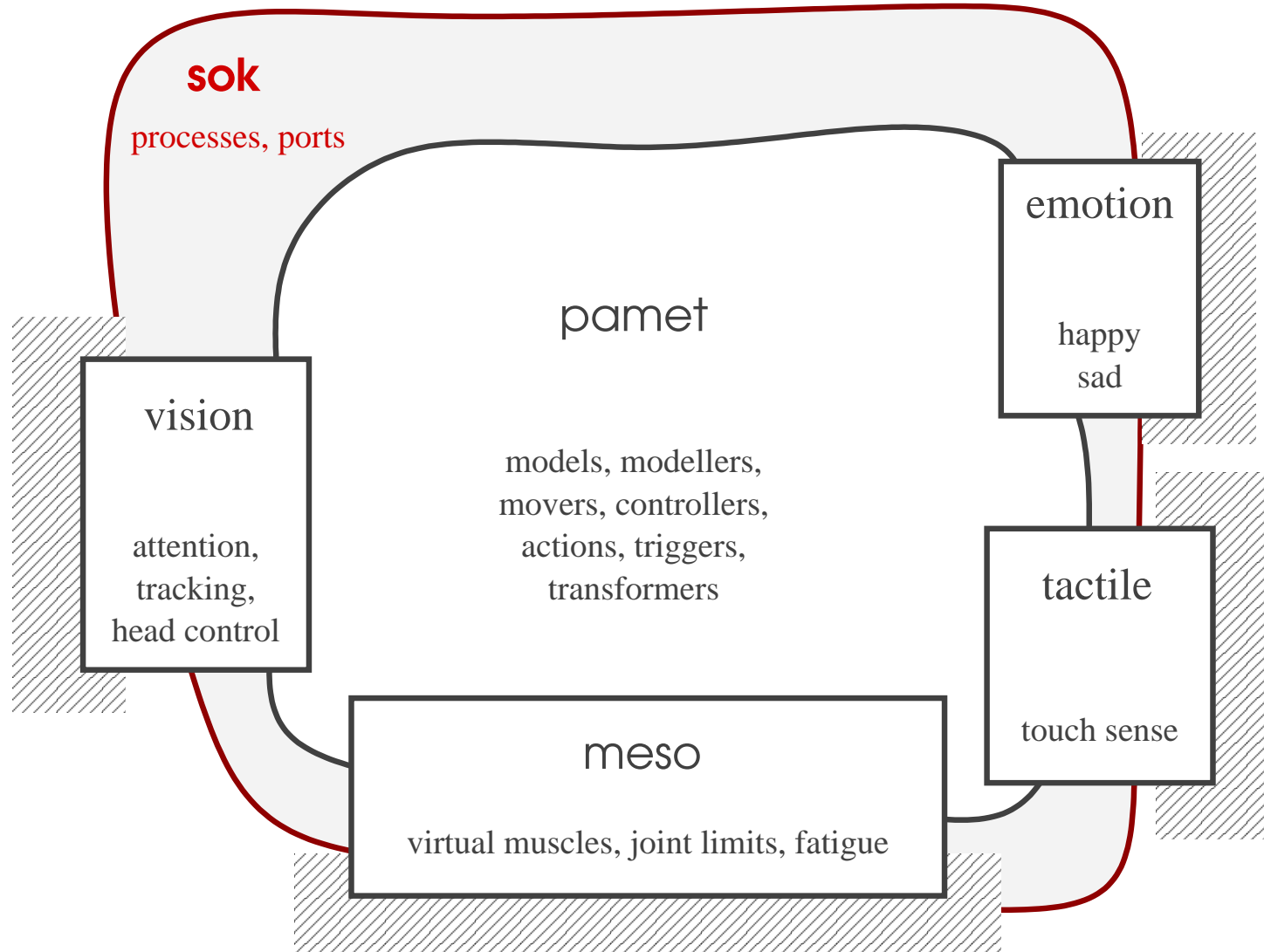


A Design Philosophy

- Dynamic: create new models/concepts.
- Transparent: compatible representations across modalities.
 - Reuse same machinery at different levels of development or abstraction.
- Malleable: states/actions/etc allowed to change/evolve.
- Distributed control: no central planner, arbitrator, action selector, modeller.
 - Only serialize operations when required by resource contention.
- Grounded close to the raw physics.



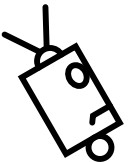
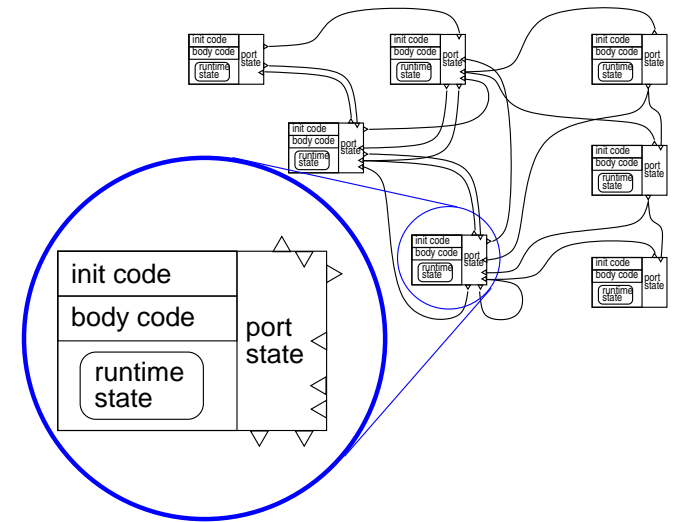
Three Pieces



sok: Behavior-based Environment

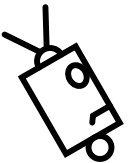
Dynamic network of *sok* processes, connected via *inports* and *outports*.

- Provides interprocess communication and process control.
- Connection-based message-passing.
- Event-driven code.
- Distributed: works transparently over a network of processors (via QNX).
- C, C++ libraries, plus utilities.



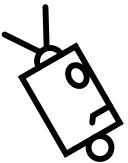
sok Features

- Processes and connections are *dynamic*.
- Network is *tangible*.
 - Processes can be aware of the network topology.
 - Processes can search for other ports/processes by traversing the network.
 - Ports are typed.
- Separation of message-handling code and *body code*.
 - Processes can be killed and restarted without affecting connectivity.
- State of *sok space* can be dumped/restored from disk.



sok Type System

- Ports are typed: C-like (or IDL)
 - 10 atomic `int` and `float` types, plus arrays and structures.
 - Can define constants, too.
- Scheme-based type compiler generates `.h` and `.c` files from `.stc` files.
- Type compiler is embedded in the sok library; type descriptions can be processed at runtime.
- Functions for walking typed buffers, generating composite type identifiers, housekeeping.



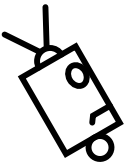
sok Arbitrators

Message passing is asynchronous and anonymous:

- Data received by an inport is buffered, and body process receives an event.
- Default behavior is to overwrite — no queueing.
- Body code doesn't know about multiple connections.

Arbitrator: code which will change reception behavior, e.g.

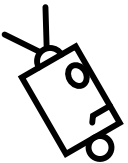
- *Summing*: Inport keeps a running sum of received data.
- *Averaging*: Body process sees the mean of all data received between reads.
- *Blocking*: One connection wins right to monopolize the port; messages from others are discarded.



Dump and Restore

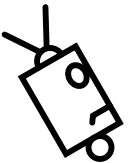
sok provides a dynamic environment, processes and connections come and go as a system develops.

- sok processes can be told to dump state to disk:
 - Connections to ports.
 - Persistent data, arbitrator state.
 - Command-line arguments, etc.
- Entire state of machine can be dumped or restored with single shell command.

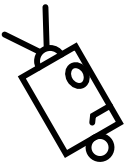
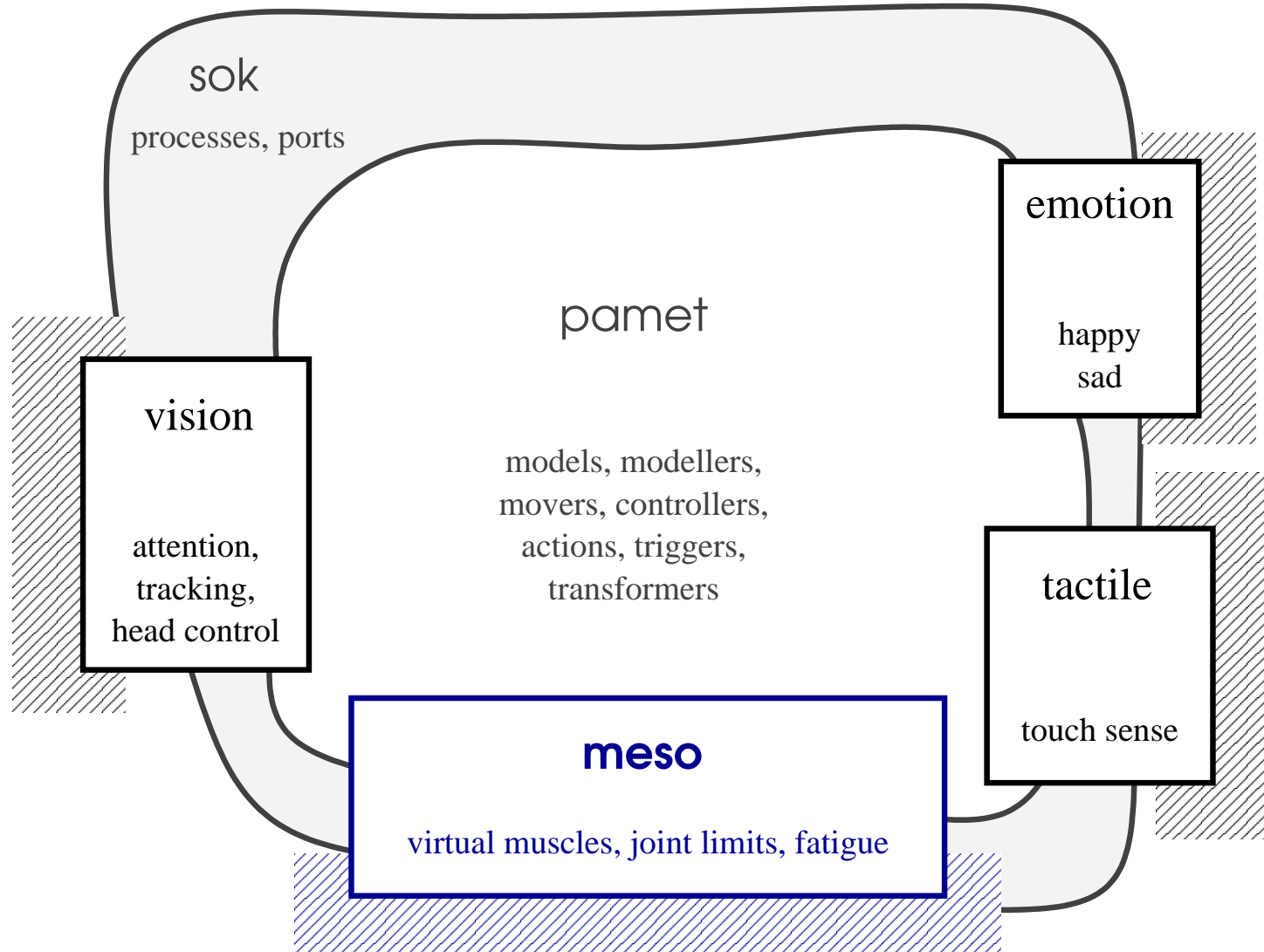


Handy Utilities

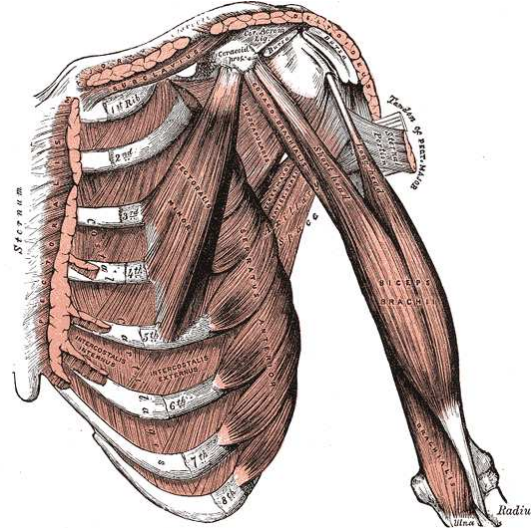
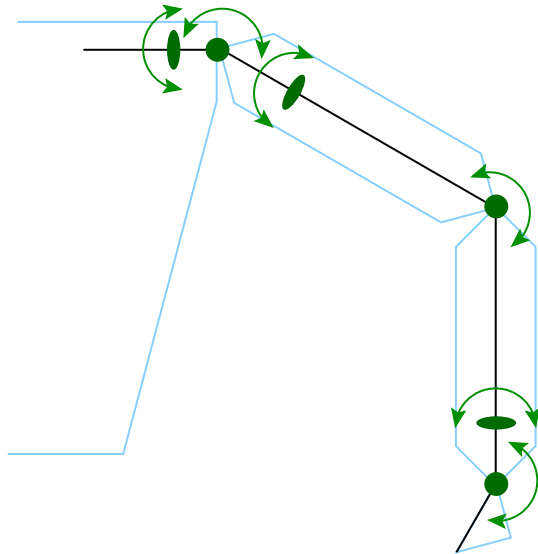
- sok command-line interface:
 - inspect network, processes, ports
 - make/break connections
 - spawn/kill processes, send signals
 - initiate dump and restore
- *Megasliderama* Swiss-army GUI:
 - create panels of widgets connected to ports
 - sliders, stripcharts, buttons, image planes, . . .



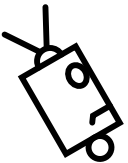
Sensory and Motor Boxes



meso: Biological Motor Control

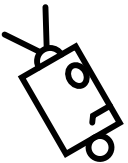


- Implements spring-like *virtual muscles*.
- Allows for *multi-joint coupling*.
- Provides performance feedback:
 - Muscle fatigue.
 - Joint pain.



Why muscles? Fatigue? Pain?

- Movement is influenced by limitations of physiology.
 - We try to minimize energy use, take advantage of physics.
 - We avoid uncomfortable motions.
- Concepts linked to physical interaction are derived from those limitations.
 - “heavy” = “things which make muscles tired”
 - “stretching limits”
- Cog’s electric motors have no innate fatigue.



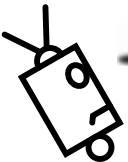
Why spring-like? Multi-joint?

Why spring-like?

- Real muscles are very non-linear force-producing elements, operate in antagonistic pairs.
- At spinal level, feedback loops make muscle groups behave like simple springs.
 - *Equilibrium-point control* hypothesis. [Bizzi, Kelso]

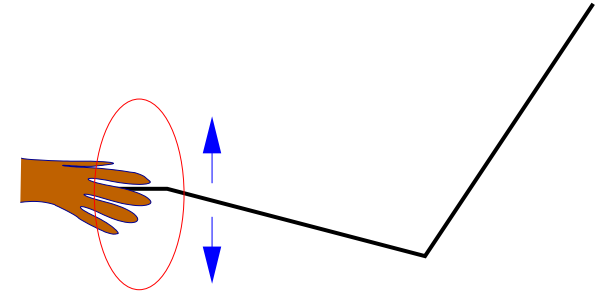
Why multi-joint coupling?

- Real muscles *do* span multiple joints.
- Necessary for complete control of endpoint stiffness. [Hogan, 1985]
- Multi-joint muscles enhance efficiency of certain movements. [Gielen, 1993]

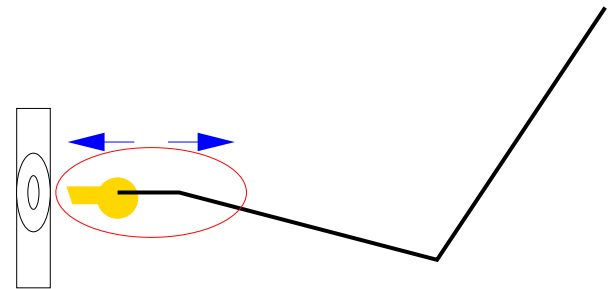


meso: Endpoint Stiffness

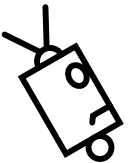
- Single-joint springs do not allow for full control of stiffness in *endpoint space*.
- Endpoint stiffness should be tuned to match the task.



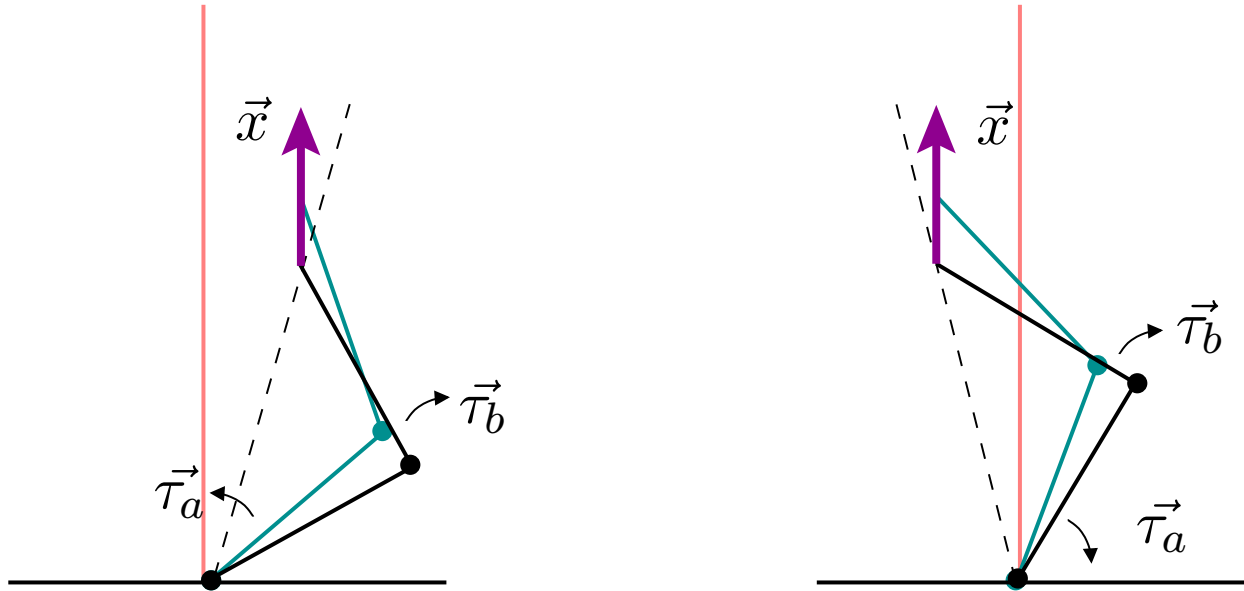
Handshake: low vertical stiffness



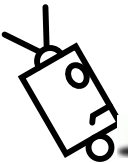
Key in lock: high vertical stiffness



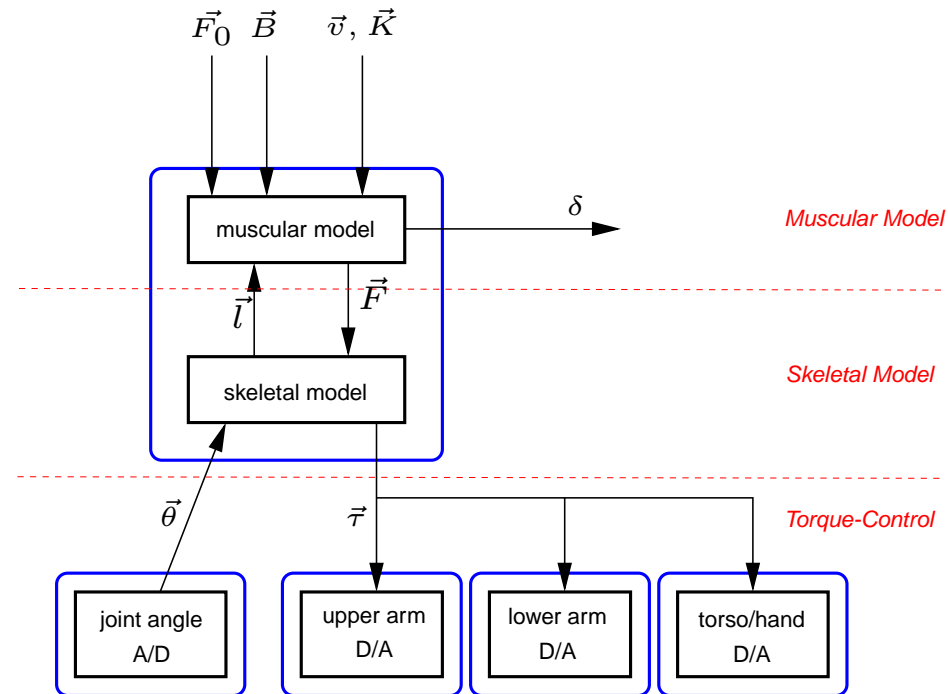
meso: Multi-joint Efficiency



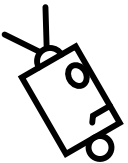
- Depending on configuration, single-joint muscles may undergo *lengthening contraction*, i.e. dissipating energy.
- A multi-joint muscle acting as stiff linkage prevents this, makes motion more efficient.
- To Cog, such motion will *feel* more efficient.



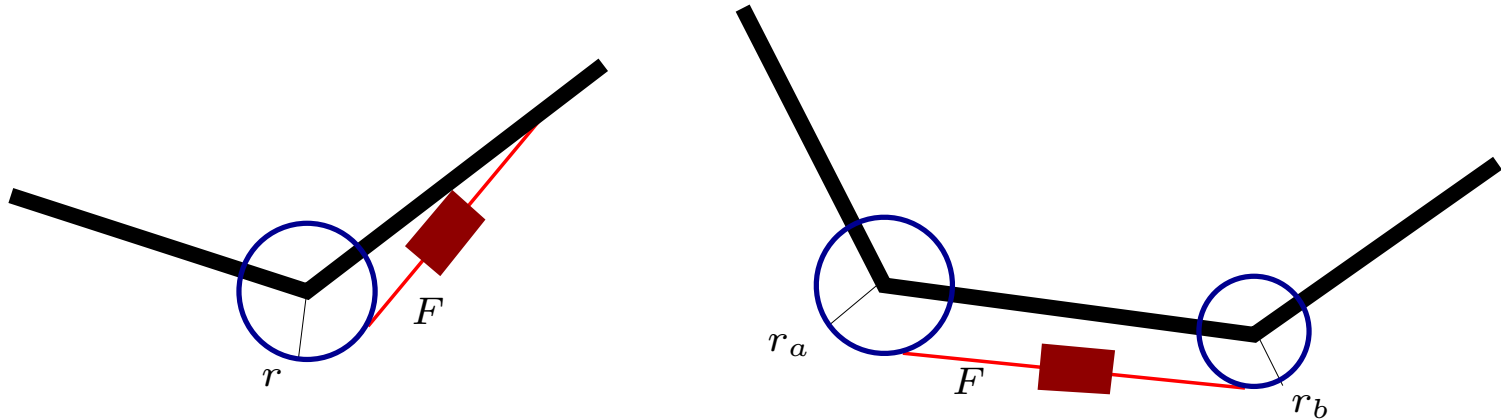
meso: Three Layers



- Low-level torque control.
- Skeletal model (muscle kinematics).
- Muscle model (muscle dynamics, fatigue).

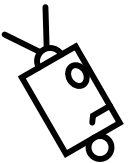


meso: Skeletal Model



- Compute muscle lengths $l(\vec{\theta})$, joint torques $\vec{\tau}(\vec{F}, \vec{\theta})$.
- Simple “pulley” model:

$$l_m = \sum_j r_{jm} \theta_j, \quad \tau_j = \sum_m r_{jm} F_m$$

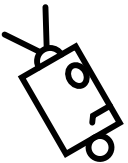


meso: Muscle Model

- Compute forces from lengths, i.e. spring-law:

$$F = K(l - l_0) - B(\dot{l}) + F_0$$

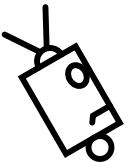
- Setpoint l_0 and stiffness K are control parameters.
- Damping constant B needs to be tuned.
- Bias force F_0 can be used for feedforward control (e.g. gravity/posture).



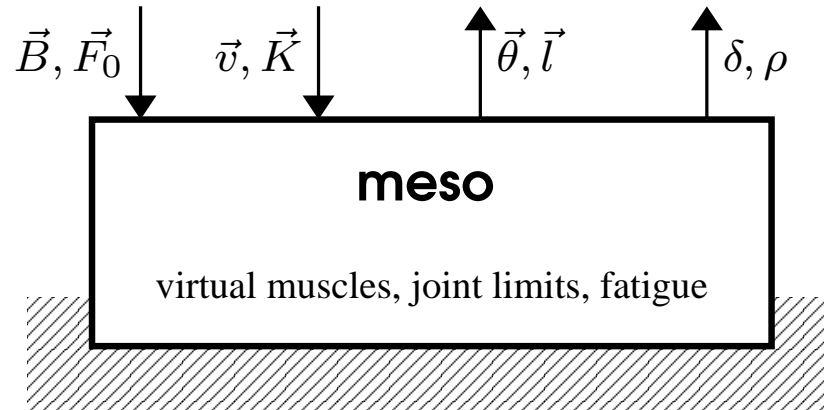
Fatigue Model

- Adams [2000]: detailed biochemical fatigue model:
 - Glucose/glycogen, adipose tissue, heart rate, insulin/glucagon/epinephrine...
- Abstracted further:
 - Required power: $P = \alpha|Fv| + \beta|F| + \gamma K$
 - Metabolic supply: P_R
 - Energy reserves: short-term S_S , long-term S_L .
- Discomfort and muscle efficiency due to S_L :

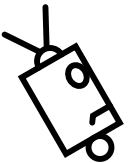
$$\delta = 1 - \left(\frac{S_L}{S_{L0}} \right), \quad \phi = \left(\frac{S_L}{S_{L0}} \right)^{1/2}$$



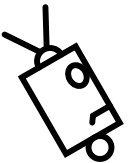
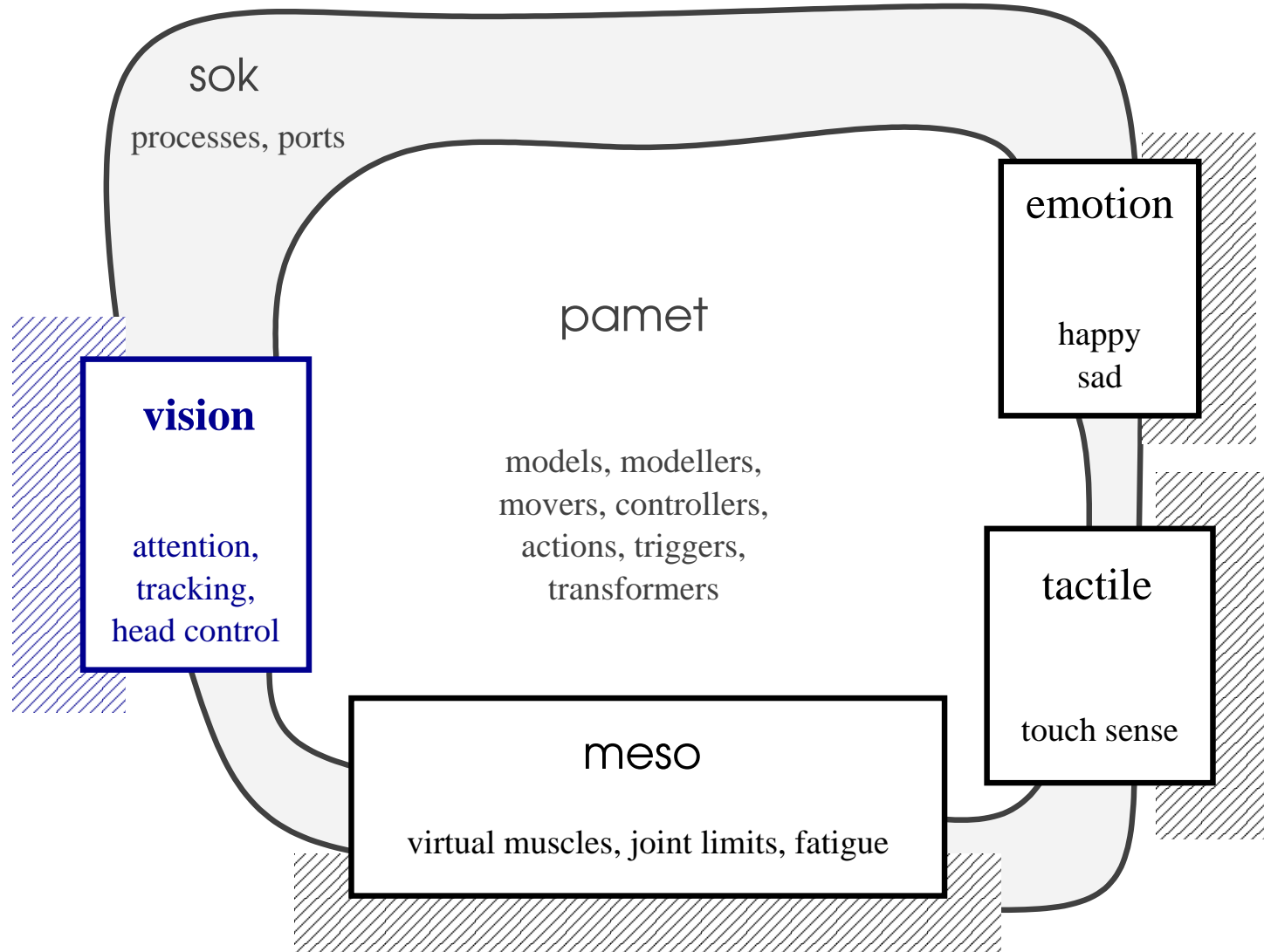
meso as a Black-box



- Inputs: muscle setpoint *velocity*, stiffness.
- Outputs: joint angles, muscle lengths, fatigue, pain.

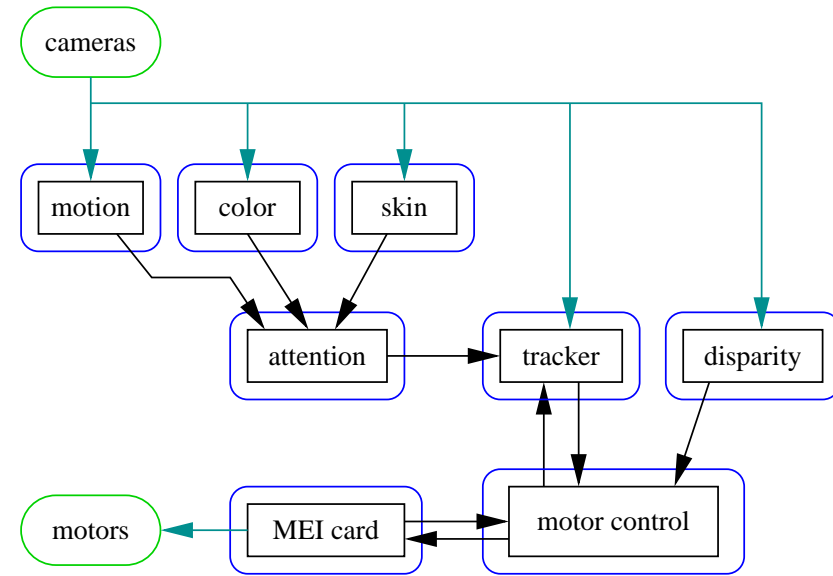


Next Box: Vision

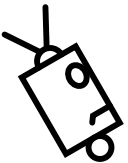


Vision System

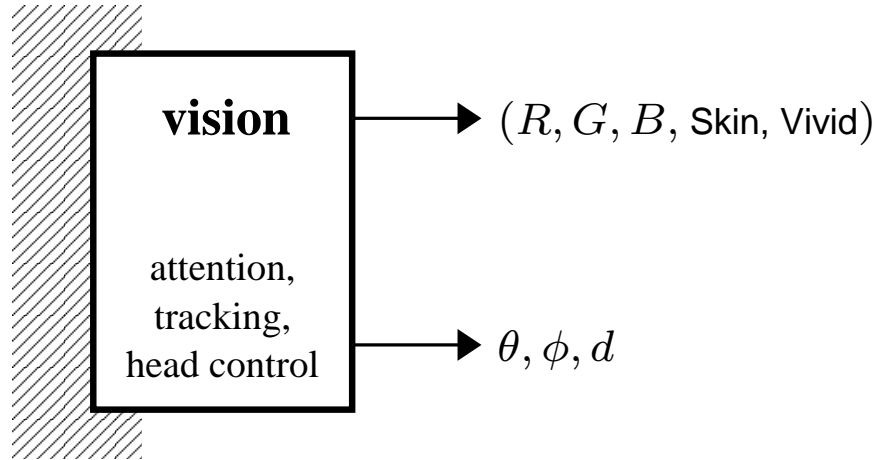
- Saliency filters:
 - Color, skin tone, motion.
- Attention:
 - Weights/adds saliencies
 - Chooses potential targets.
- Tracking system:
 - Locks onto image patch.
 - Follows it around.



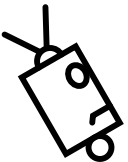
(thanks Paul and Giorgio!)



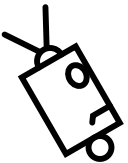
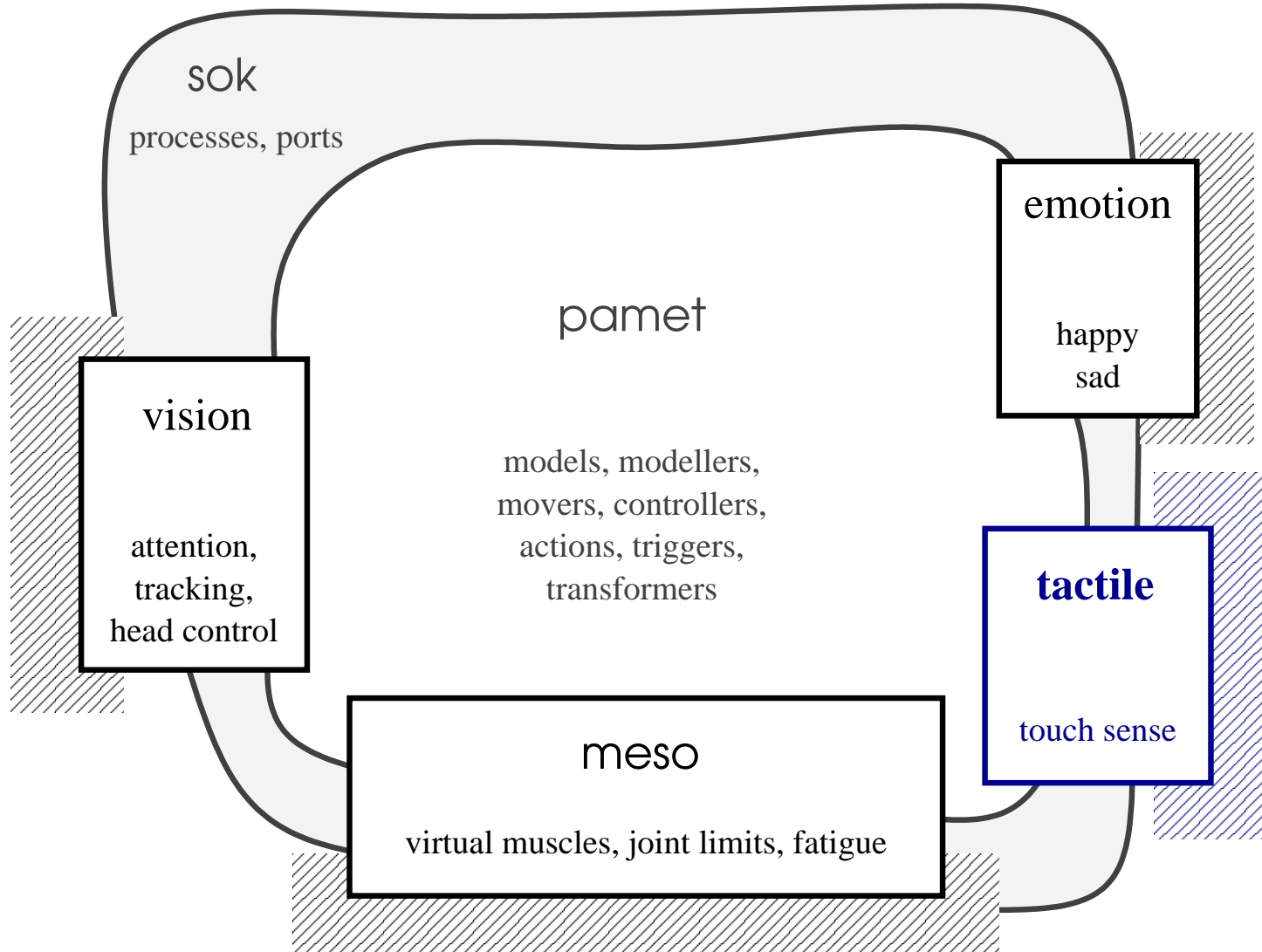
Vision as a Black Box



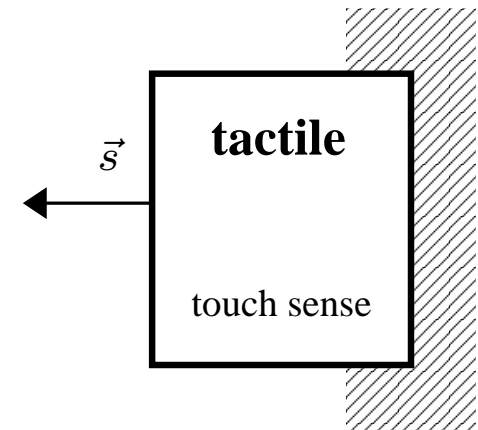
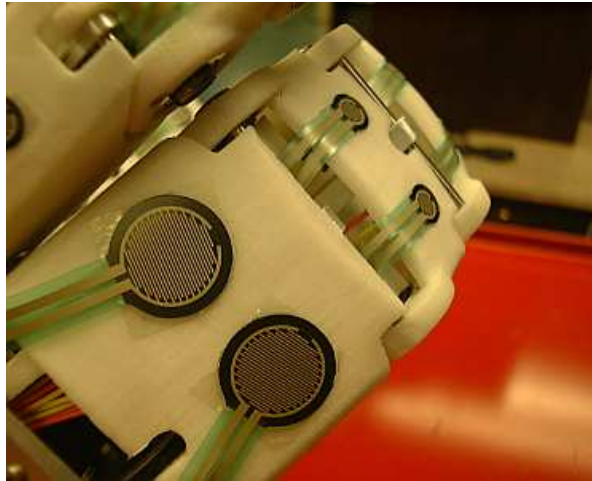
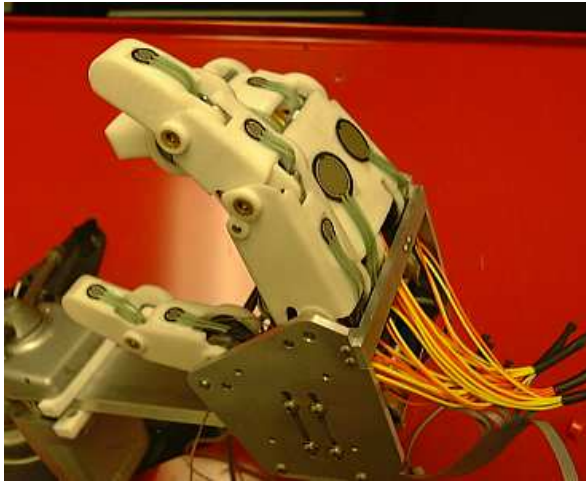
- Outputs only:
 - Target gaze-angles, disparity: (θ, ϕ, d)
 - Visual features of target: $(R, G, B, \text{Skin}, \text{Vivid})$



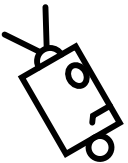
Next Box: Tactile Sense



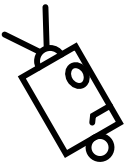
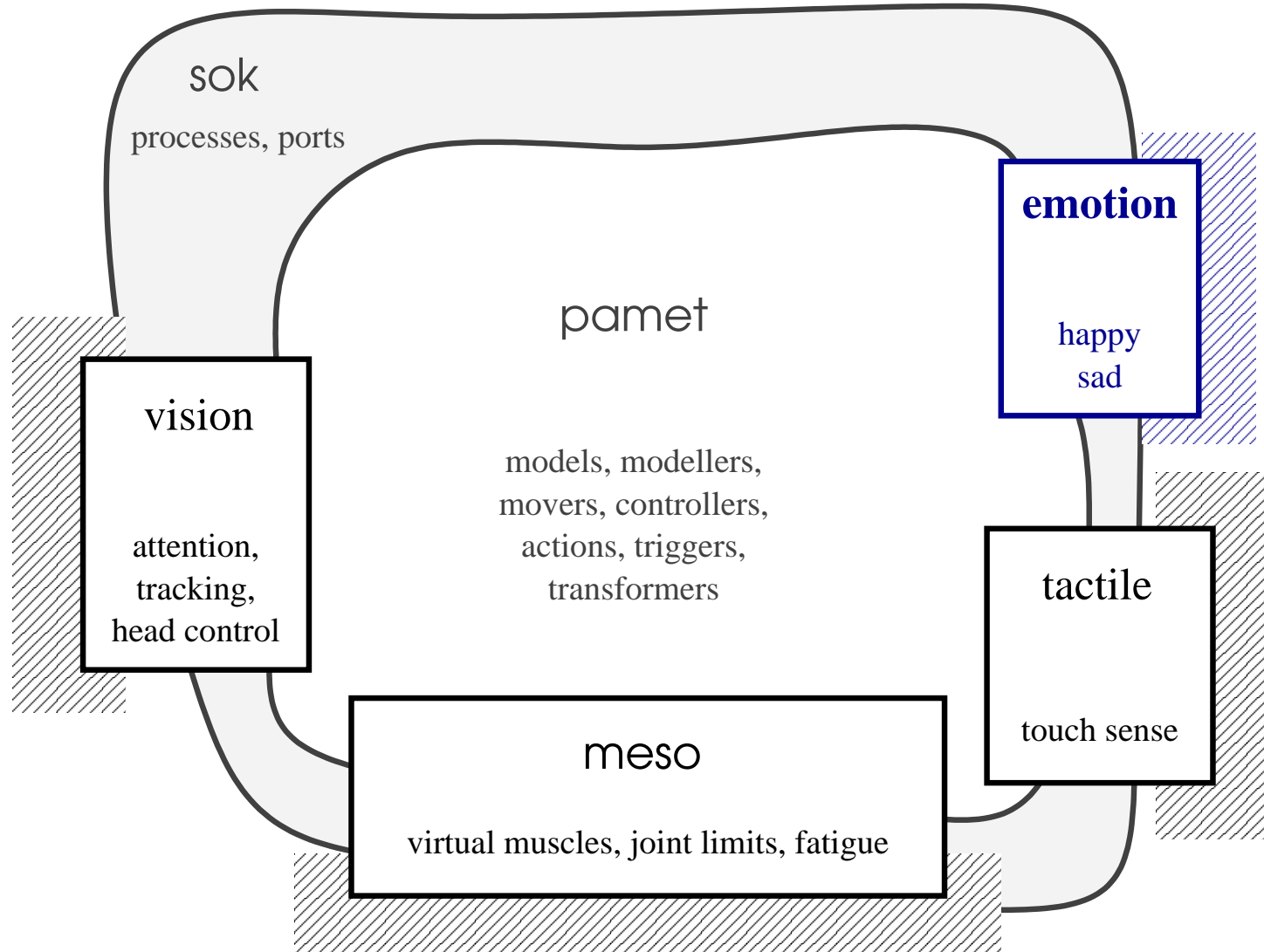
Tactile Sense



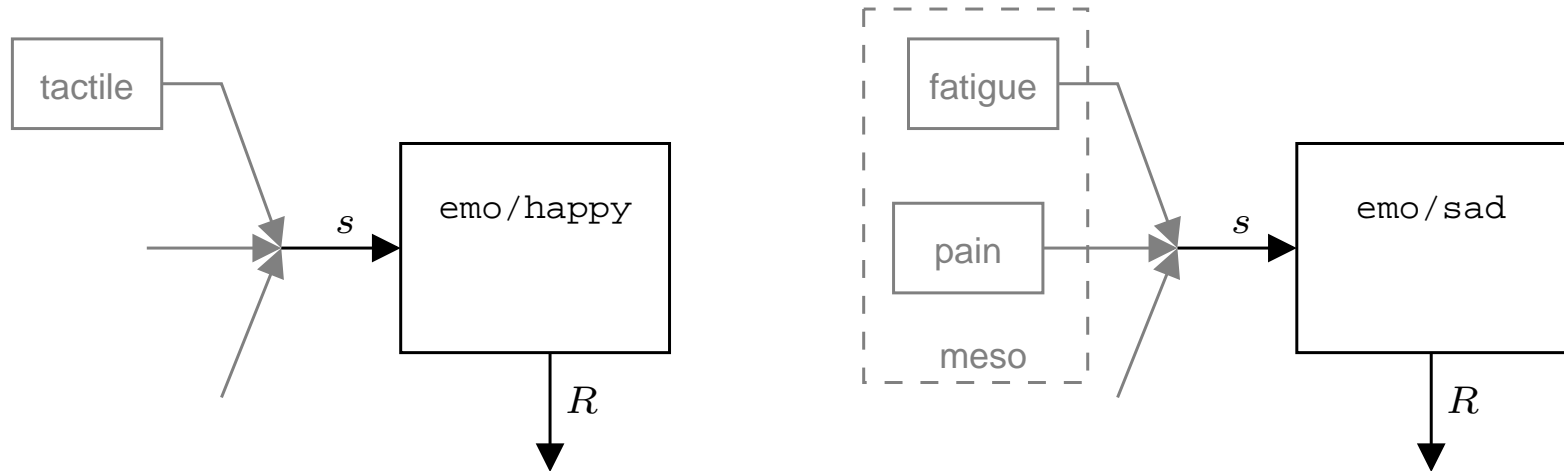
- 22 force-sensitive-resistor pads.
- Wired in parallel to yield six sensor surfaces.
 - Vector of six values, $[0, 1]$.



Last Box: “Emotion”

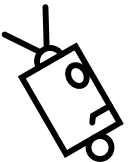


“Emotion”

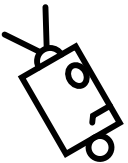
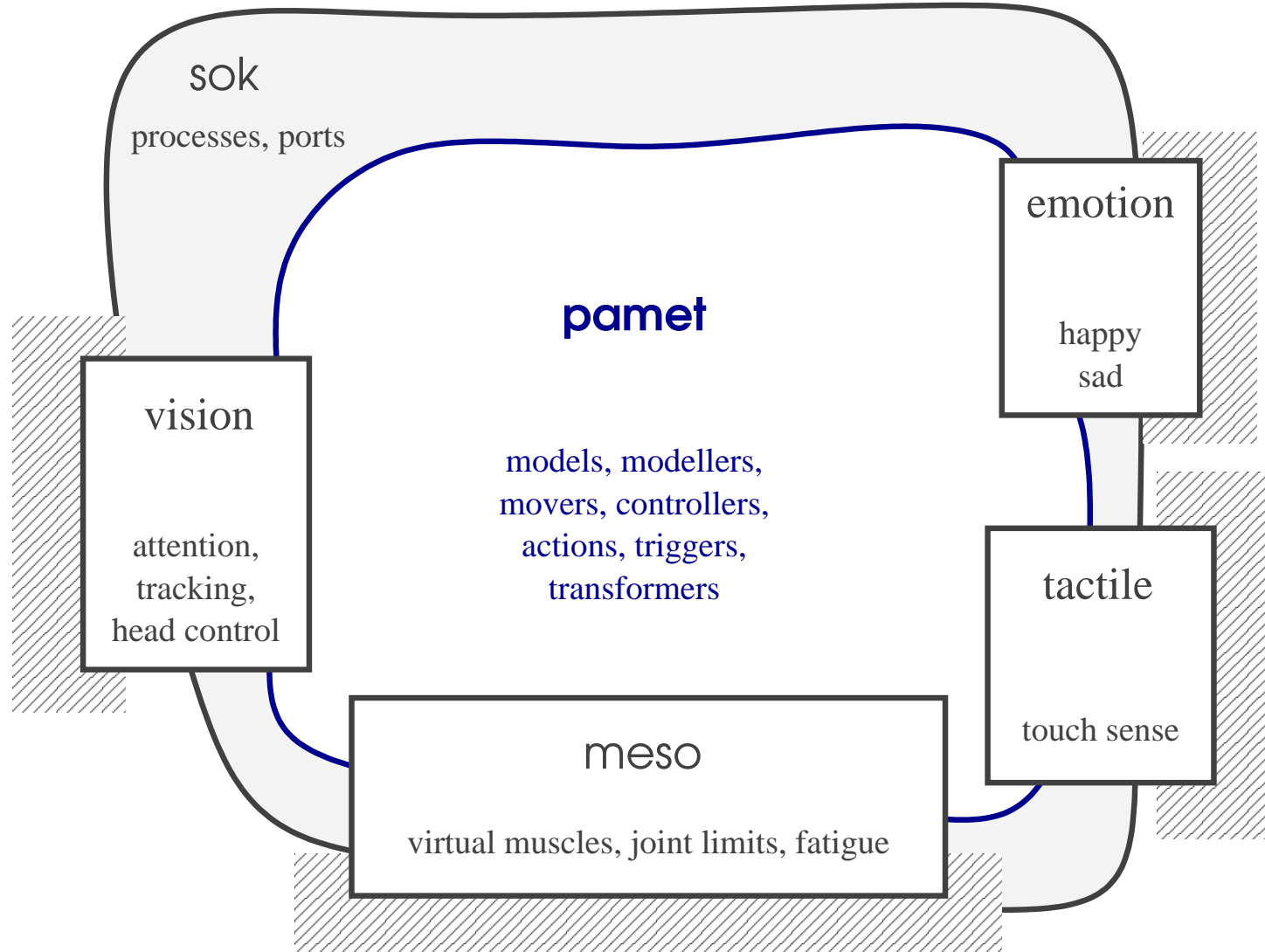


- Combines sources of innate positive/negative reward.
 - Positive: hand-squeezes.
 - Negative: muscle fatigue, joint pain.
- Leaky integrator dynamics:

$$R(t) = \lambda R(t - 1) + \sum r_i(t - 1, t)$$

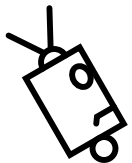


Final layer: pamet

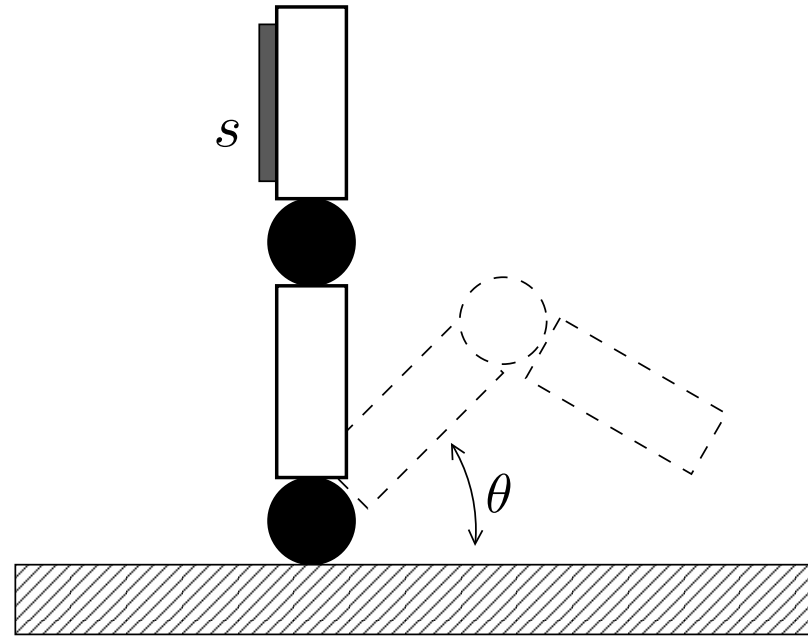


pamet: connecting, learning

- Static modules (sok processes) provide initial structure:
 - Sensory and motor primitives (black boxes, movers).
 - *Proto-modeller* modules to create modellers.
- *Modeller* modules try to discover relations between state parameters, and create models.
 - Mover models, action models, trigger models, transform models.
- *Instance* modules use the models to produce behavior, create new state parameters.
 - Controllers, actors, triggers, transformers.
- Knowledge is acquired in network structure and models.



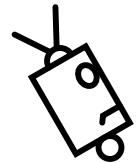
An Example: The FingerBot



- One degree-of-freedom: joint angle θ .
- Controlled by a single virtual muscle, length l .
- Single tactile sensor s .

 Goal: *Teach the finger to point in response to touch.*

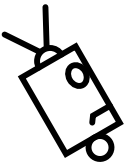
Implementation of the FingerBot



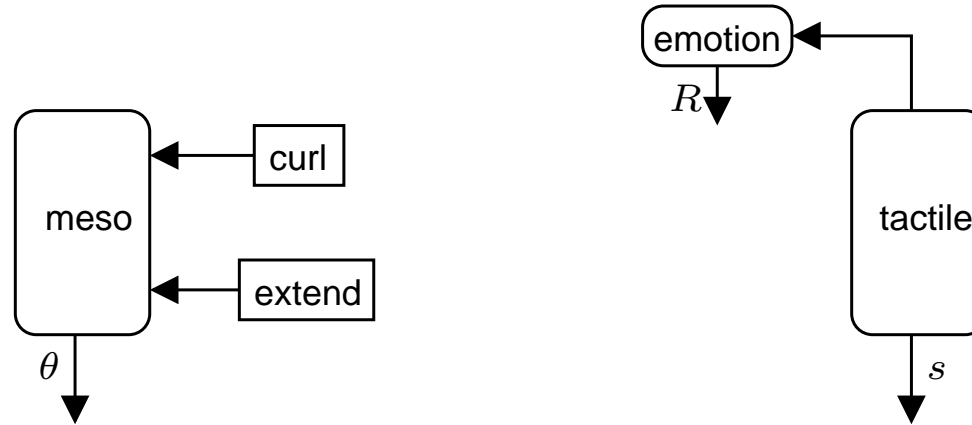
A Menagerie of Modules

<i>Module</i>	<i>Subclass</i>	<i>Inputs</i>	<i>Outputs</i>
mover	meso	A	
controller		\vec{v}	A
actor	position-constant	A, \vec{s}	\vec{v}
	position-parameter	A, \vec{s}_1, \vec{s}_2	“
	velocity-constant	A, \vec{s}	“
trigger	position	\vec{s}	A
	activation-delay	A_1, A_2	A
transformer		\vec{s}_1, \vec{v}_2	\vec{s}_2, \vec{v}_1, A

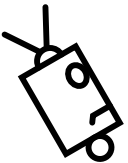
- Basic data types: state parameters \vec{s} , activations A , drive signals \vec{v}



FingerBot initial state



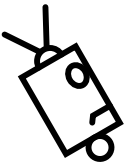
- Two hard-coded *mover modules*: “curl” and “extend”.
- *Mover* modules activate at random: exploration.
- Random activation is suppressed by explicit activation.



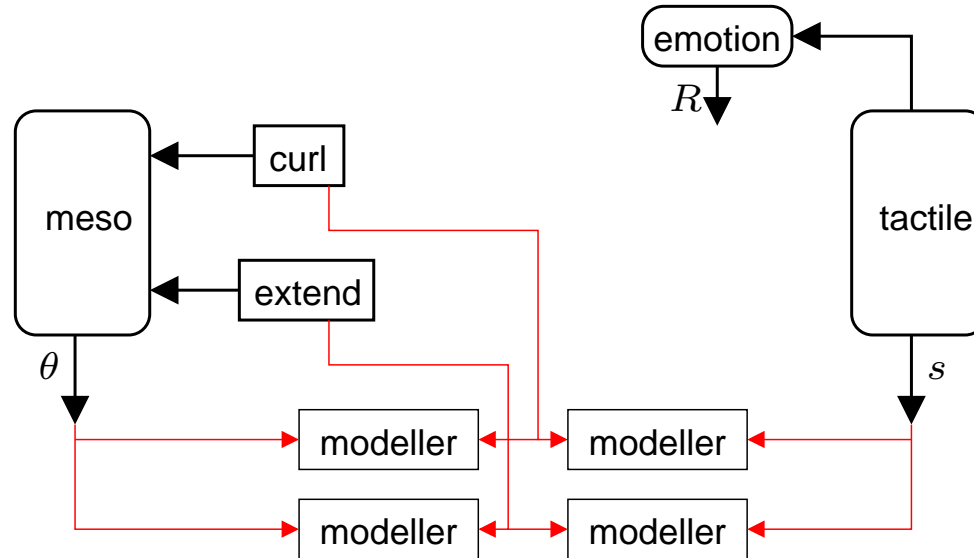
Mover

“Causes movement, rate modulated via a scalar parameter.”

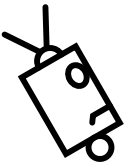
- *meso movers* are the primitive connections to the motor system.
 - Send a vector of muscle velocities, scaled by control parameter (and fixed stiffness).
- Effect on state parameters is modelled by *mover models*.



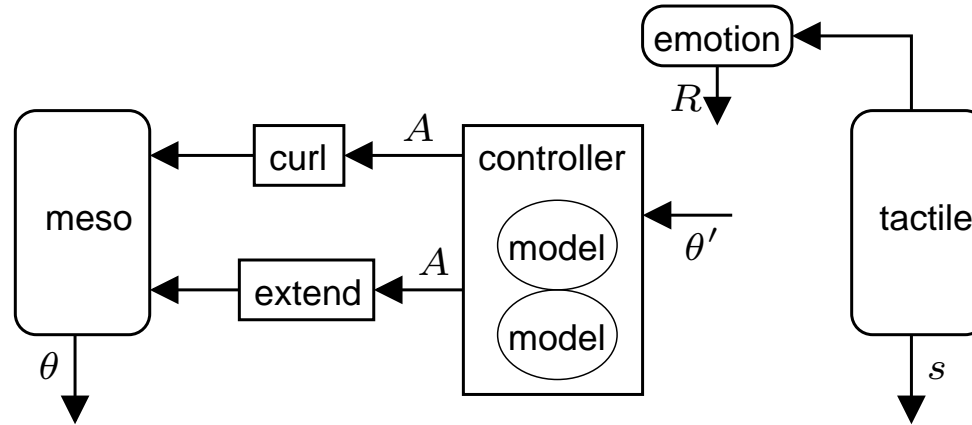
FingerBot mover modelling



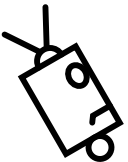
- *Mover modellers* are spawned for each pair of state parameter and mover activation.
- Learn/discover the relationship between the movers and the joint velocity.



FingerBot controller



- A *controller* is created for the joint angle: controls joint velocity by activating movers.
- Joint angle becomes a *controllable parameter*.

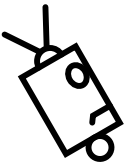
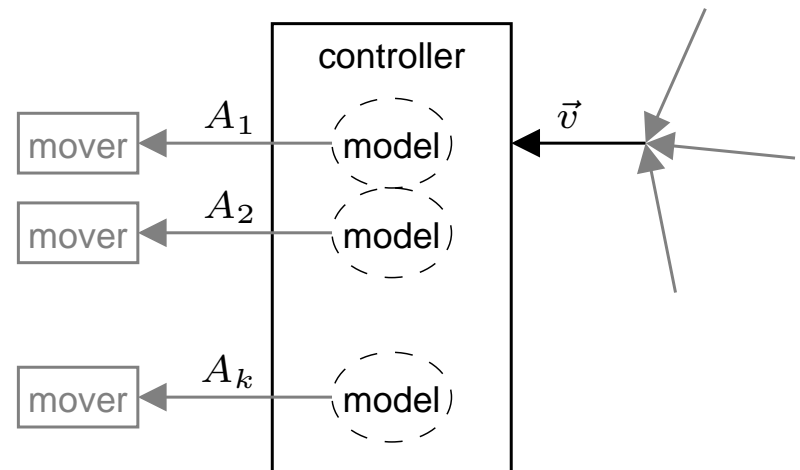


Controller

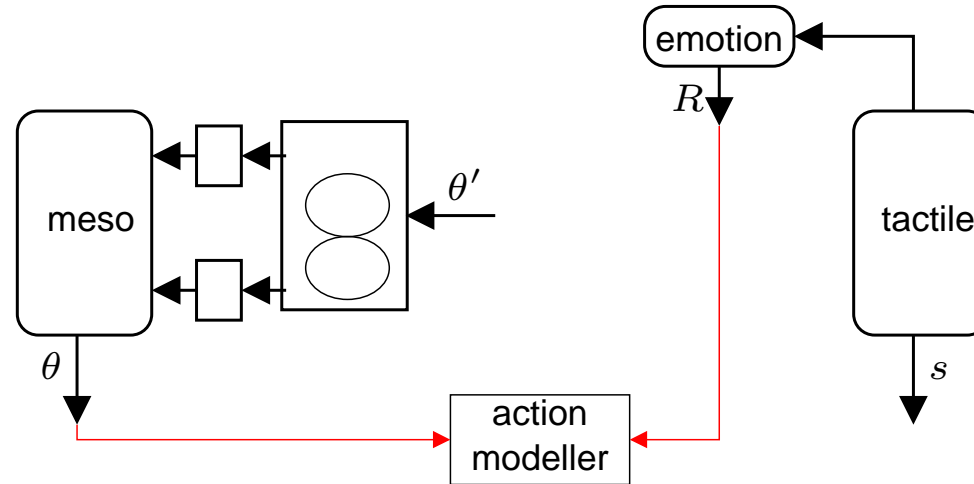
“Controls the velocity of a state parameter by activating movers.”

- Uses the mover models to determine how movers will affect state parameter.
- At each instant, activates the mover which will yield the velocity closest to the control input \vec{v} :

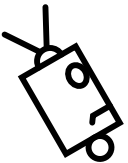
$$m = \arg \max \left(\frac{\vec{v} \cdot \vec{v}_m}{\|\vec{v}_m\|} \right)$$



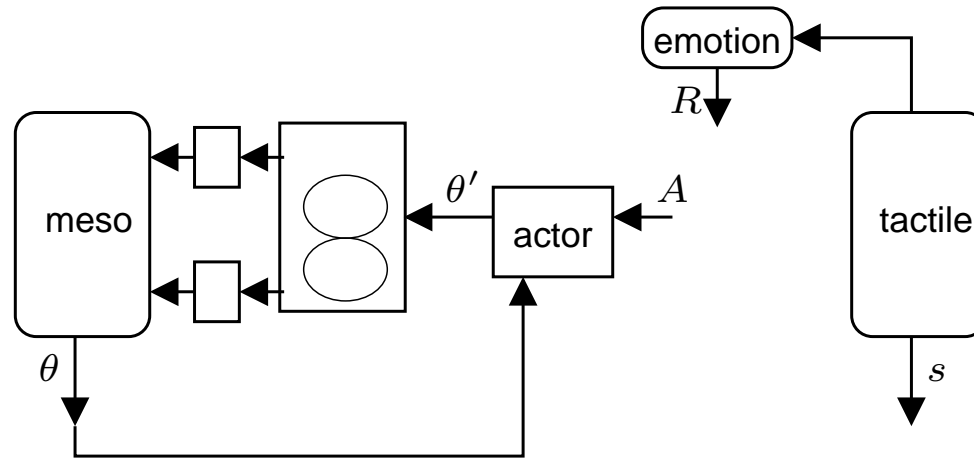
Training FingerBot to Point



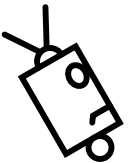
- An *action modeller* is created for each controllable parameter.
- Correlates reward with joint angle; creates an *action model* for the pointing posture.



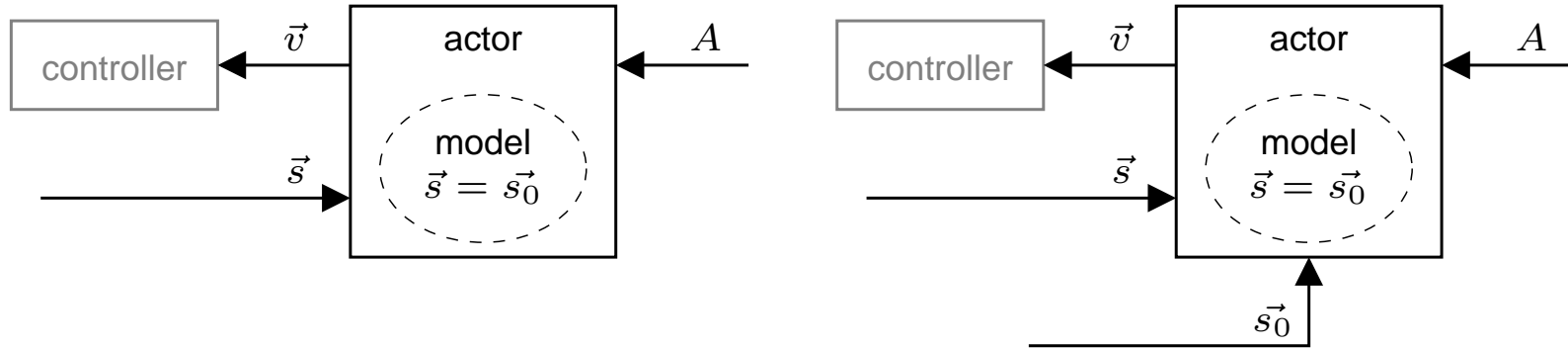
Training FingerBot to Point



- An *actor* is spawned, which moves finger to the pointing position at random times.

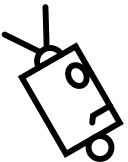


Actor

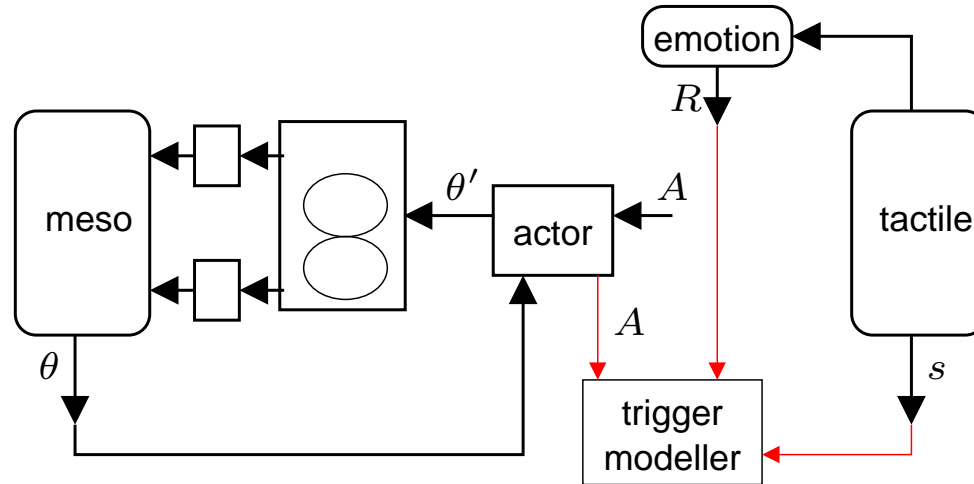


“Drives a controllable parameter to a goal value.”

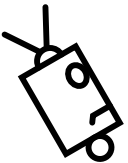
- *position-constant*: constant prototype value in action model.
- *position-parameter*: goal derived from another input parameter.
- Have random activation.
- Unused actors/actions will expire.



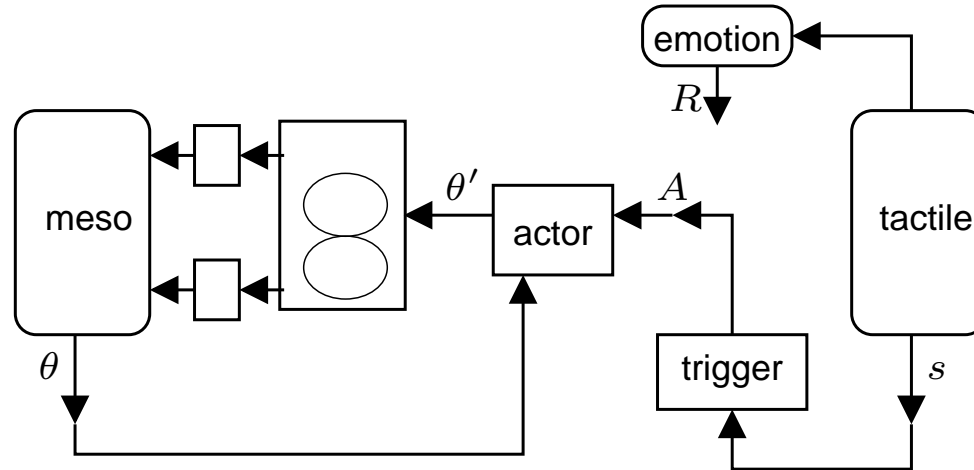
Pointing in response to Touch



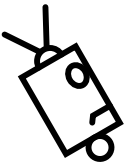
- A *trigger modeller* is created for pairs of actors and state parameters.
- Correlates state parameter with reward and activation.
- Creates a *trigger model* linking pointing action to a range of tactile sense values.



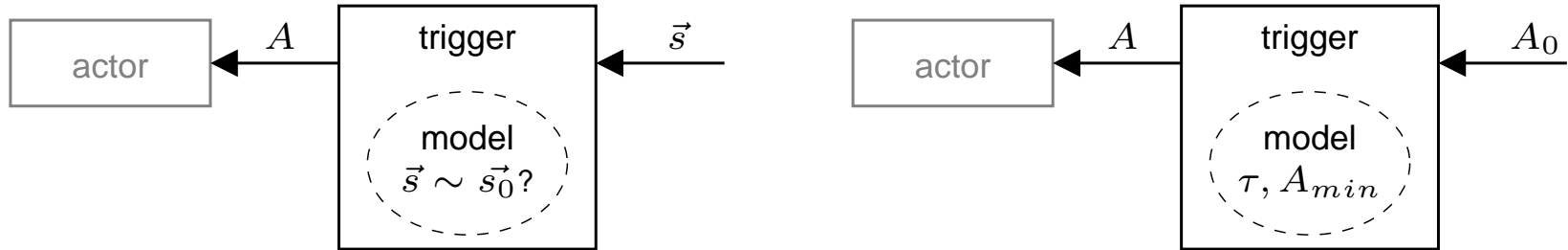
Pointing in response to Touch



- A *trigger* is spawned, which activates the pointing actor in response to touch.

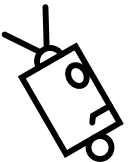


Trigger

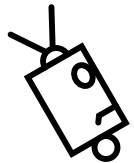


“Activates an actor when input state satisfies a context.”

- *position*: context is a region in input state space.
- *activation-delay*: context is another activation signal.
- Activation output indicates how well context is satisfied.



Video of Three Arm Actions

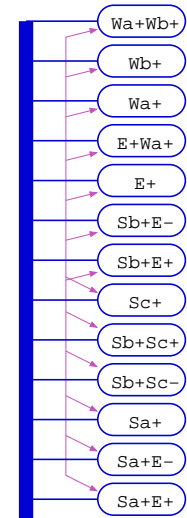


Cog, Initial State

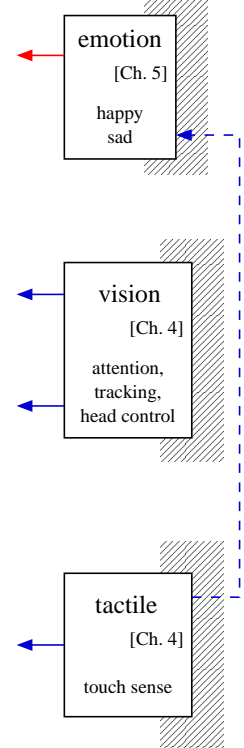
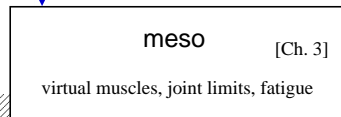
proto-mover-modeller

proto-action-modeller

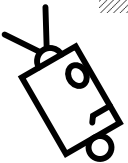
proto-trigger-modeller



proto-controller



proto-transform-modeller



Mover Modelling

Modeller's question:

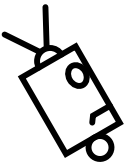
“Which state parameters are affected by the mover?”

- Linear model of state velocity as a function of activation

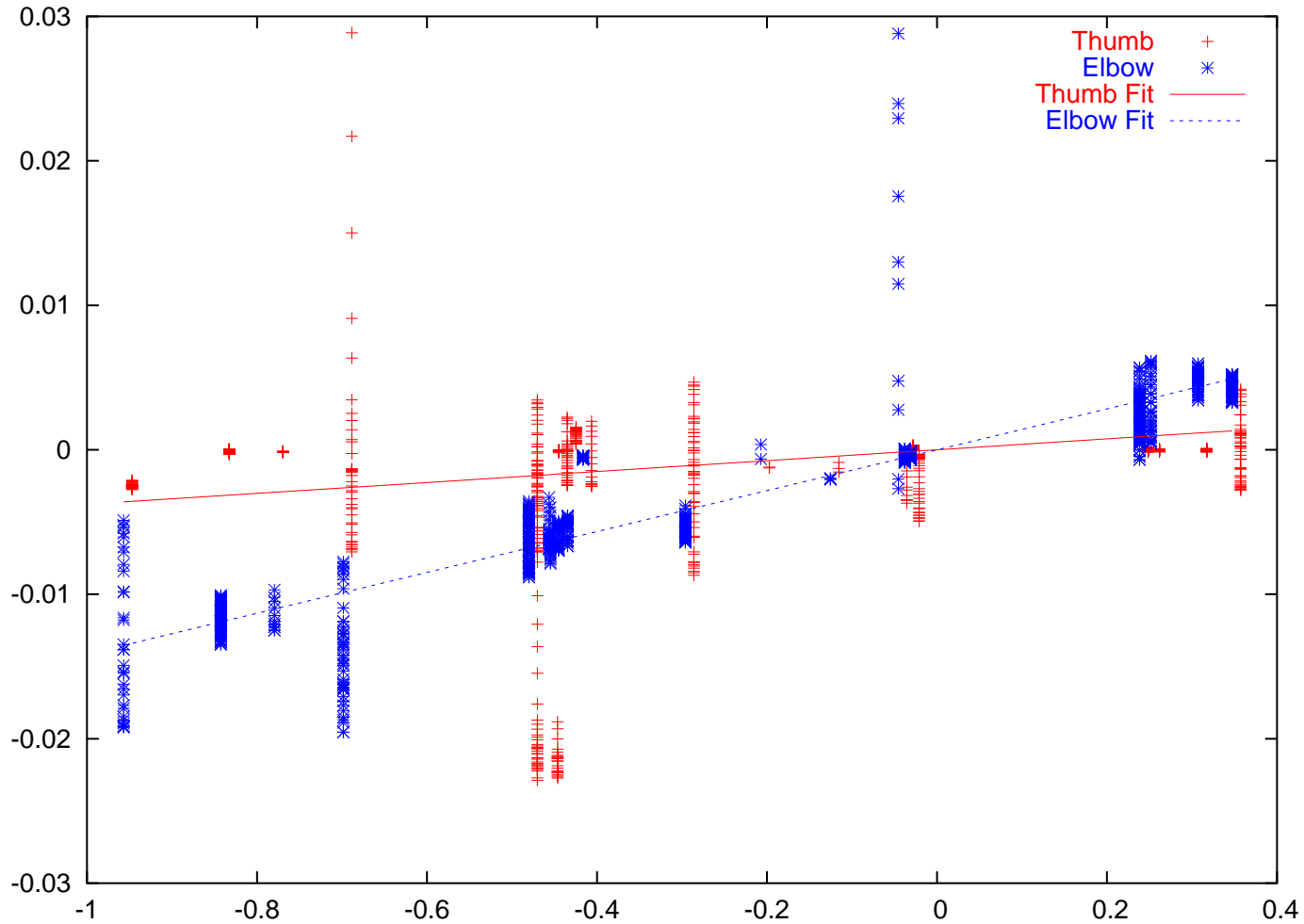
$$\vec{v}_s = A\vec{m}$$

- Modeller operation:

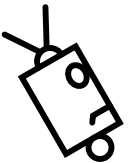
1. Record samples (\vec{s}, A) ; calculate velocities \vec{v} .
2. Perform linear regression to estimate \vec{m} .
3. Check correlation coefficient R^2 for each axis of \vec{v} .



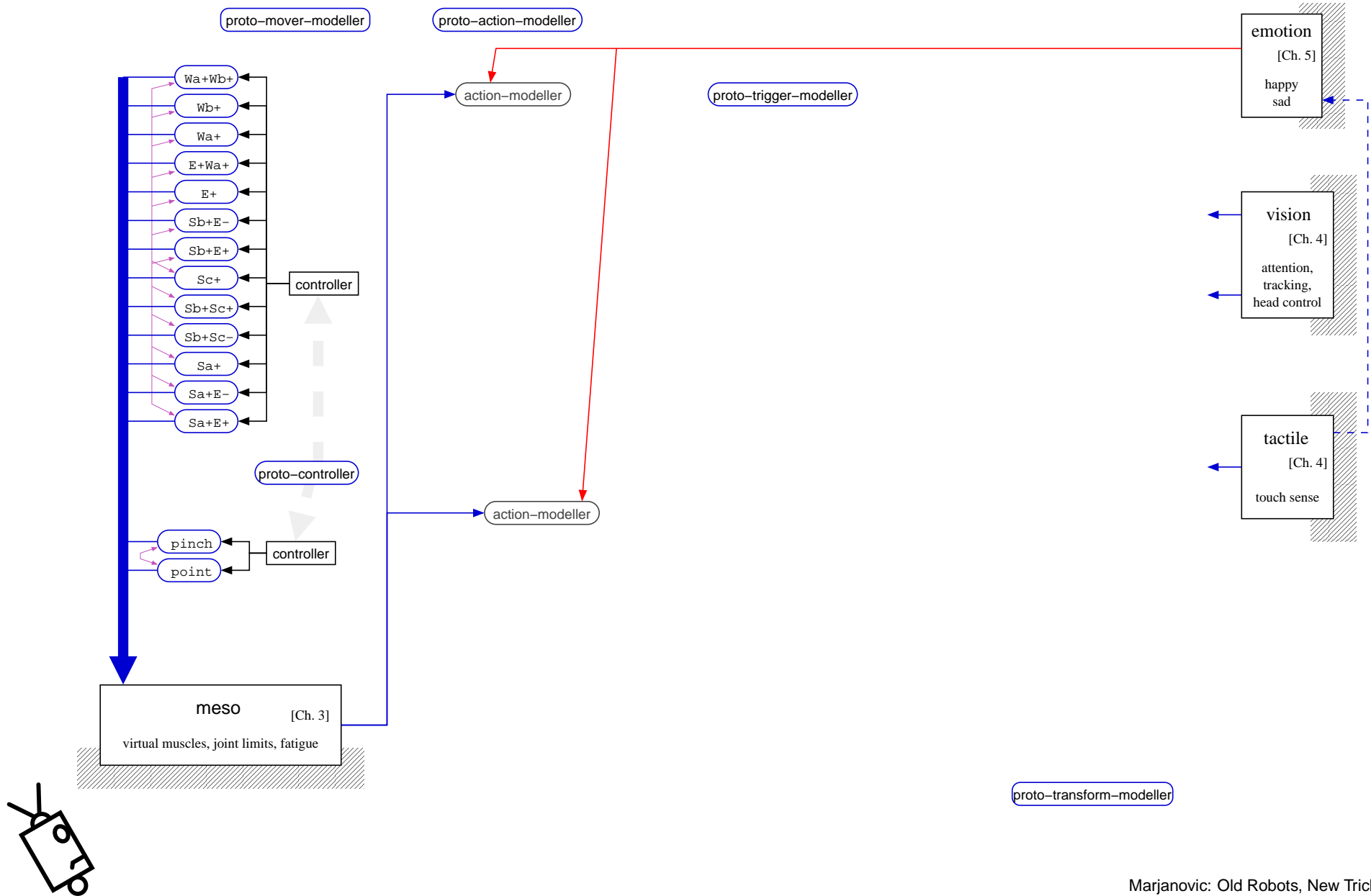
Elbow Mover (vs. Thumb)



Elbow: $R^2 = 0.82$, Thumb: $R^2 = 0.08$

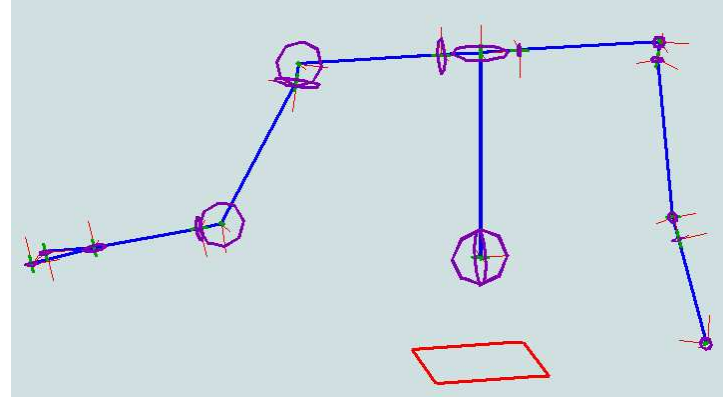


Cog, with Controllers

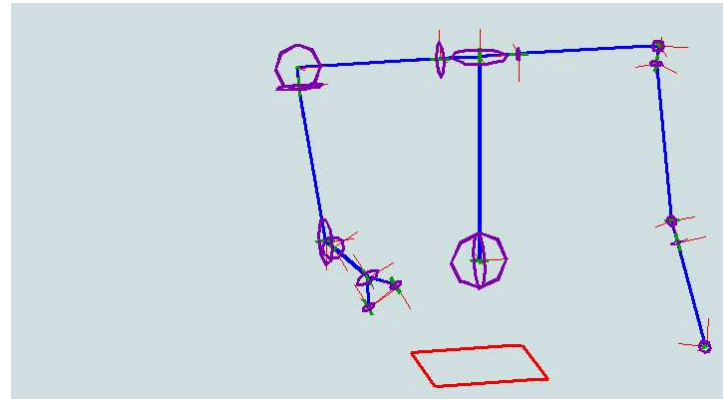


Three Arm Actions

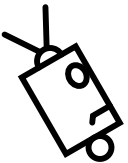
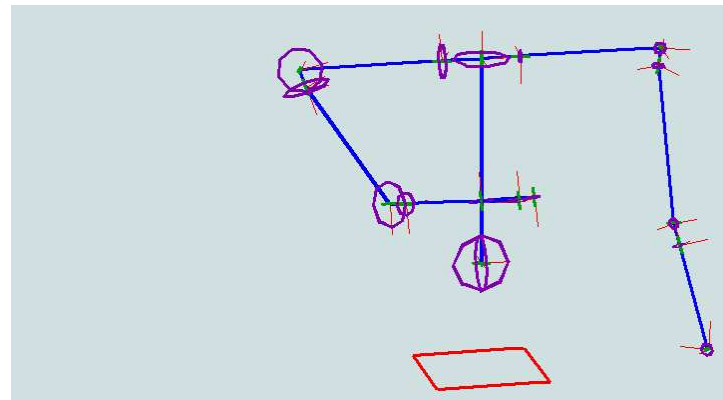
outward



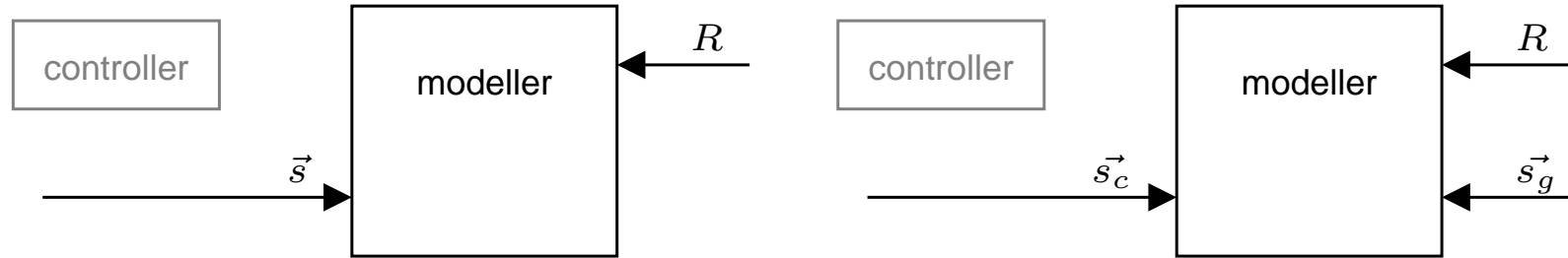
forward



across



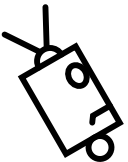
Action Modelling



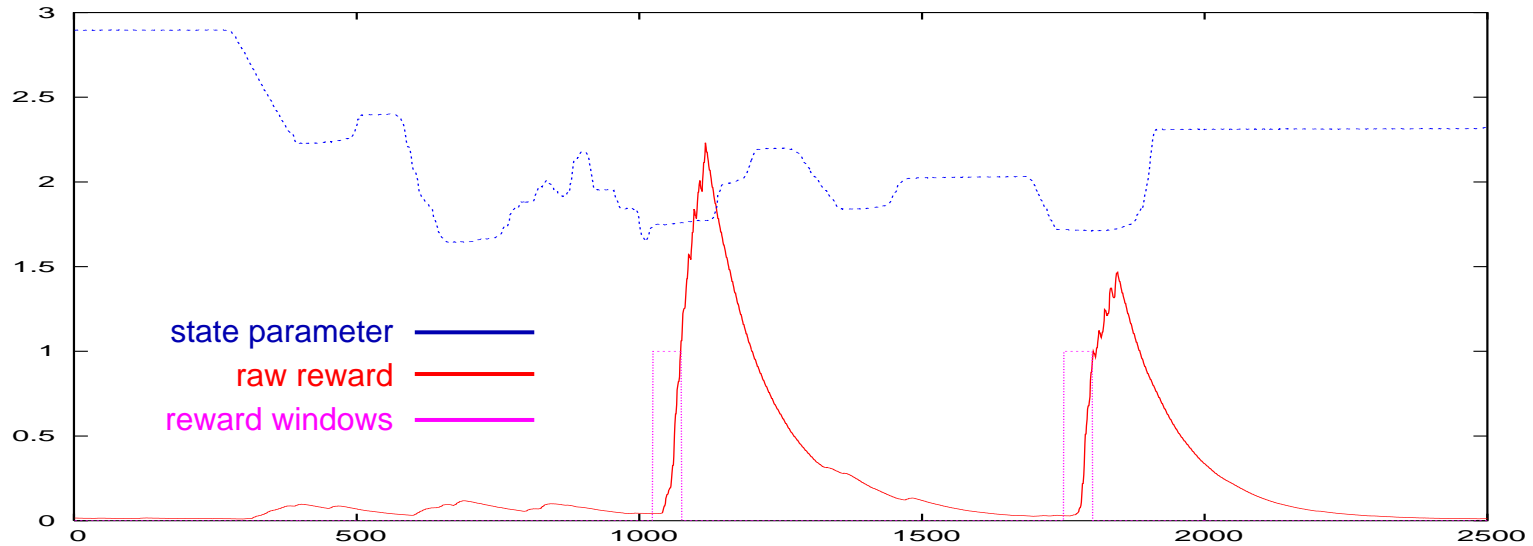
Modeller's question:

- Is there a prototype state sample being rewarded?
- If so, what is it?

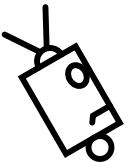
Model acts as a binary classifier: *rewarded* vs. *unrewarded*.



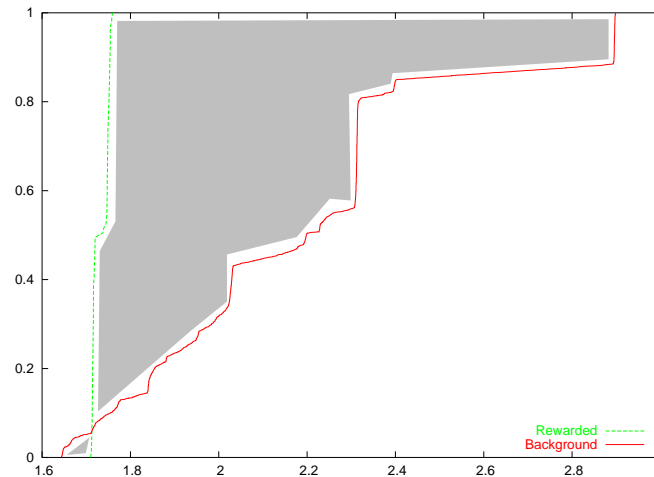
Action Modelling, cont.



- Collect samples (\vec{s}, R) .
- Calculate *reward windows*, preceding the reward.
- Label \vec{s} samples:
 - Within windows: rewarded, “T”.
 - Outside windows: unrewarded, “F”.



Is there an Action?



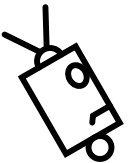
- Compare per-axis distributions $p(s_i|T)$ and $p(s_i|F)$.
- Measure absolute areal difference of CDF's:

$$\alpha_i = \int |P(s_i|T) - P(s_i|F)| ds_i$$

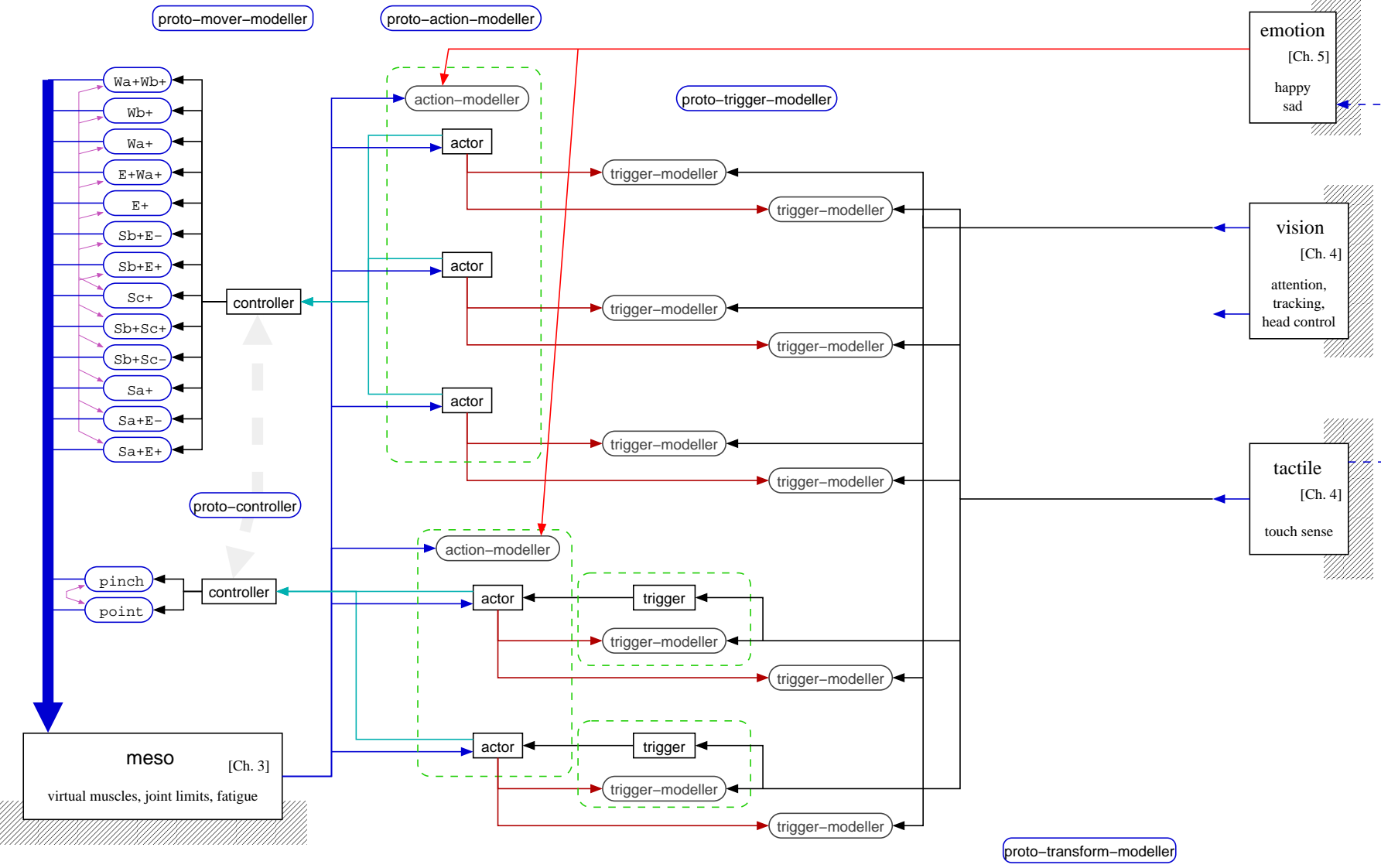
- If $\alpha_i > 0.1$, axis i is *relevant*. (None = no model!)

What is the Action?

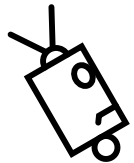
- Model distributions $p(s_i|T)$ of relevant axes by gaussian.
 - Measure mean and variance of rewarded samples.
- Mean is the *prototype position* — goal of action.



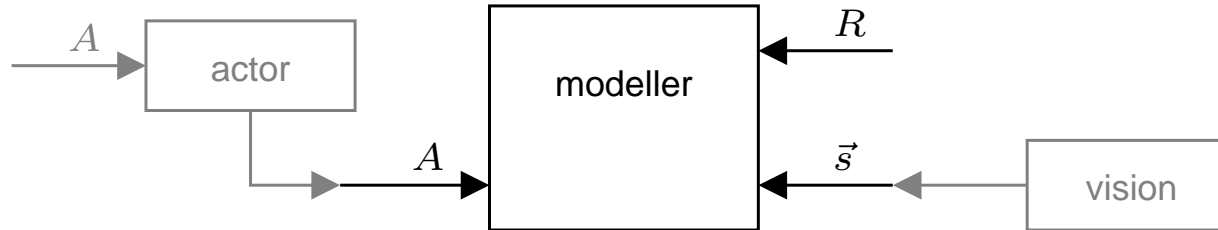
Cog, with Actors



Visual Triggers for the Arm



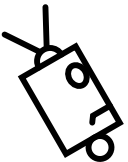
Trigger Modelling



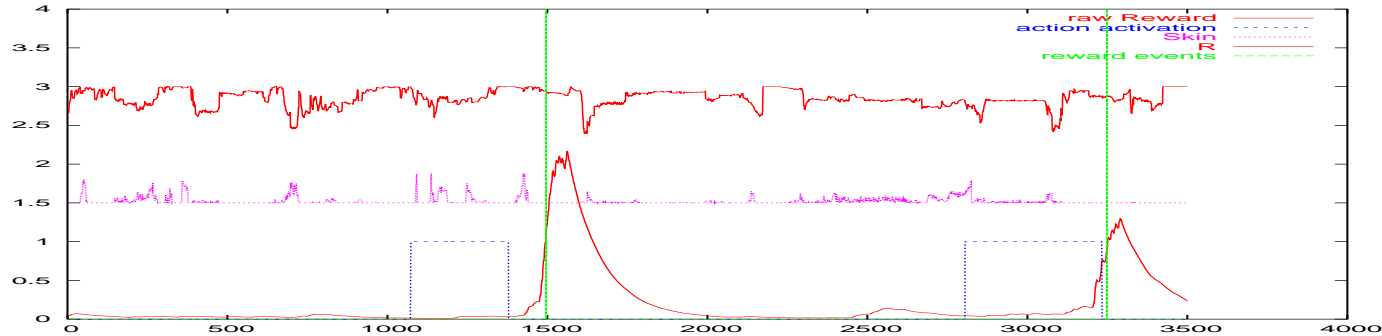
Modeller's question:

- Is there a prototype stimulus coincident with both action and reward?
- If so, what is it?

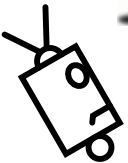
Model acts as a binary classifier: *stimulus vs. background.*



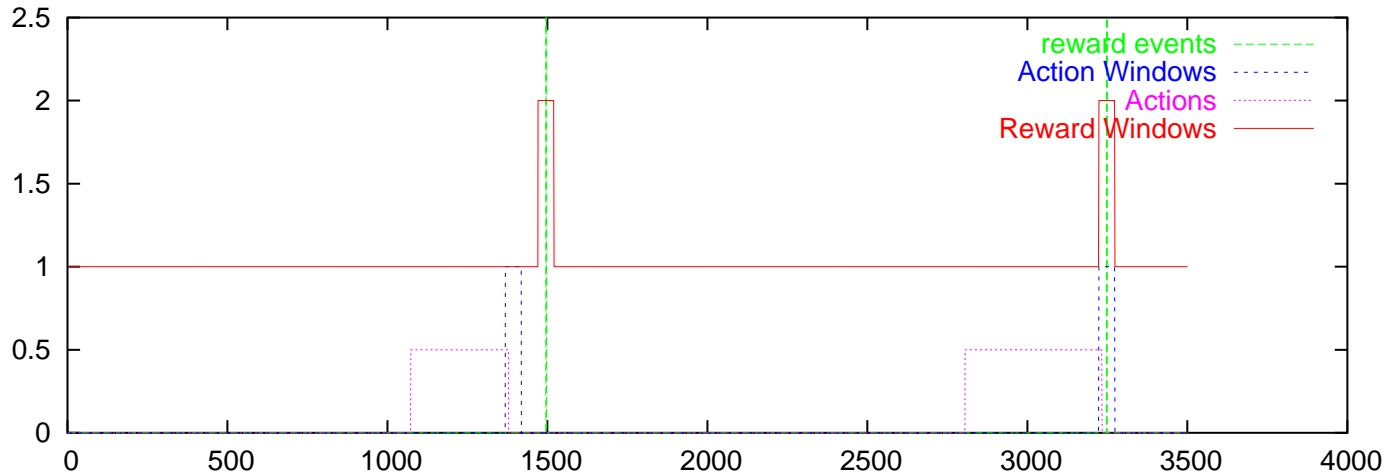
Trigger Modelling, cont.



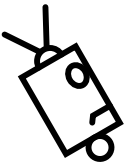
- Collect samples (\vec{s}, A, R) .
- Determine *reward windows* and *action windows*.
- Label samples \vec{s} :
 - Within both windows: stimulus, “T”.
 - Outside both windows: background, “F”.
- Compare distributions of T and F samples, per axis.



Trigger Modelling Windows



- Reward is “associated” with action if near action endpoint.
- Reward windows relative to reward event.
- Action windows = reward windows for associated rewards.

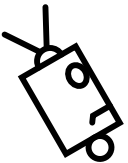


Position Trigger

- Relevant axes of T and F modelled by gaussian distributions.
- “Stimulus” and “background” distributions determine salient region of state space:

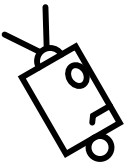
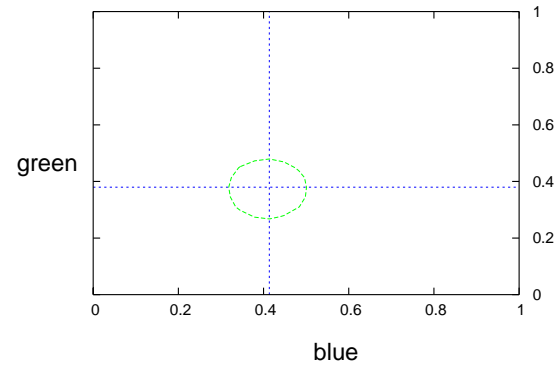
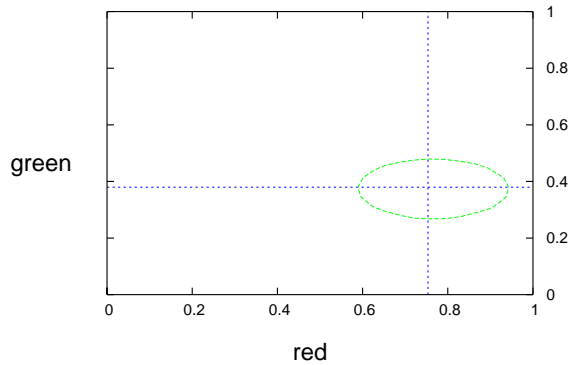
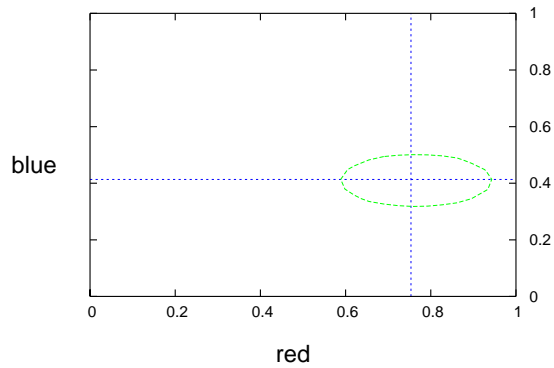
$$\rho = P(T|\vec{s}) = \frac{p(\vec{s}|T)P(T)}{p(\vec{s}|T)P(T) + p(\vec{s}|F)P(F)}$$

- Trigger context is satisfied when $\rho > 0.5$.
 - ρ sent as activation value to actor.
- Background distribution is updated/adapted over time.
 - Trigger will habituate to a continuous stimulus.

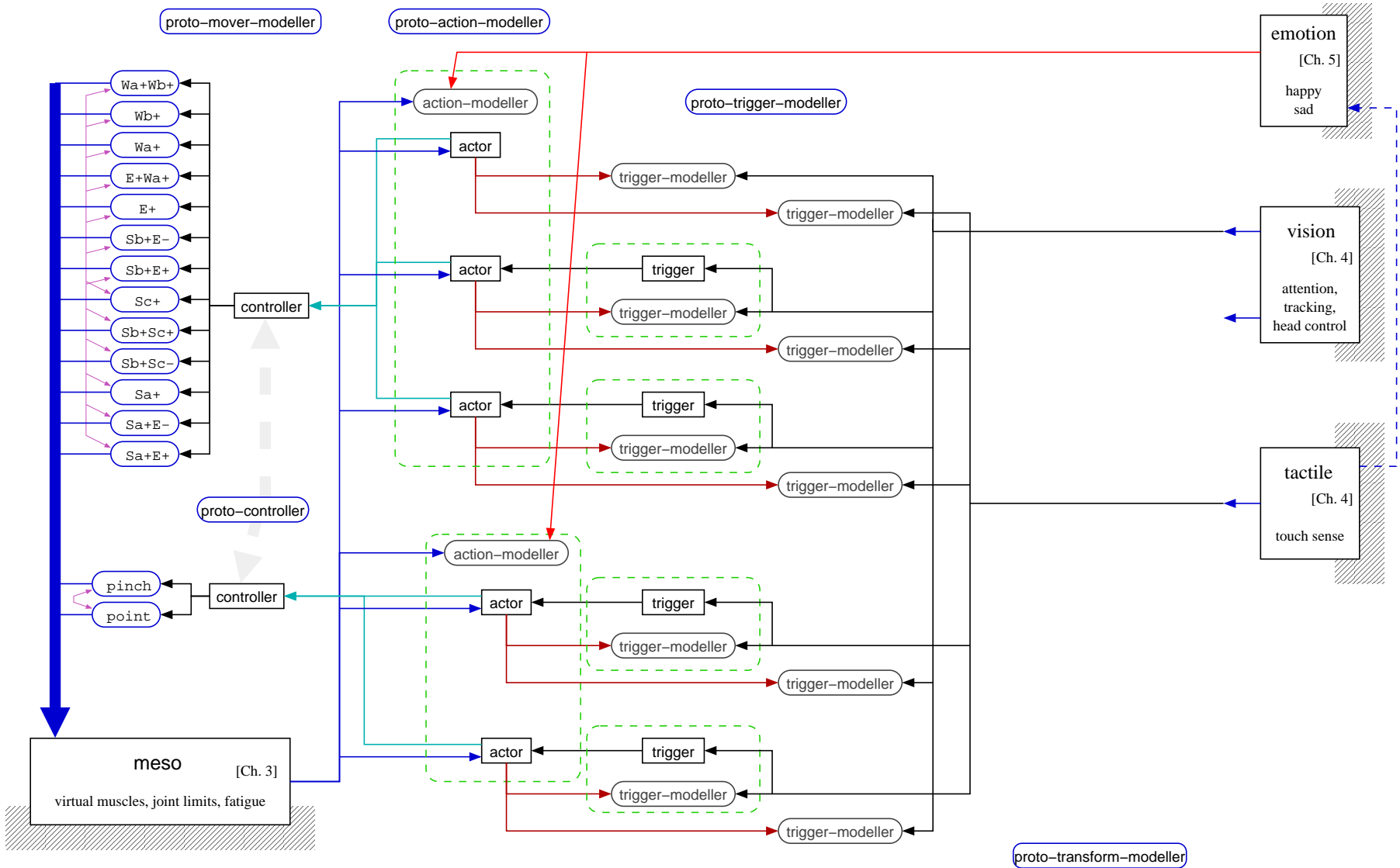


Example Trigger Context

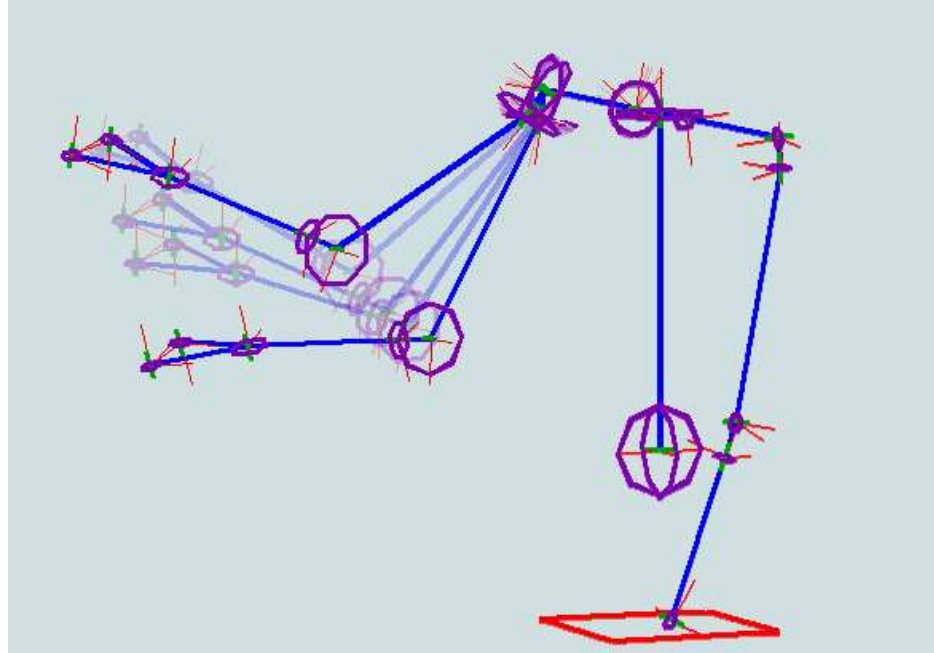
Decision boundary of “Red Ball” trigger:



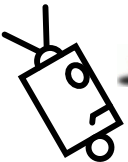
Cog, with Triggers



Action Model Refinement

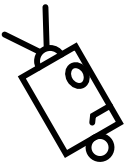


- Action modeller continues to collect data, to discover new actions.
- If a new model would be similar to an existing one, the old model is *refined*.
- Connections to triggers, etc., remain intact.



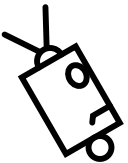
Conclusion

- Robot learns from interaction with self and environment.
- Robot can be taught a few simple behaviors.
- Holds true to design philosophy:
 - Dynamic: new models, structure created.
 - Malleable: models can be refined.
 - Distributed: no central planner/learner.
 - Real robot, real world conditions.



Future Work

- Negative reward/reinforcement
 - Using the muscle-fatigue/joint-pain signals.
- Inhibition and un-learning
 - Learning when *not* to do something.
 - Forgetting triggers.
- Accounting/distributing reward.
- Consistency, “success” as a reinforcer.



Future Work, cont.

- Models for Johnson's "important" image schemata?

CONTAINER

BALANCE

COMPULSION

BLOCKAGE

COUNTERFORCE

RESTRAINT REMOVAL

ENABLEMENT

ATTRACTION

MASS-COUNT

PATH

LINK

CENTER-PERIPHERY

CYCLE

NEAR-FAR

SCALE

PART-WHOLE

MERGING

SPLITTING

FULL-EMPTY

MATCHING

SUPERIMPOSITION

ITERATION

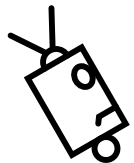
CONTACT

PROCESS

SURFACE

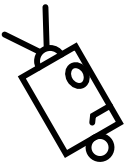
OBJECT

COLLECTION



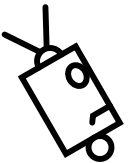
Future Work, cont.

- Incorporate earlier/other work into framework:
 - Richer perceptual primitives.
 - Social primitives; emotional system.
 - Reflexes which encourage interaction.
- ... but, “black boxes” should not be opaque.

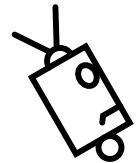


Brain-teasers...

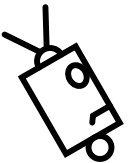
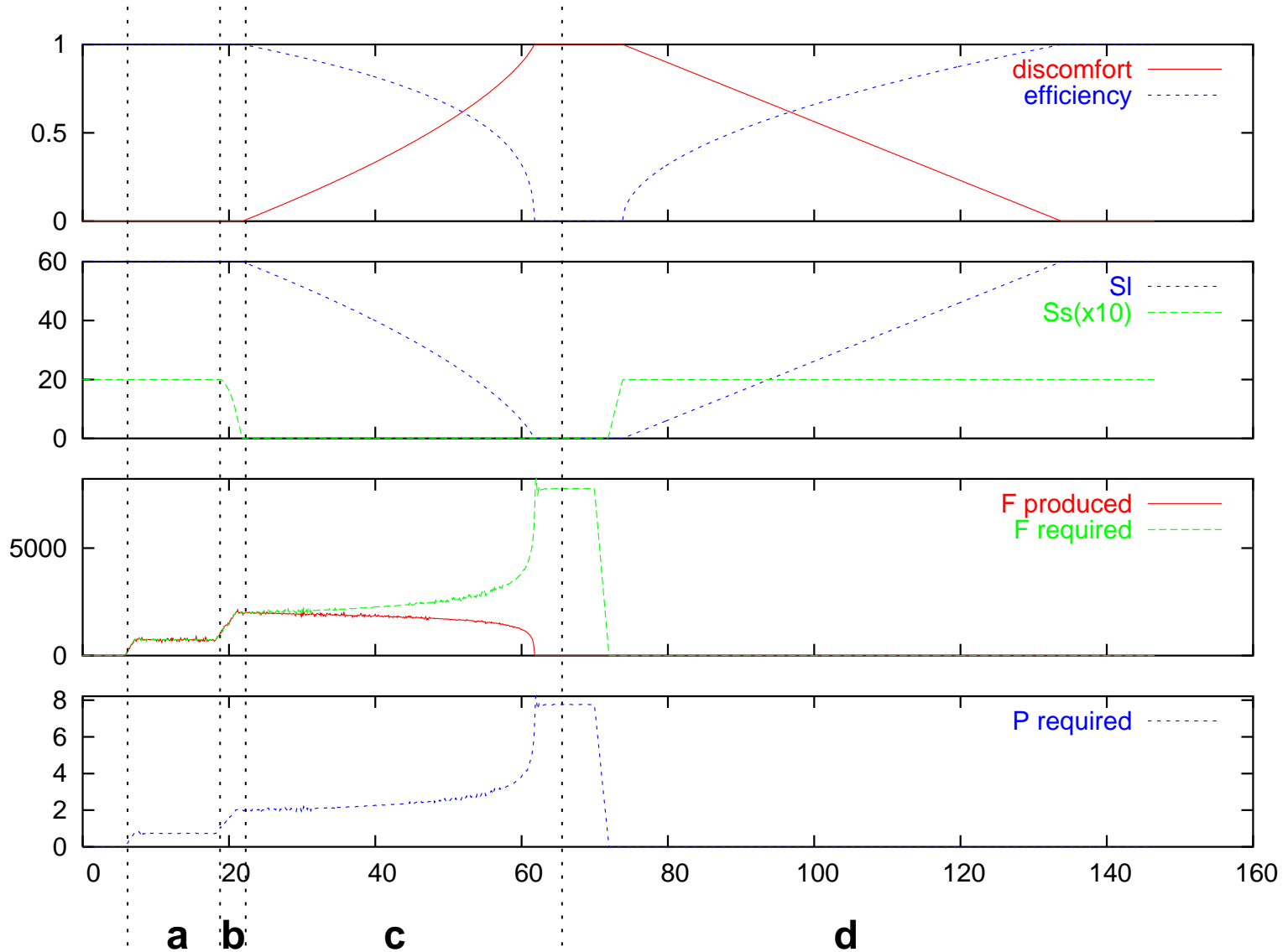
- How many primitives do we need to implement?
- How small do the building blocks need to be?
- How dense must the interconnections be?
- Do we need to simulate *cells*? *Proteins*?



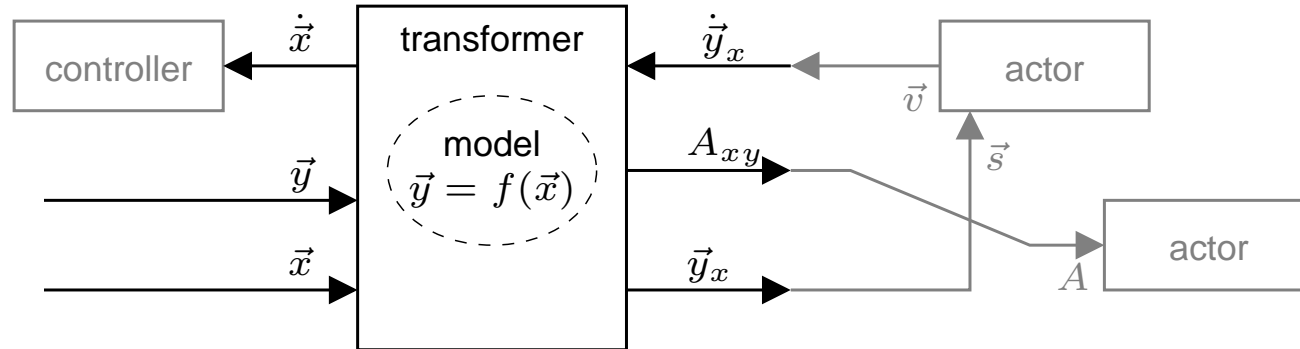
EXTRA SLIDES



Phases of Fatigue

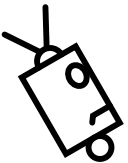


Transformer

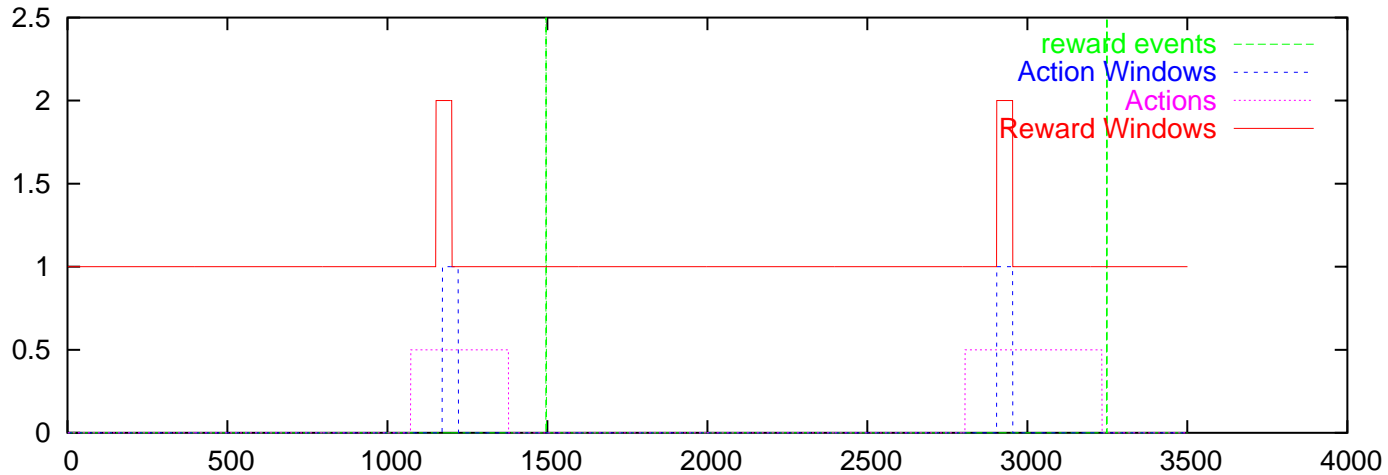


Transformer module can do three things:

- Predict state of \vec{x} in y coordinate frame. ($\vec{y}_x = f(\vec{x})$)
- Decide whether or not \vec{x} and \vec{y} are observing the same process. (A_{xy})
- Control \vec{x} via its velocity $\dot{\vec{y}}_x$ in the y coordinate frame. ($\dot{\vec{x}} = F^{-1}\dot{\vec{y}}_x$)



Trigger Modelling Windows, v1.0



- Action is “rewarded” if reward event soon after action endpoint.
- Action windows near action onset.
- Reward windows = action windows for rewarded actions.
- To be effective, need to slide action windows,

