



Learning, development and plasticity

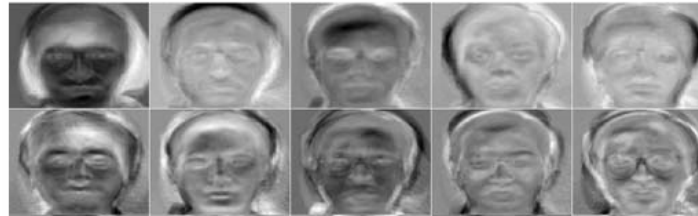
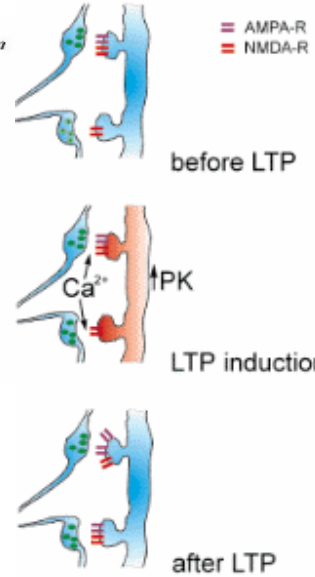
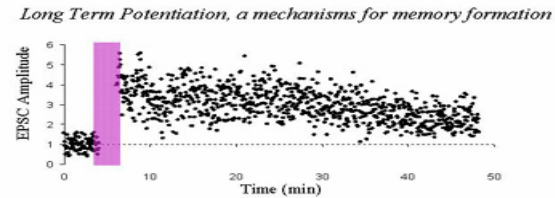
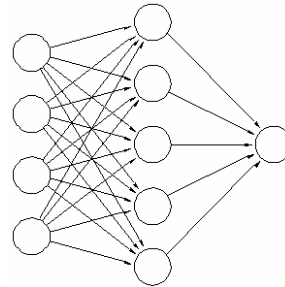
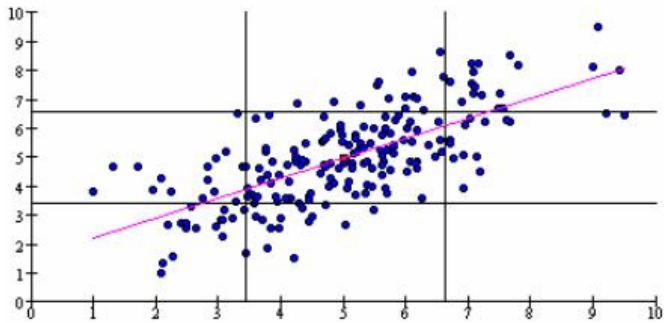
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Can we develop an integrated theory of learning, in computational, behavioral and neural terms?

- The “standard model”



Supervised

$$E = \frac{1}{2} \sum_{t=1}^n (y_t - w \cdot x_t)^2$$

$$\Delta w \propto -\frac{\partial E}{\partial w} = \sum_{t=1}^n (y_t - w \cdot x_t) x_t$$

Unsupervised

$$E = \frac{1}{2} \sum_{t=1}^n y_t^2 = \frac{1}{2} \sum_{t=1}^n (w \cdot x_t)^2$$

$$\Delta w \propto -\frac{\partial E}{\partial w} = \sum_{t=1}^n y_t \cdot x_t$$

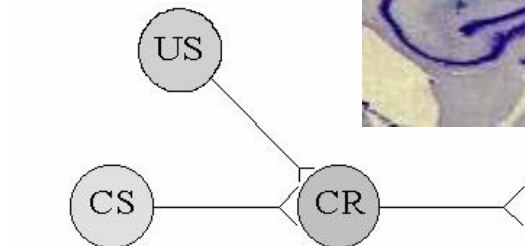
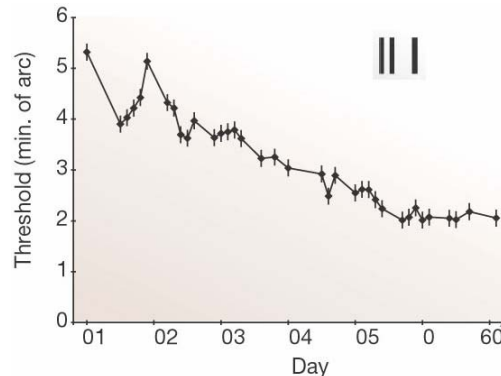
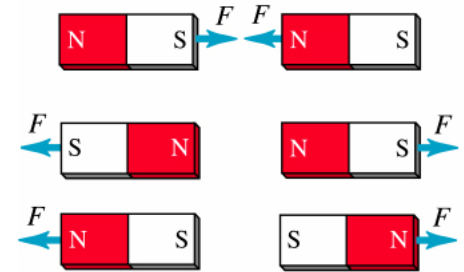
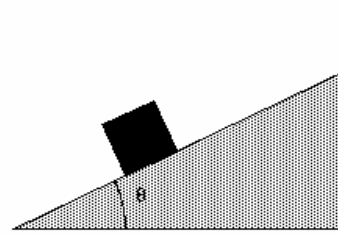
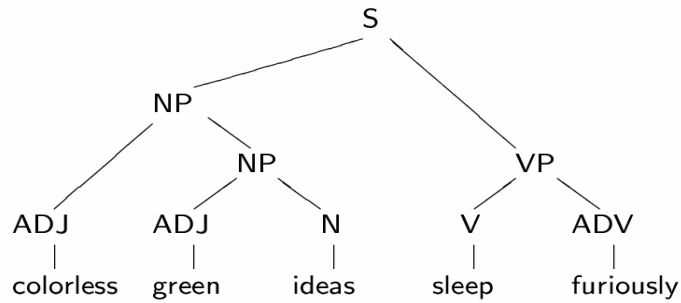
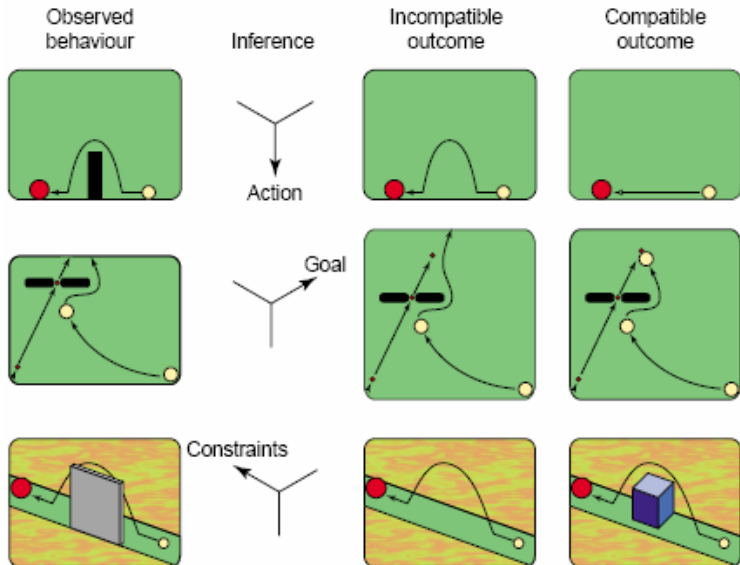
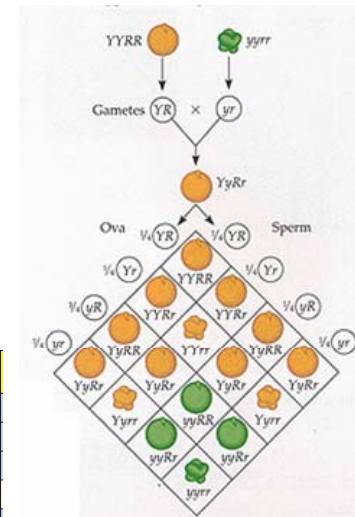
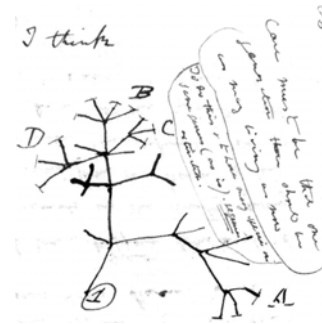
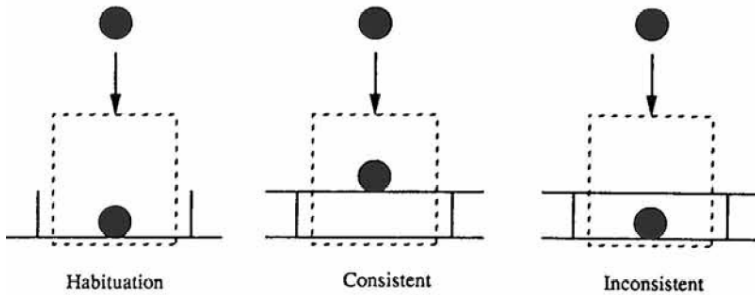


Fig 1.1: Hebbian Synapse neuro-modulators work across the synapse between the facilitator and motor neuron.

The really hard problems



$$F = m a$$



Group	I	II	III	IV	V	VI	VII
Period 1	H=1						
2	Li=7	Be=9.4	B=11	C=12	N=14	O=16	F=19
3	Na=23	Mg=24	Al=27.3	Si=28	P=31	S=32	Cl=35.5
4	K=39	Ca=40	?=44	Ti=48	V=51	Cr=52	Mn=55
5	Cu=63	Zn=65	?=68	?=72	As=75	Se=78	Br=80
6	Rb=85	Sr=87	?Yt=88	Zr=90	Nb=94	Mo=96	?=100
7	Ag=108	Cd=112	In=113	Sn=118	Sb=122	Te=125	J=127



Two cultures

“Nature”

Innate structured
representations

Grounded in cognition

versus

“Nurture”

Statistical learning,
plasticity

Grounded in the brain

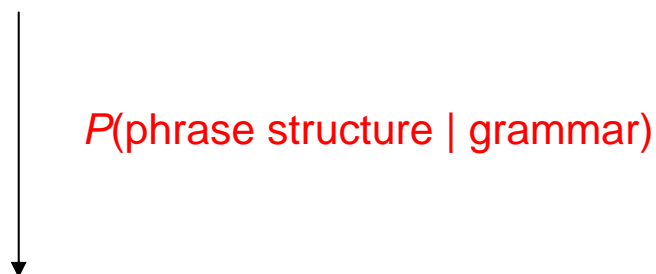
Recent causes for optimism

- New models from machine learning, AI
 - Structured statistical models
 - Probabilities defined over structured representations: graphs, causal networks, grammars, predicate logic.*
 - Multilevel (hierarchical) statistical models
 - Inference at multiple levels of abstraction and multiple timescales.*
 - Flexible statistical models
 - Hypothesis spaces grow as new data are encountered.*
- New technologies
 - “Supercomputers” on the desktop, grid computing
 - Life-size datasets for modeling cognitive development
 - Mainstream functional MRI

“Universal Grammar”



Grammar



Phrase structure



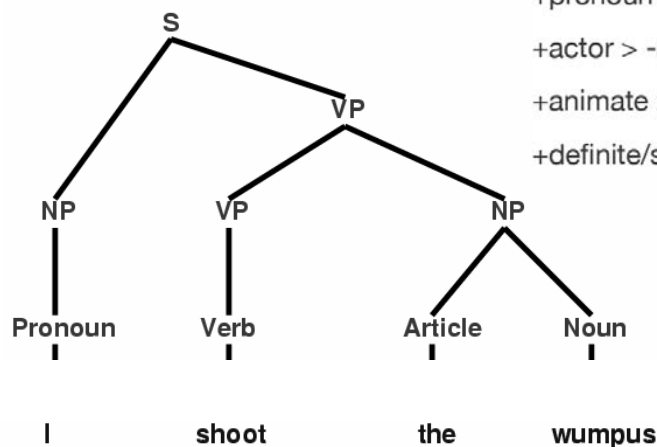
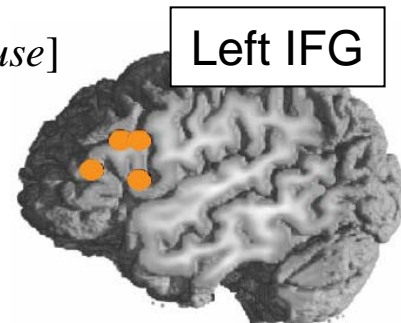
Utterance



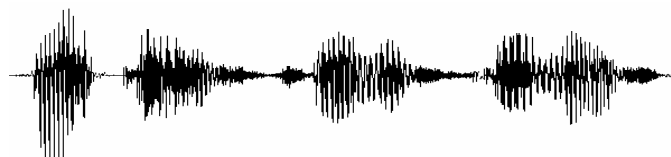
Speech signal

Hierarchical phrase structure grammars (e.g., CFG, HPSG, TAG)

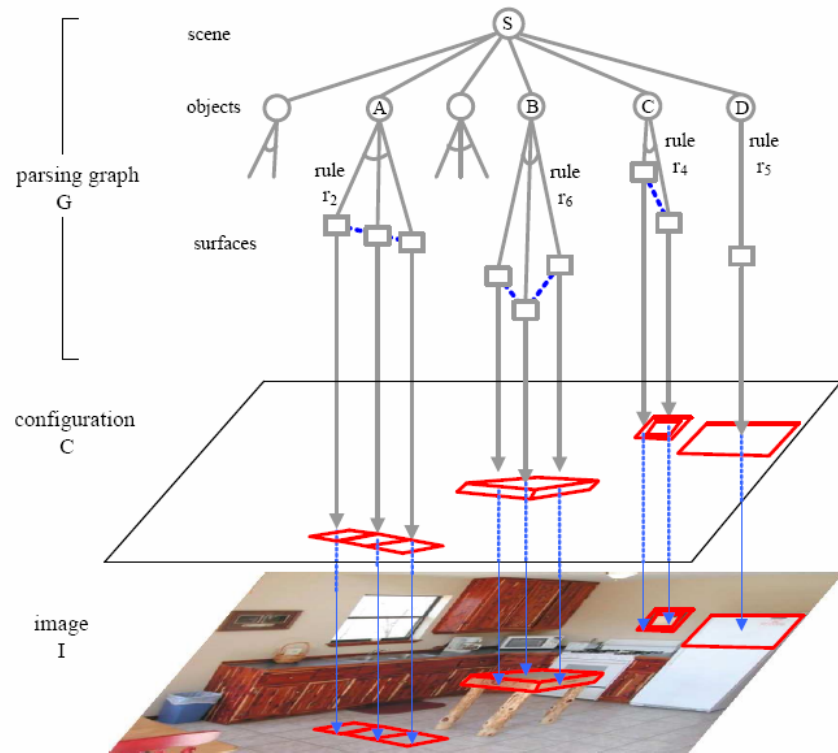
$S \rightarrow NP VP$
 $NP \rightarrow Det [Adj] Noun [RelClause]$
 $RelClause \rightarrow [Rel] NP V$
 $VP \rightarrow VP NP$
 $VP \rightarrow Verb$



- +subject > -subject
- +pronoun > -pronoun
- +actor > -actor
- +animate > -animate
- +definite/specific > -definite/specific



Probabilistic scene parsing



```

type Aircraft; type Blip;

random R6Vector State(Aircraft, NaturalNum);
random R3Vector ApparentPos(Blip);

nonrandom NaturalNum Pred(NaturalNum) = Predecessor;

generating Aircraft Source(Blip);
generating NaturalNum Time(Blip);

#Aircraft ~ NumAircraftDistrib();

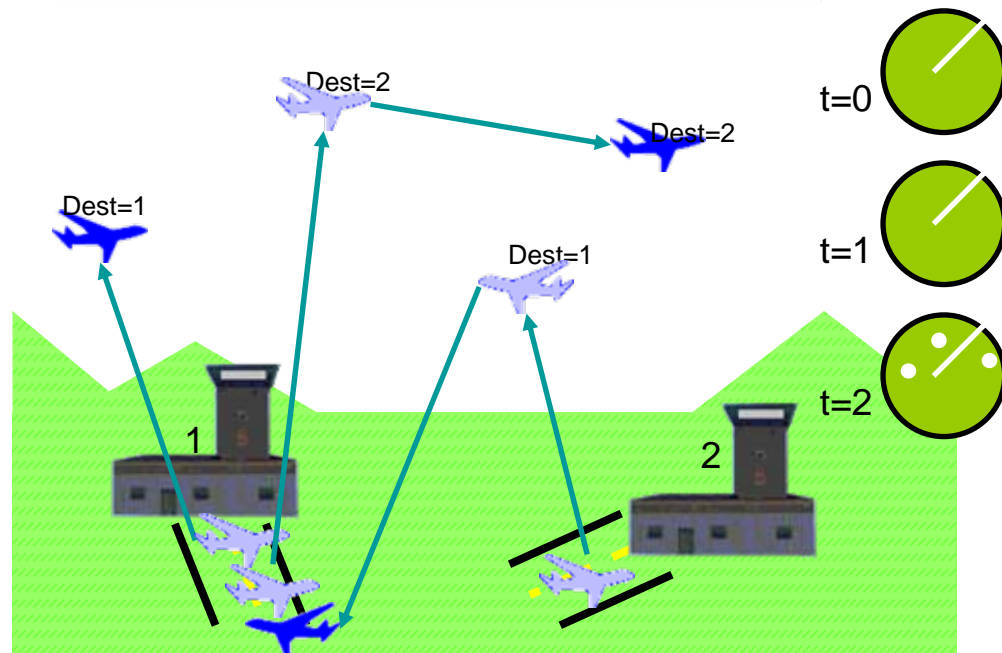
State(a, t)
  if t = 0 then ~ InitState()
  else ~ StateTransition(State(a, Pred(t)));

#Blip: (Source, Time) -> (a, t)
  ~ DetectionDistrib(State(a, t));

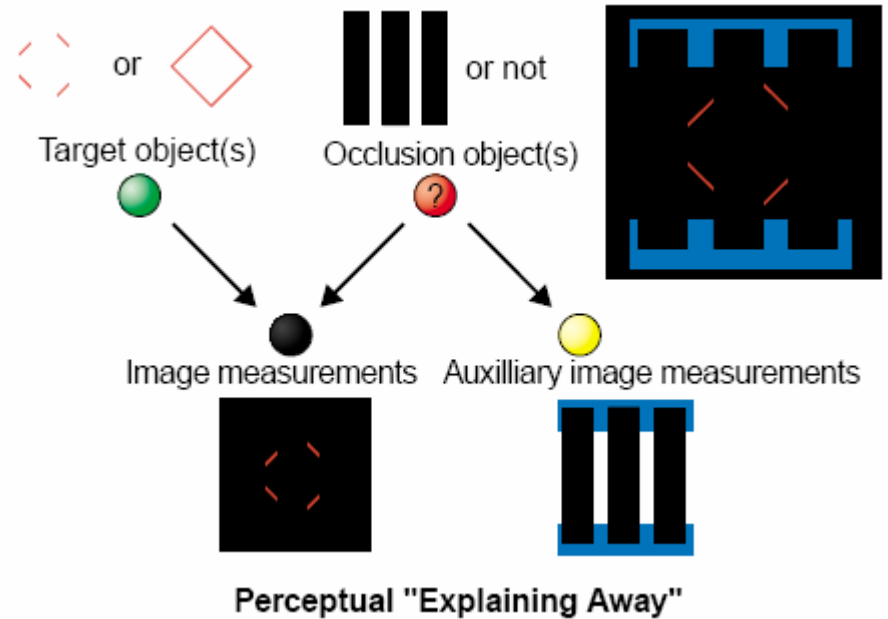
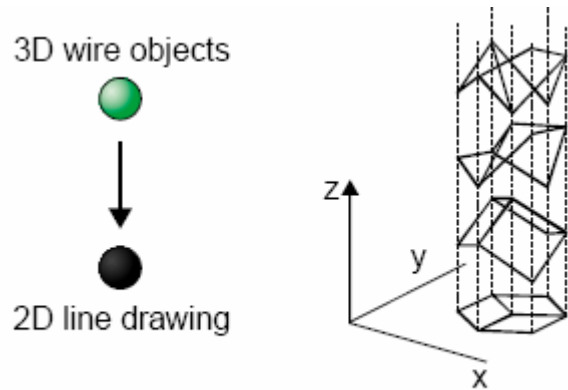
#Blip: (BlipTime) -> (t)
  ~ NumFalseAlarmsDistrib();

ApparentPos(r)
  if (BlipSource(r) = null) then ~ FalseAlarmDistrib()
  else ~ ObsDistrib(State(Source(r), Time(r)));
    
```

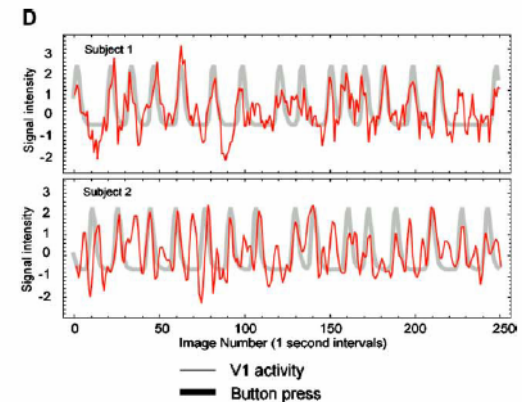
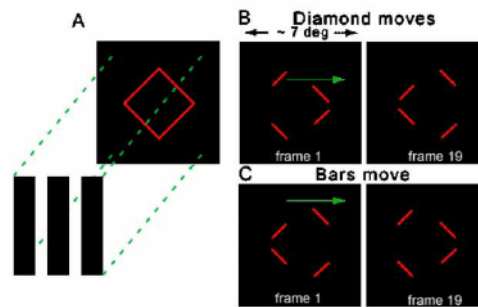
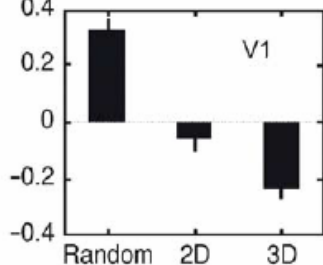
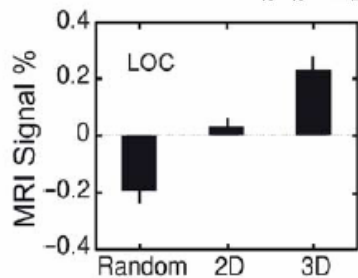
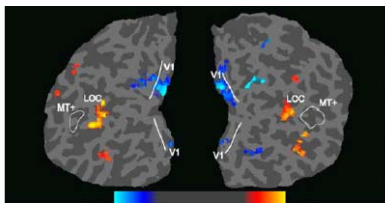
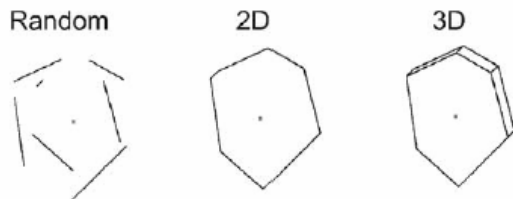
BLOG
(Bayesian
Logic)



Probabilistic scene parsing



Basic Bayes



Learning domain structures

F : form



$P(\text{structure} \mid \text{form})$

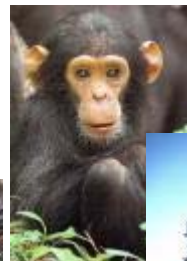
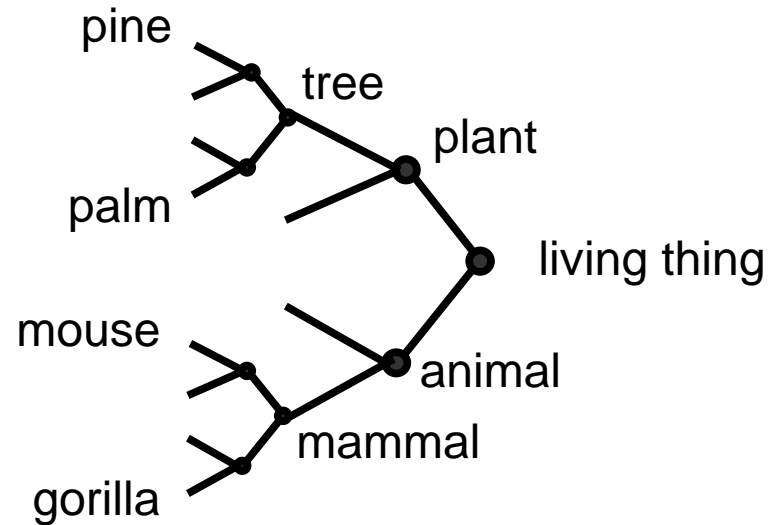
S : structure



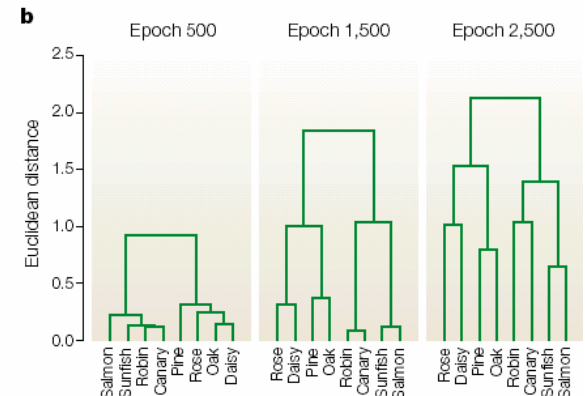
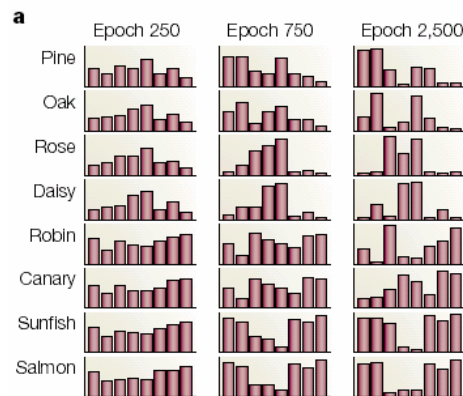
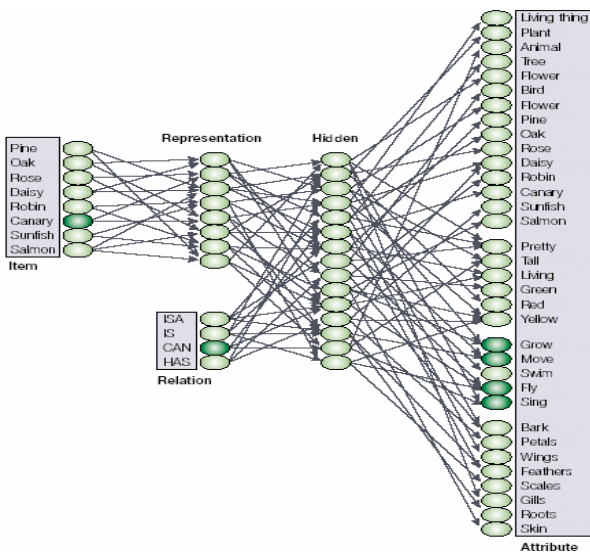
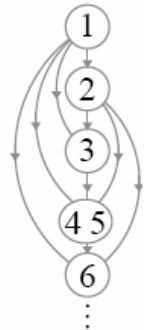
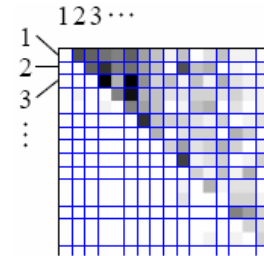
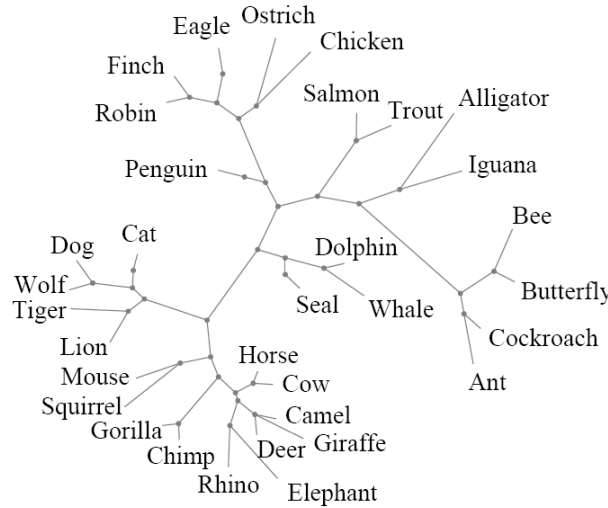
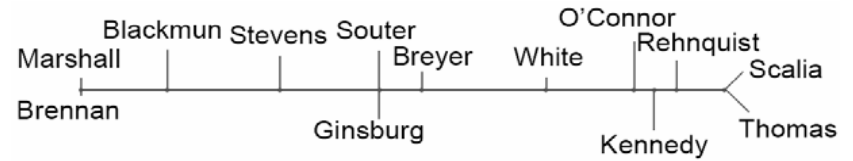
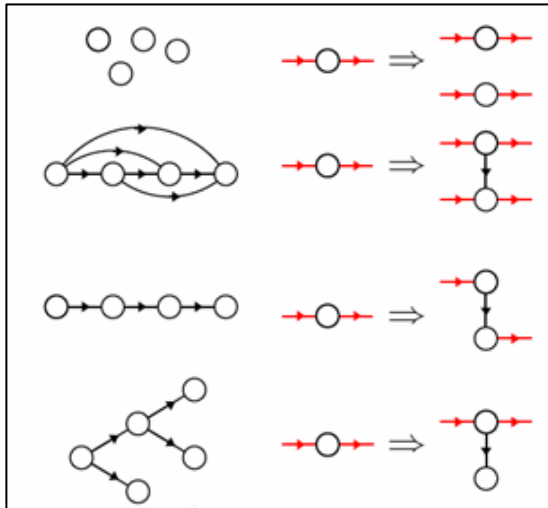
$P(\text{data} \mid \text{structure})$

D : data

Tree with objects at leaf nodes



Learning domain structures

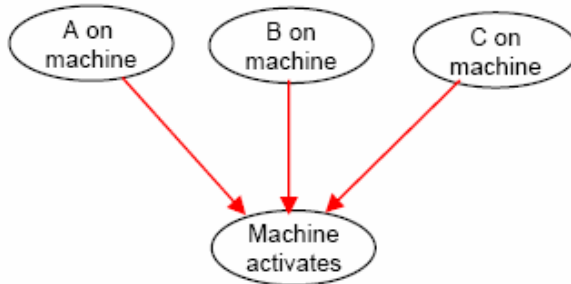


Learning causal theories

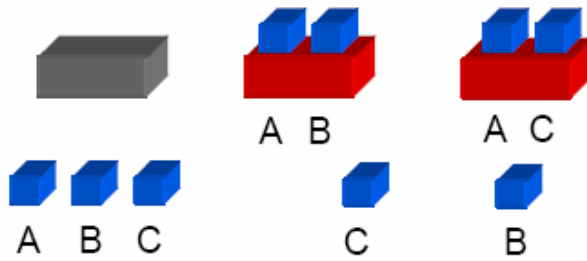
Abstract Principles

Objects can activate Machines
Activation requires contact
Machines are (near) deterministic

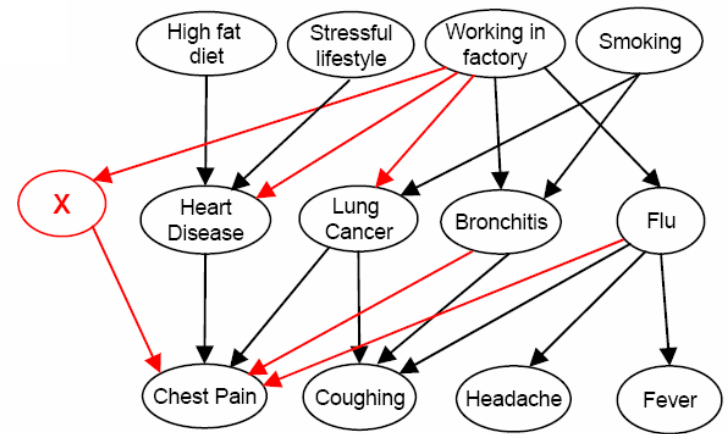
Structure



Data

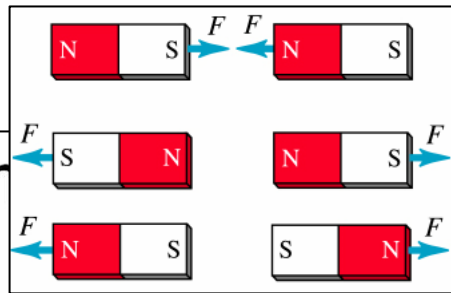


Classes: {R, D, S} (Risks, Diseases, Symptoms)
Causal laws: $R \rightarrow D$, $D \rightarrow S$



Patient 1: Stressful lifestyle
Chest Pain
Patient 2: Smoking
Coughing
Patient 3: Working in factory
Chest Pain
...

Learning the laws of magnetism

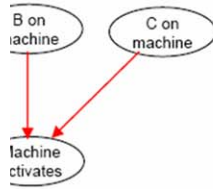


Learning Principles

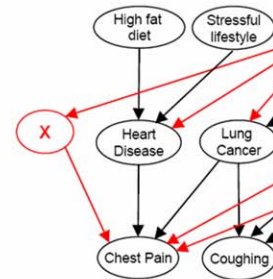
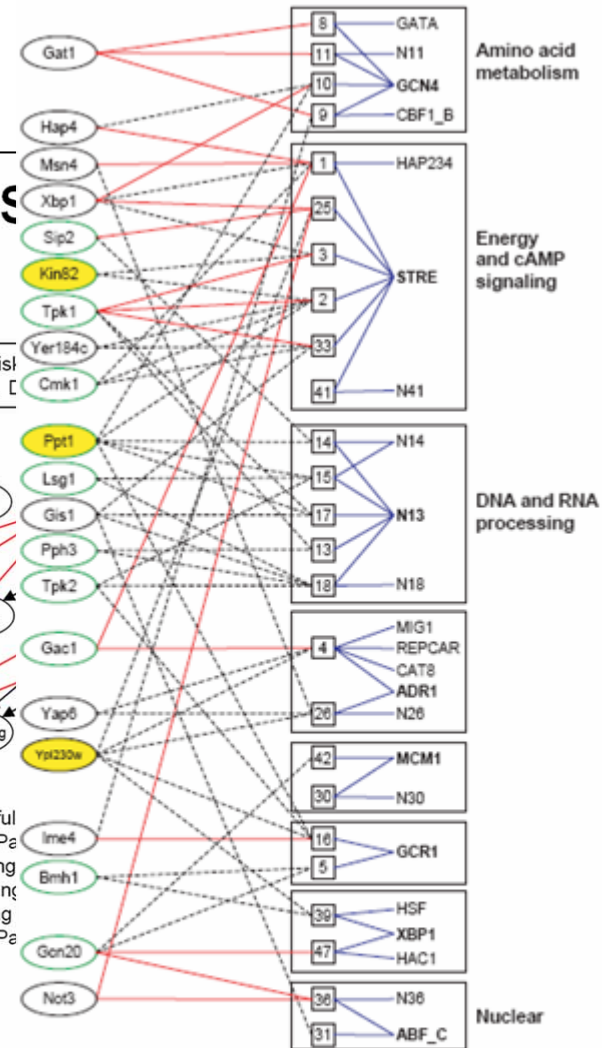
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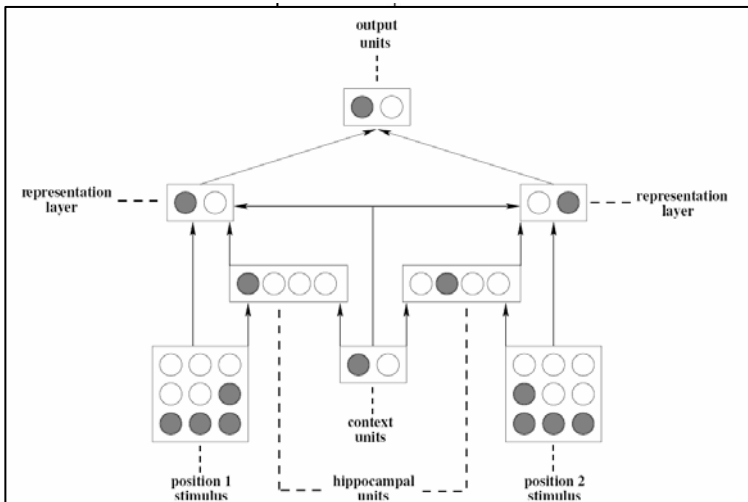


Learning regulatory modules in genetics



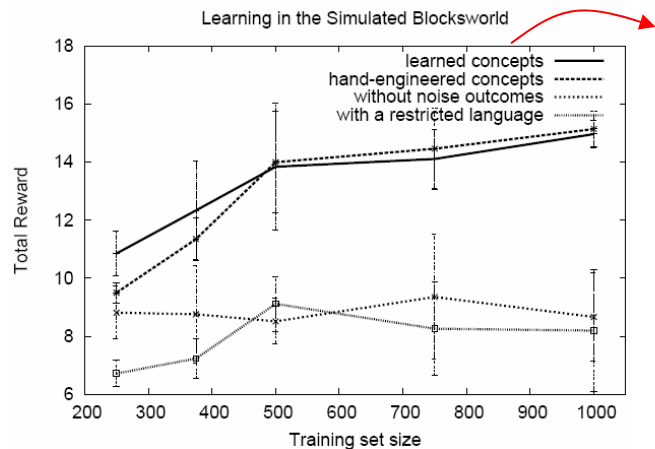
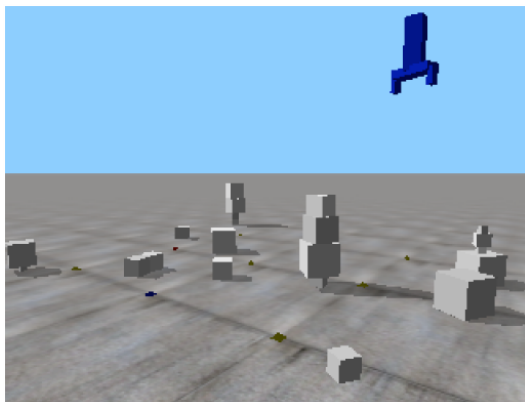
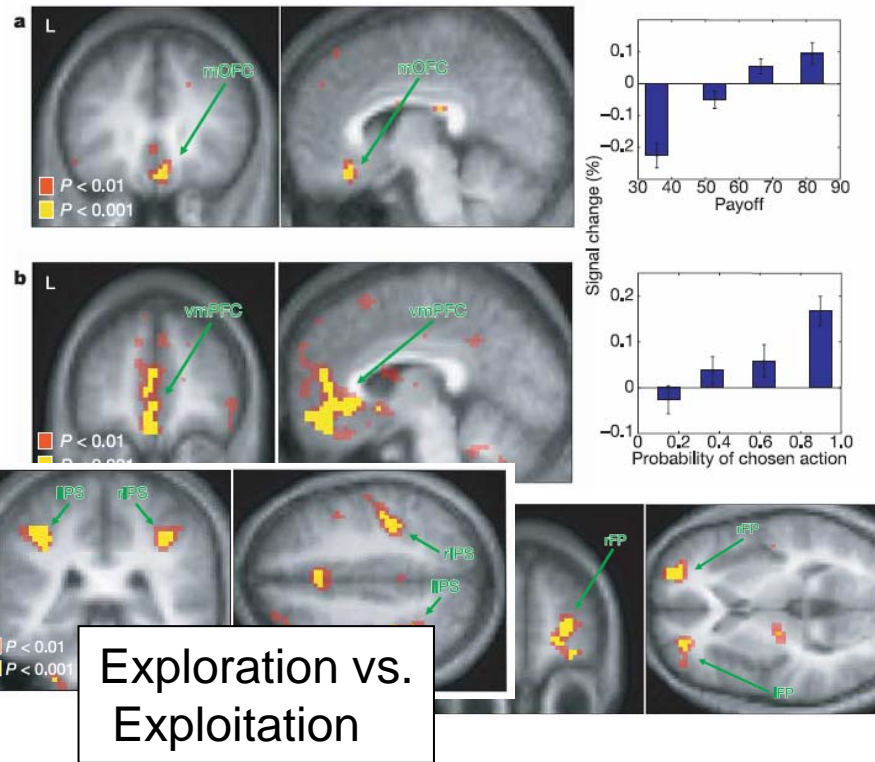
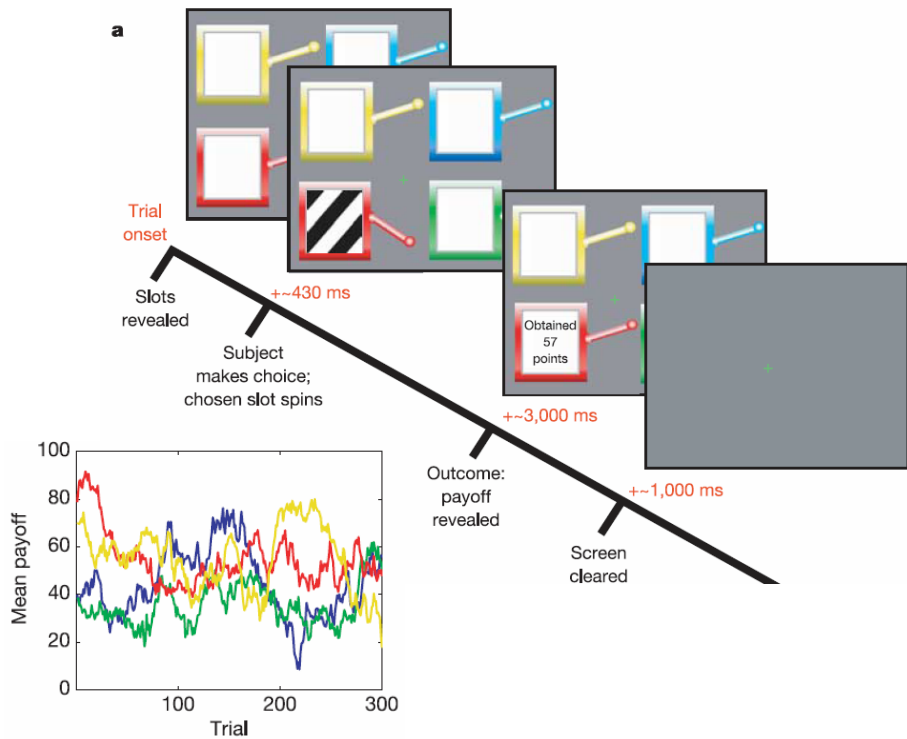
Patient 1: Stressful Chest Pa
Patient 2: Smoking Coughing
Patient 3: Working Chest Pa
...

Causal learning with complementary "cortical" and "hippocampal" networks



- Module (number)
- Regulator (signaling molecule)
- Regulator (transcription factor)
- ⋯ Inferred regulation
- Regulation supported in literature
- Enriched cis-regulatory motif
- Experimentally tested regulator

Learning to act



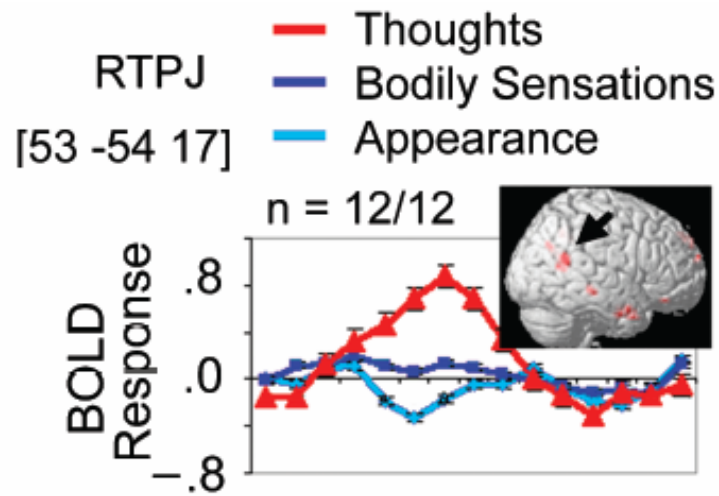
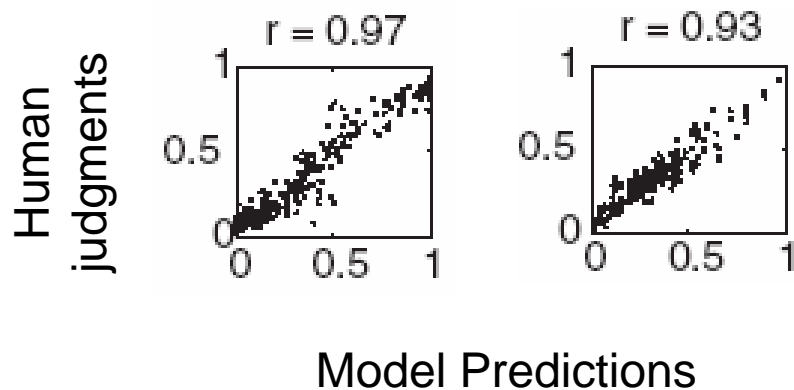
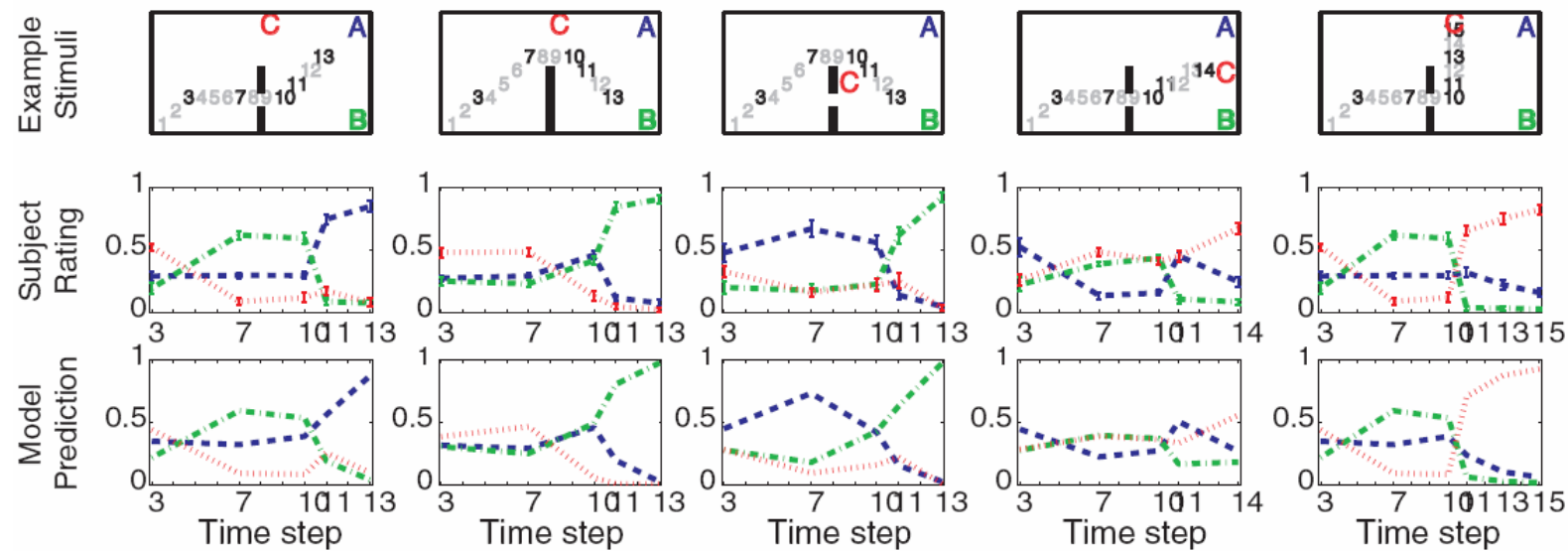
Concepts learned:
Clear,
Inhand
Topstack
Above
Height
 ...

Understanding actions: goal inference

Constraints Goals

Rational planning
(PO)MDP

↓
Actions



The grand challenge

Cognitive science of
human learning



Design of artificial
learning systems



Brain structures and
mechanisms that
support learning