Predict

bottom-up prediction

……… learning, least-squares and function approximation

…………. prediction, optimization and control

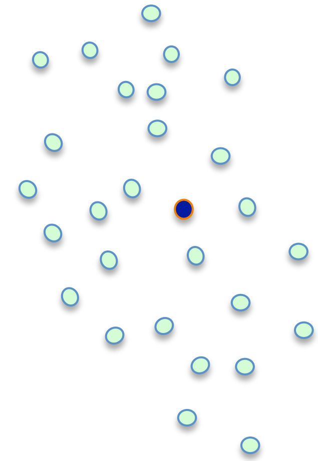
………………… hierarchical temporal memory: prediction

……………………… top-down/bottom-up blackboard architecture

…………………………. web-intelligence; brains; adaptive BI

……………………………….. challenge problems

learning and prediction



m data points each having (i) *features* $x_1 \dots x_{n-1}$ = **x**

and (ii) *output variable(s)* $y_1 \dots y_k$.

e.g. *prices* (numbers for Y); x_i can be numbers or categories

for now assume k=1, i.e. just one output variable y

linear prediction:

$f(\mathbf{x}) = E[y|\mathbf{x}]$ also minimizes*:

$\varepsilon = E[\text{error}] = E[y - f(\mathbf{x})]^2 \approx \frac{1}{m}\Sigma_m(y_i - f(\mathbf{x_i}))^2$

suppose $f(\mathbf{x}) = [\mathbf{x};1]^T\mathbf{f} = \mathbf{x'}^T\mathbf{f}$

i.e. *linear* in **x**; so we want $X\,\mathbf{f} \approx \mathbf{y}$

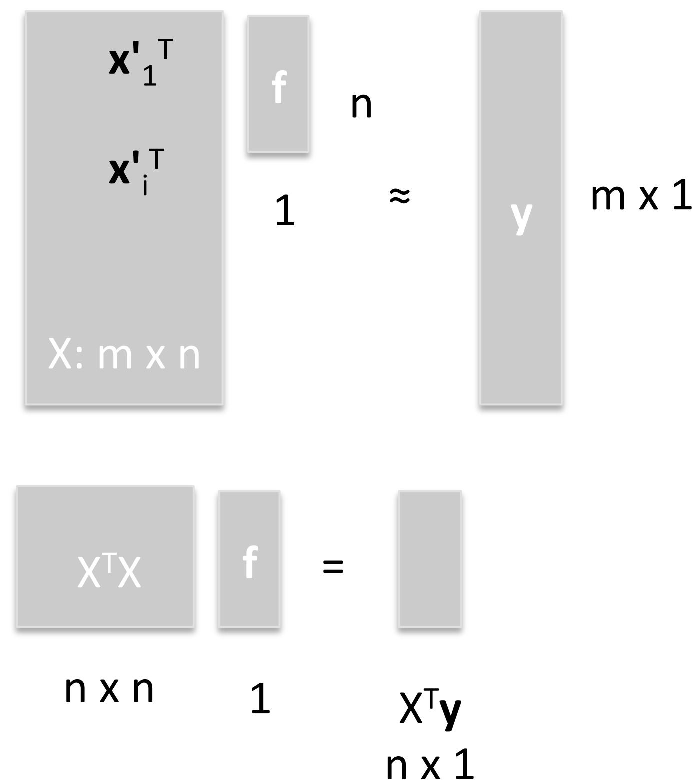
$\Sigma_m(y_i - \mathbf{x'_i}^T\mathbf{f})^2 = (X\,\mathbf{f} - \mathbf{y})^T (X\,\mathbf{f} - \mathbf{y})$

minimized if derivative = 0, i.e.

$X^TX\,\mathbf{f} - X^T\mathbf{y}$ .. "normal equations"

once we have **f**, our "least-squares"

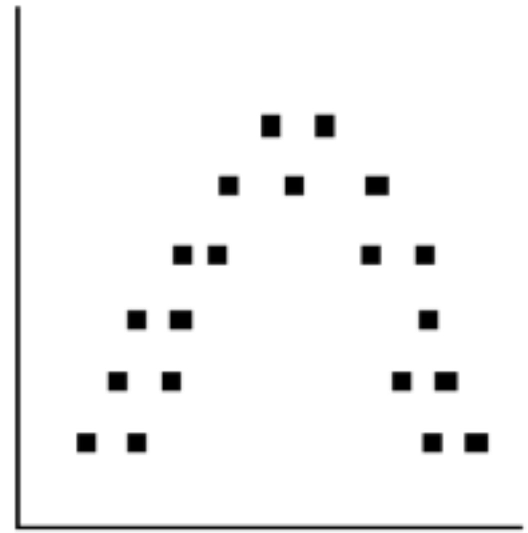
estimate of $y|\mathbf{x}$ is $f^{LS}(\mathbf{x}) = \mathbf{x'}^T\mathbf{f}$



some examples

x	y
10	1.2
22	1.8
42	4.6
15	1.3

$$\begin{array}{ccccc} X & & f & & y \\ \begin{bmatrix} 10 & 1 \\ 22 & 1 \\ 42 & 1 \\ 15 & 1 \end{bmatrix} & & \begin{bmatrix} 0.11 \\ -0.26 \end{bmatrix} & \approx & \begin{bmatrix} 1.2 \\ 1.8 \\ 4.6 \\ 1.3 \end{bmatrix} \end{array}$$



how good is the 'fit' ? $$R^2 \equiv 1 - \frac{\sum_i (f^T x_i - y_i)^2}{\sum_i (\bar{y} - y_i)^2} = .95$$

example 2*:

[y, **x**] = [wine-quality, winter-rainfall, avg-temp, harvest-rainfall]

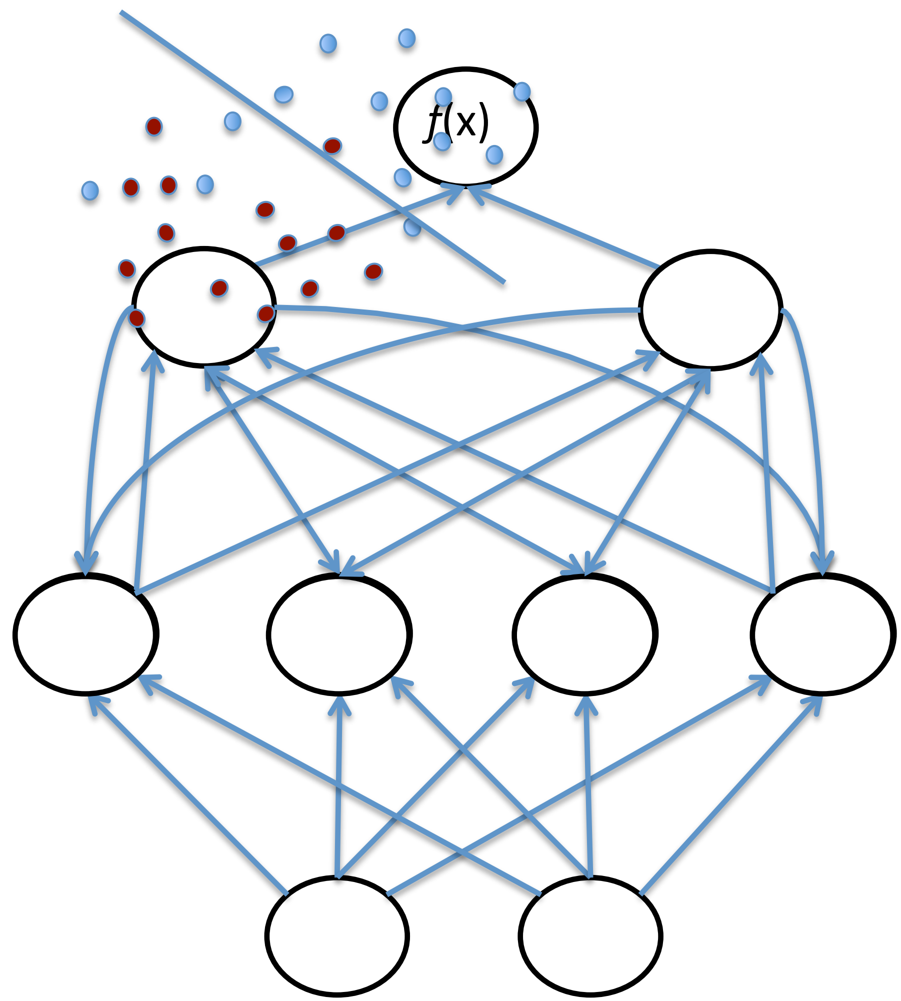
$f^{LS}(\mathbf{x})$ = 12.145 + 0.00117 × winter-rainfall + 0.0614 × avg-temperature − 0.00386 × harvest rainfall

*Super-crunchers, Ian Aryes 2007: Orley Ashenfelter

beyond least-squares

categorical data
- logistic regression
- support-vector-machines
  - complex f :
    - 'kernel'-parameters also learn

neural networks
- linear = least-squares
- non-linear
  - like logistic etc.
- feed-forward, multi-layer
  - more complex f
- feed-back
  - like a belief n/w;
    - "explaining-away" effect



deep-belief network

learning parameters

whatever be the model:

need to minimize $|f(x) - y| = \varepsilon(\mathbf{f})$

complex f => no formula

so, iterative method ; start with $\mathbf{f}^0$

$\mathbf{f}^1 = \mathbf{f}^0 + \delta\mathbf{f}$

$f^{i+1} = f^i - \alpha \nabla_f \varepsilon(f^i)$ gradient-descent

use $\varepsilon(\mathbf{f}^i)-\varepsilon(\mathbf{f}^{i-1})$ to approximate derivative

works fine with numbers, i.e. x in $\mathbf{R}^n$

.. *caveats*: local minima, constraints

for categorical data:

convert to binary, i.e. $\{0,1\}^N$

"fuzzyfication": convert to $\mathbf{R}^n$

neighborhood-search; heuristic search, genetic algorithms ..

probabilistic models, i.e. deal with probabilities instead

related matters

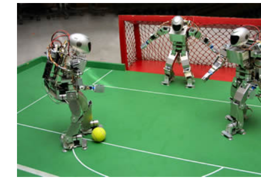
"best" solution

$\mathbf{w}$: maximize $\phi(\mathbf{w})$

control actions: $\boldsymbol{\theta}^i$: $\mathbf{s}^{i+1}=S(\boldsymbol{\theta}^i)$

minimize $|\mathbf{s} - \Xi|$

predict – decide - control



robo-soccer

predict where the ball *will* be; decide best path; navigate there

predict how *other* players will move

self-driving cars

predict the path of a pedestrian; decide path to avoid; steer car

predict traffic; decide *all* optimal routes to destination

energy-grid

predict energy demand; decide & control distribution

predict supply by 'green-ness'; adjust prices *optimally*

supply-chain

predict demand for products; decide best production plan; execute it

detect potential risk & evaluate impact; re-plan production; execute it

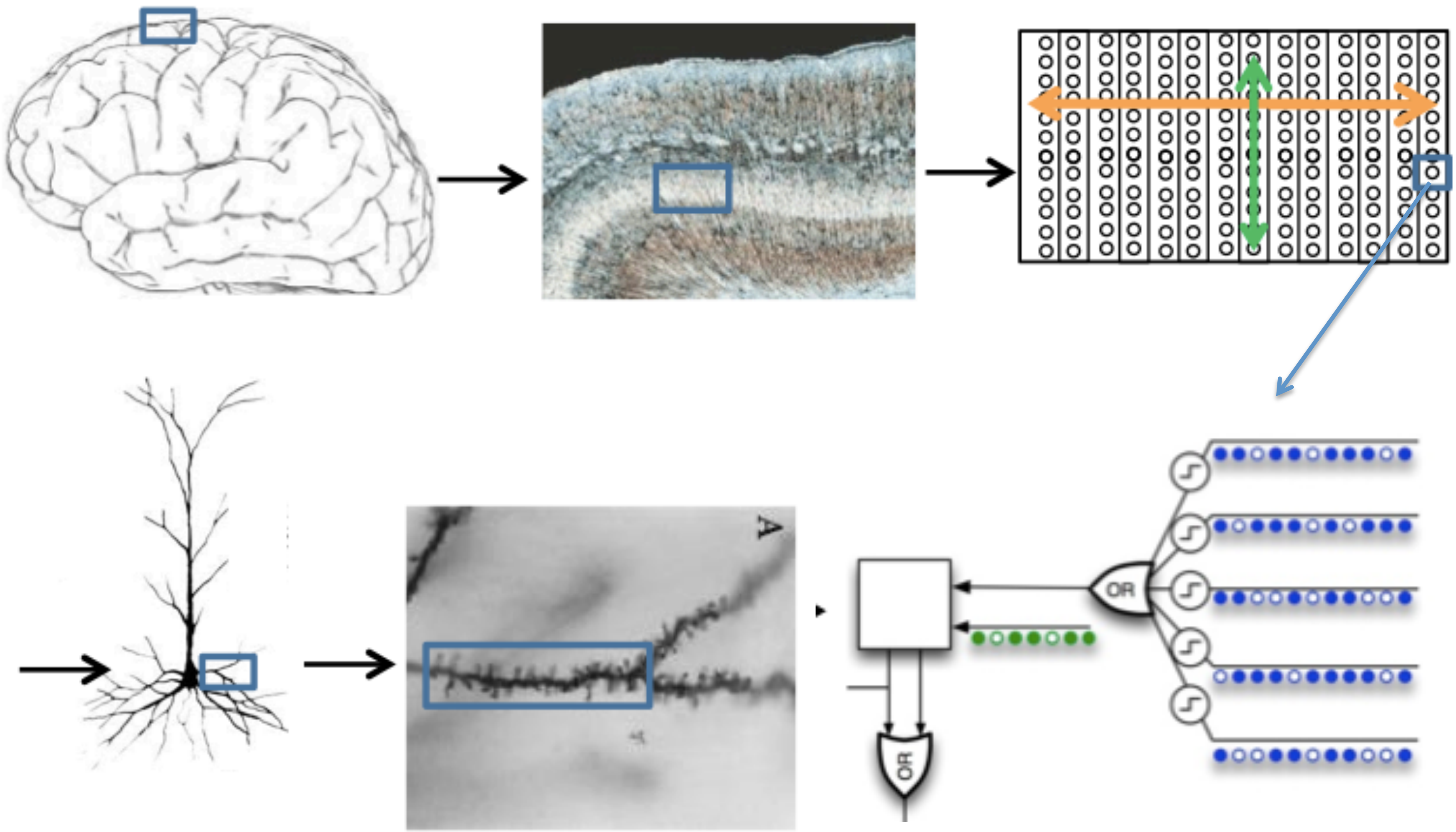
marketing

predict demand; decide promotion strategy by region; execute it

which learning/prediction technique?

	features (i.e. X)	target (i.e, Y)	correlation	technique
	numerical	numerical	stable / linear	**linear regression**
prediction	categ			feature oding)
	nume			-level, ar)
	nume			
classification	nume			**es**
				ng)
	categ			Models

hierarchical temporal memory



extracted from Jeff Hawkins's ISCA 2012 charts

sparse distributed representations

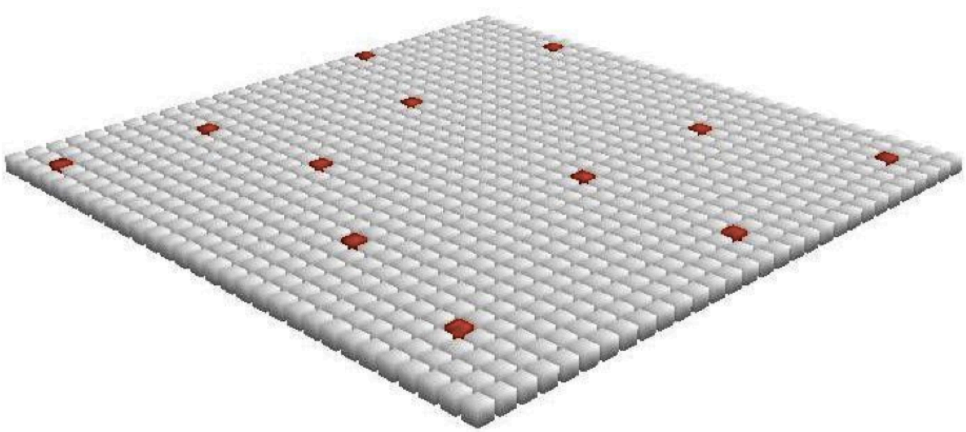
remember the properties of $\{0,1\}^{1000}$:

very low chance that patterns differ in less than 450 places

forced sparse pattern: e.g. 2000 bits with only 40 1^s

very low chance of a random sparse pattern matching any 1^s

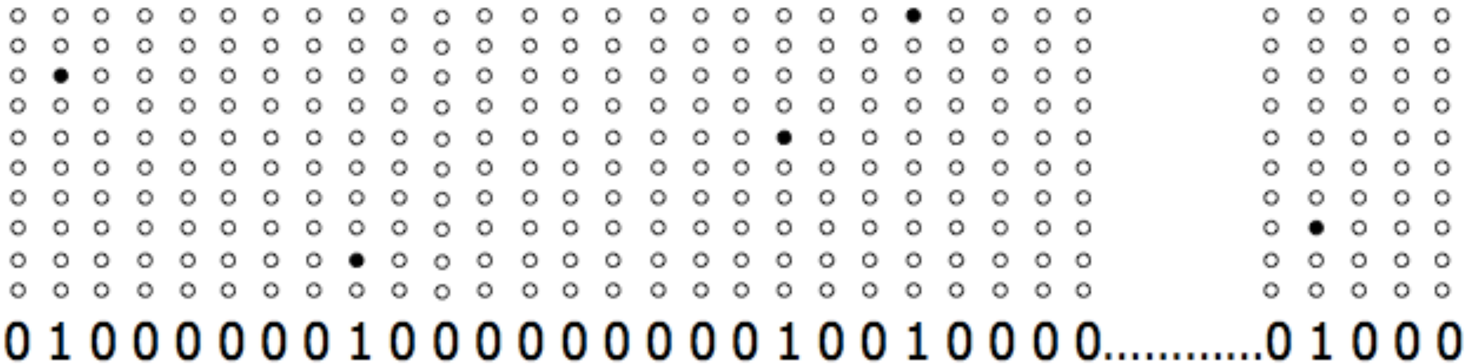
even if we drop all but 10 random positions; another sparse pattern matching some of these 10 is most likely another instance of the same sparse 40 1^s pattern (sub-sampled differently)



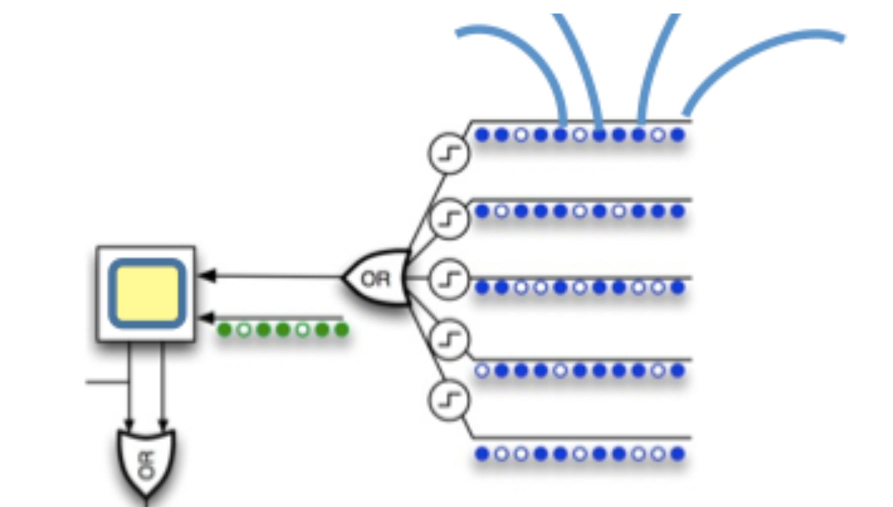
similar 'scene' will give similar sparse pattern even after sub-sampling

Jeff Hawkins's ISCA 2012

sequence learning



40 active bits, 10 cells per column
10^{40} ways to represent the same input in different contexts



each cell tracks the
previous configuration – again sparsely;
via ‘synapse connections;
these form and are forgotten
or reinforced if predicted value <u>occurs</u>
column per cell – predicts further ahead

Jeff Hawkins’s ISCA 2012

hierarchy; linkages; applications

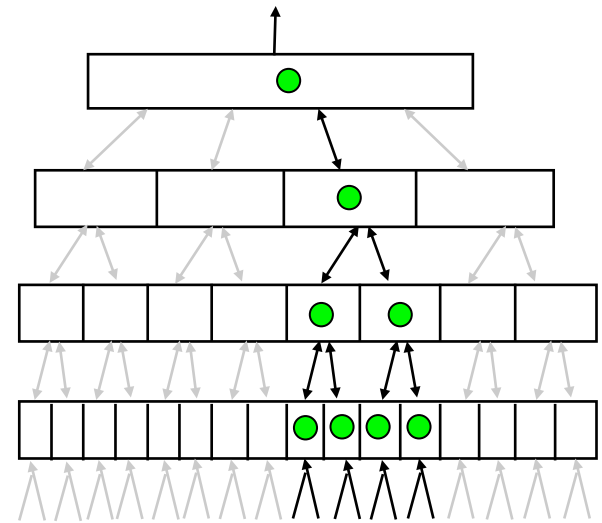
multiple ‘regions’ in a hierarchy

bottom-up (feed-forward)

<u>plus</u> top-down (feed-back)

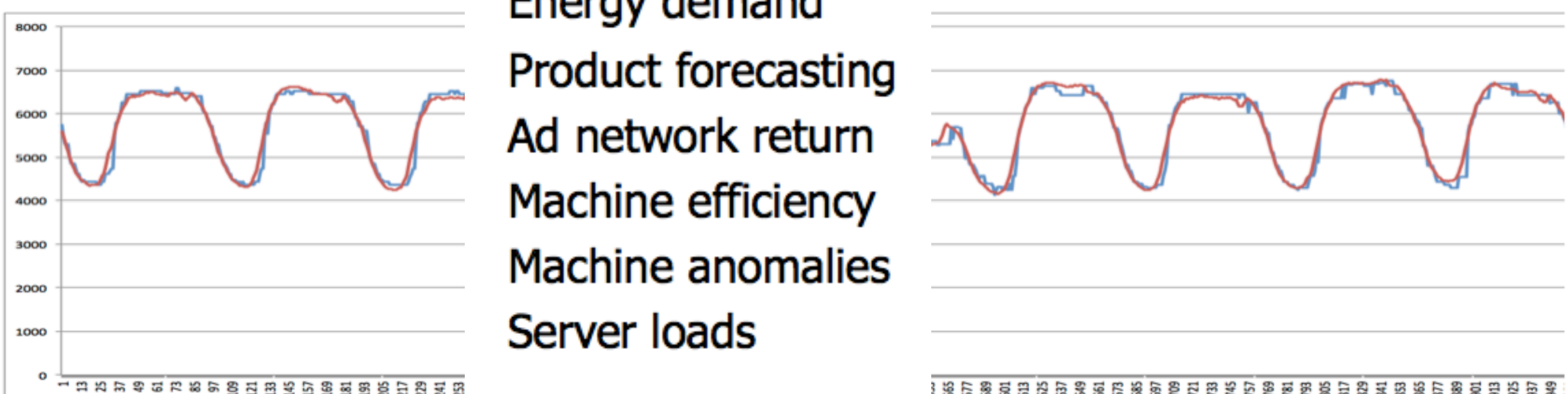
mathematically

HTM is ≈ deep belief network



applications:

- Energy pricing
- Energy demand
- Product forecasting
- Ad network return
- Machine efficiency
- Machine anomalies
- Server loads



Jeff Hawkins’s ISCA 2012

Regional energy load

something missing?

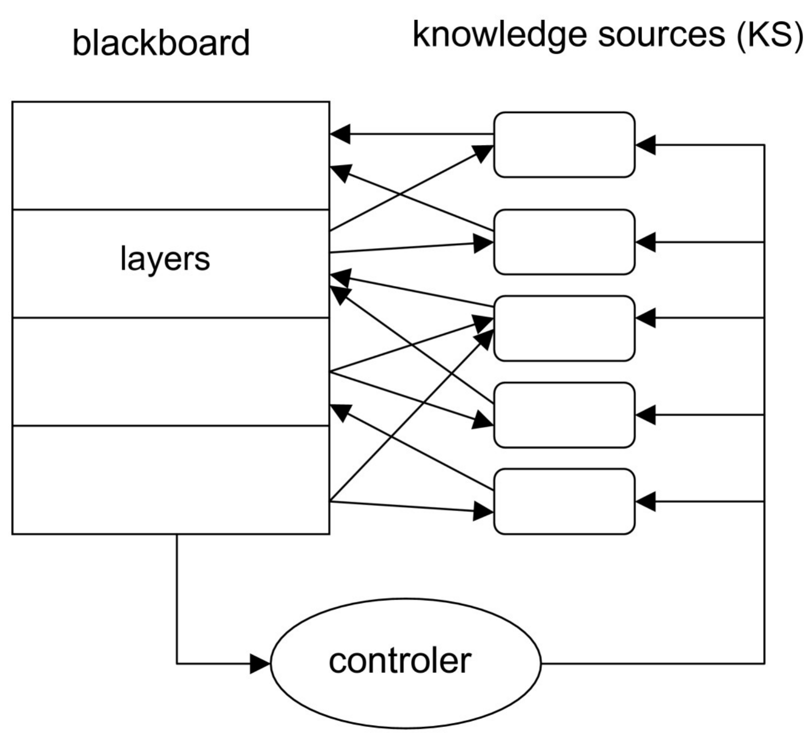
"predict how other players/pedestrians will move"

"`predict' the consequences of a decision": what-if?

- use these 'predictions' to re-evaluate / re-look at inputs and re-plan

missing element: symbolic reasoning, optimization etc.

can they work together: `blackboard' architecture



knowledge Sources:
- feature-learning
- clustering
- sequence-miners
- classifiers
- rule-engines
- decision-engines

hierarchical
- Bayesian…

examples:
- speech
- analogy

what does *data* have to do with *intelligence*?

"any fool can know … the point is to understand."
- Albert Einstein

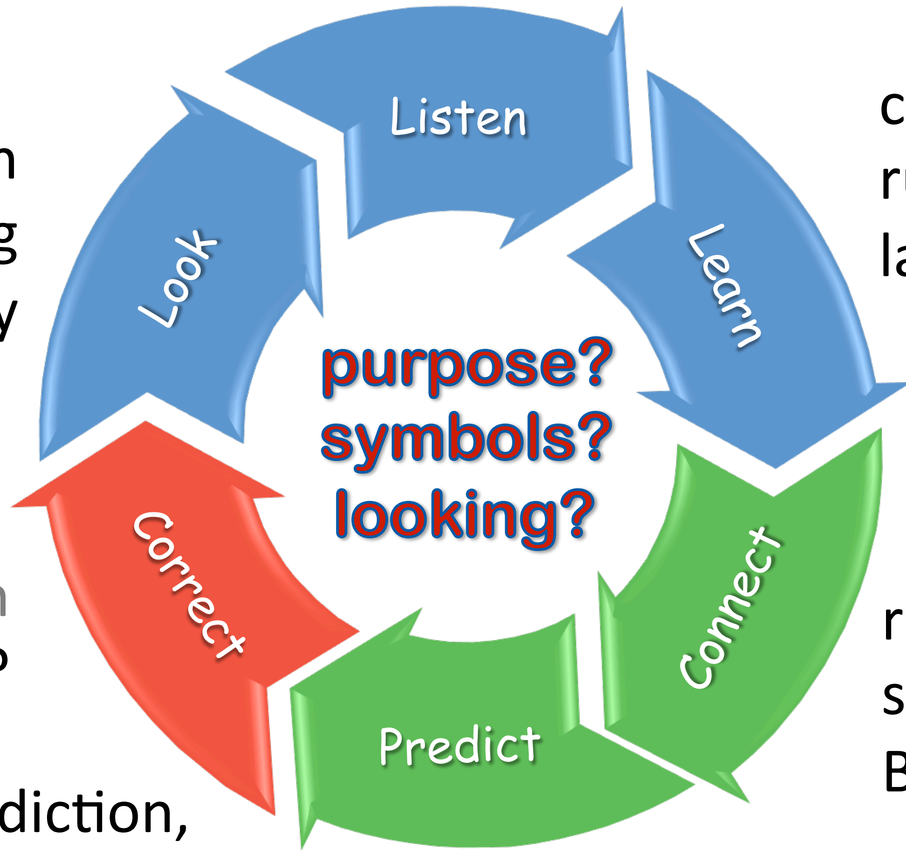
and … the goal of understanding is to <u>predict</u>

recap and challenges

NB classifier; information

search
hashing
memory

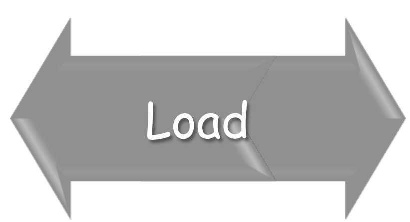
clustering,
rule mining
latent models



optimization
next time?

reasoning,
semantic web
Bayesian networks

linear prediction,
neural net, HTM, blackboard



map-reduce
database evolution