

Solving Graph Isomorphism Problems via Hyperdimensional Noise



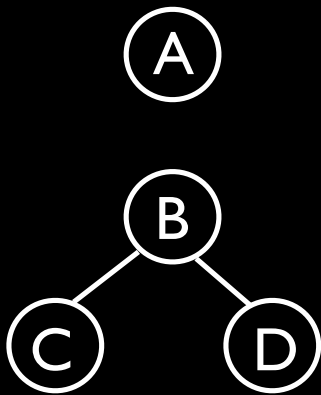
Simon D. Levy
Dept. of Computer Science & Program
in Neuroscience
Washington & Lee University

30 April 2009

Outline

1. Graphs: what & why
2. Solving graph isomorphism via Motzkin-Straus Theorem & replicator equations
3. Computing with hyperdimensional noise vectors
4. Solving graph isomorphism with hyperdimensional noise
5. Conclusions

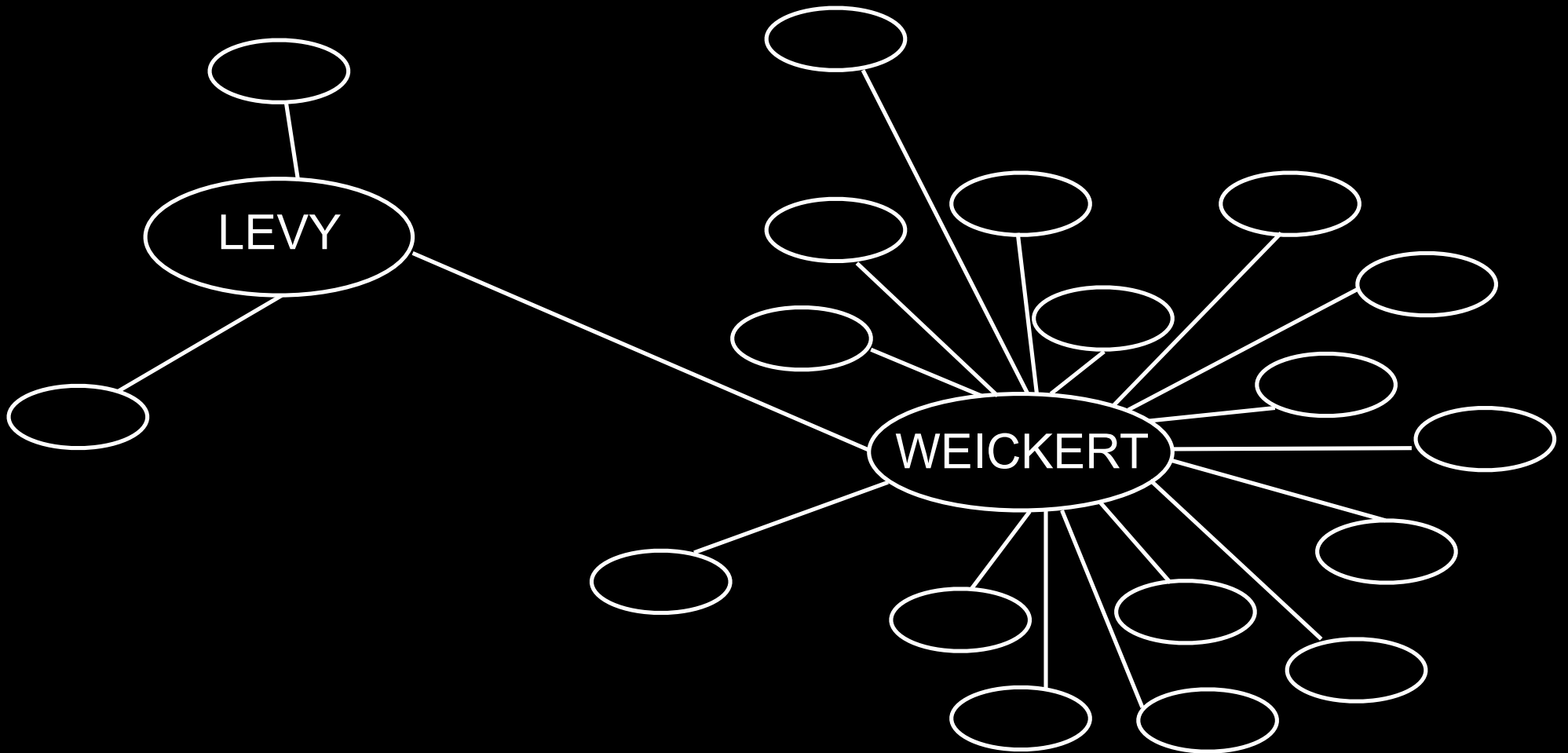
Graphs: What



- Formally, a set of **vertices** V and **edges** $E \subseteq V \times V$
- Here, $V = \{A, B, C, D\}$,
 $E = \{ (B,C), (B,D) \}$
- I'll ignore the difference between directed & undirected graphs

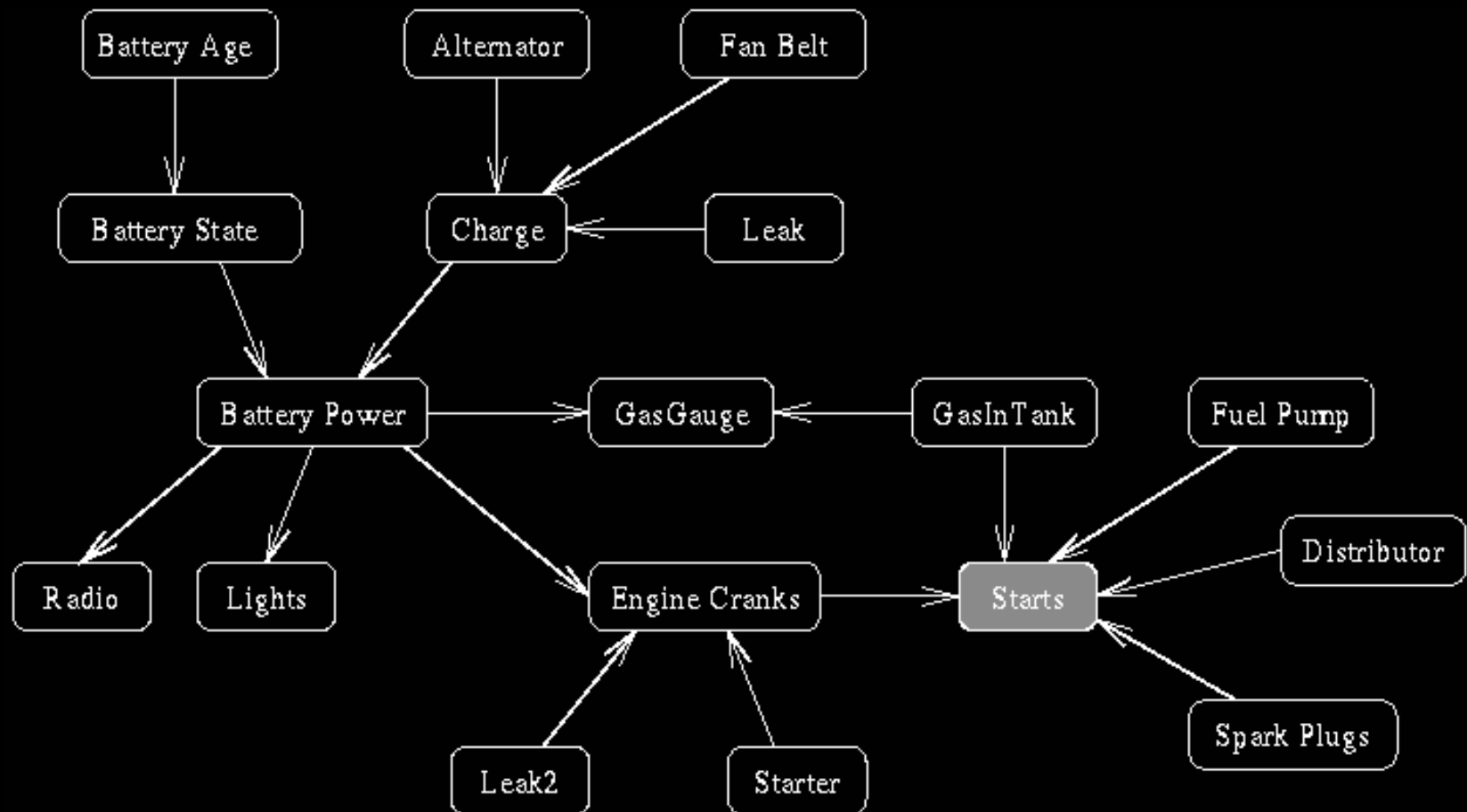
Graphs: Why

Social networks



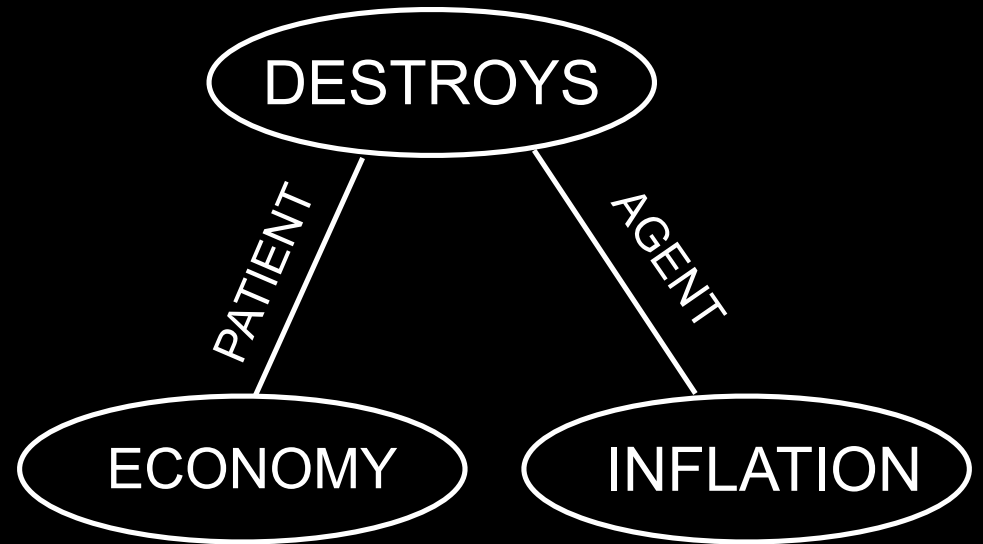
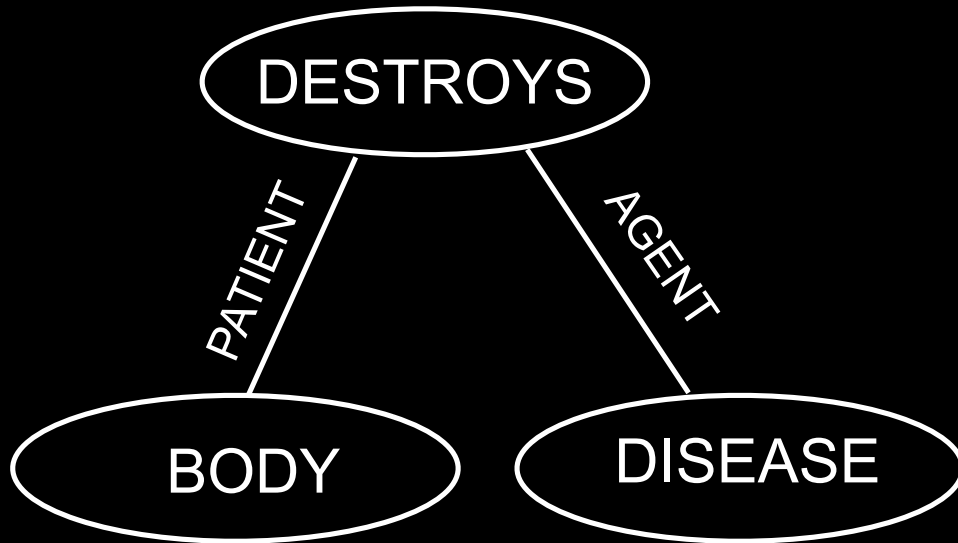
Graphs: Why

Belief Networks



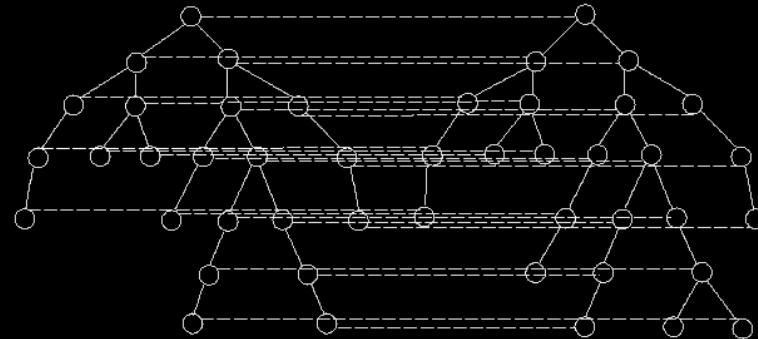
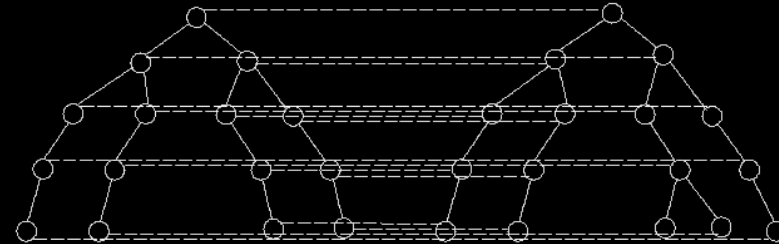
Graphs: Why

Language / Analogy

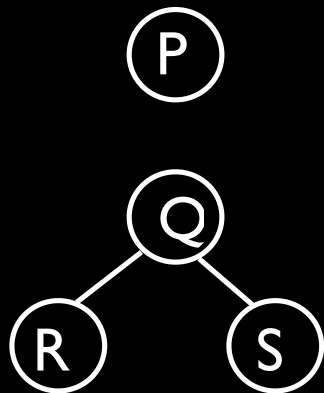
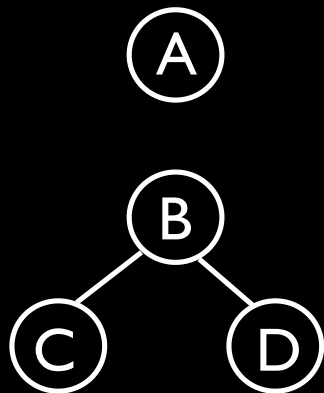


Graphs: Why

Shape Recognition
(Pelillo 1999)



The Graph Isomorphism Problem



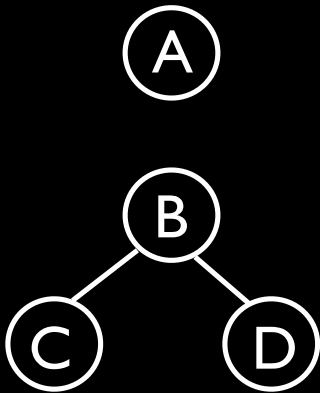
- Find good **mappings** to preserve edge relations:

$A=P, B=Q, C=R, D=S$

$A=P, B=Q, C=S, D=R$

- Believed to lie between P (“easy”) and NP (“hard”) problem classes

Adjacency Matrix



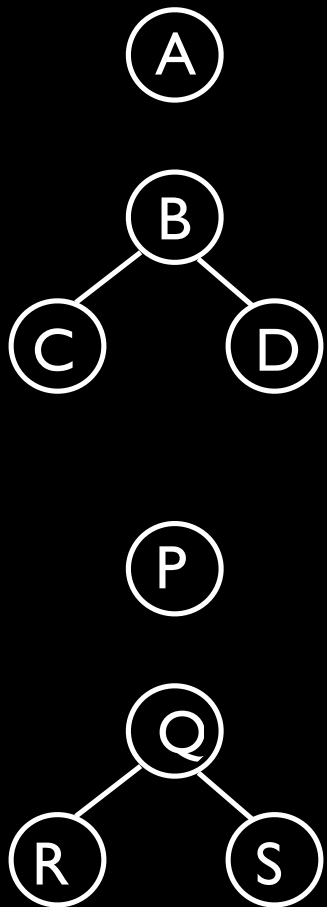
	A	B	C	D
A	0	0	0	0
B	0	0	1	1
C	0	1	0	0
D	0	1	0	0

Association Graph

Given a graph G' of size N (vertices) with an $N \times N$ adjacency matrix $A' = a'_{ij}$ and a graph G'' of size N with an $N \times N$ adjacency matrix $A'' = a''_{hk}$, their **association graph** G of size N^2 can be represented by an $N^2 \times N^2$ adjacency matrix $A = (a_{ih,jk})$ whose edges encode pairs of edges from G' and G'' :

$$a_{ih,jk} = \begin{cases} 1 - (a'_{ij} - a''_{hk})^2 & \text{if } i \neq j \text{ and } h \neq k \\ 0 & \text{otherwise} \end{cases}$$

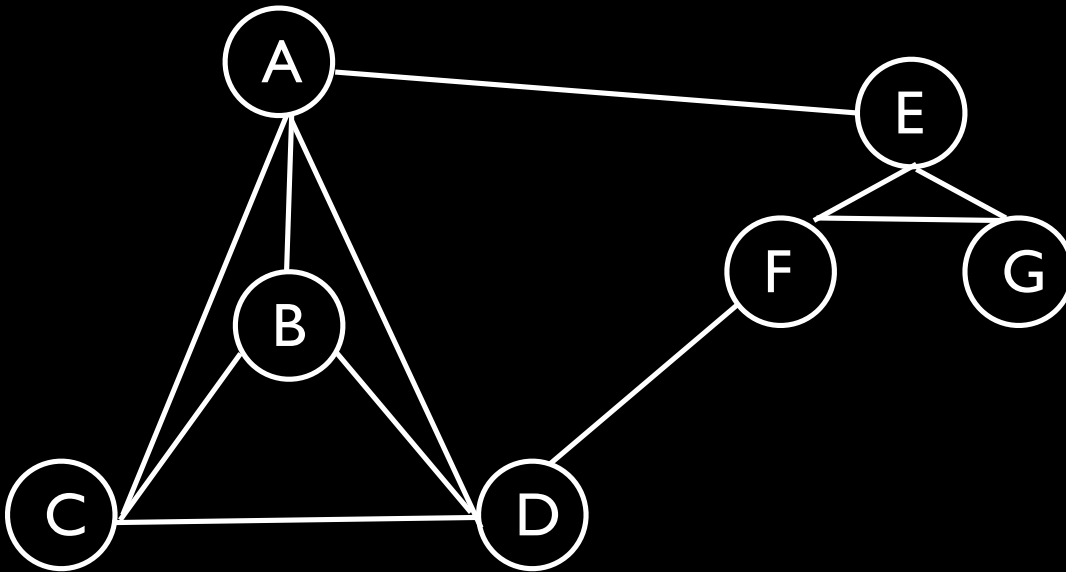
Association Graph



	AP	AQ	AR	AS	BP	BQ	BR	BS	CP	CQ	CR	CS	DP	DQ	DR	DS
AP	0	0	0	0	0	1	1	1	0	1	1	1	0	1	1	1
AQ	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
AR	0	0	0	0	1	0	0	1	1	0	0	1	1	0	0	1
AS	0	0	0	0	1	0	1	0	1	0	1	0	1	0	1	0
BP	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
BQ	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1
BR	1	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0
BS	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0
CP	0	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1
CQ	1	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0
CR	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	1
CS	1	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0
DP	0	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0
DQ	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
DR	1	0	0	1	0	1	0	0	1	0	0	1	0	0	0	0
DS	1	0	1	0	0	1	0	0	1	0	1	0	0	0	0	0

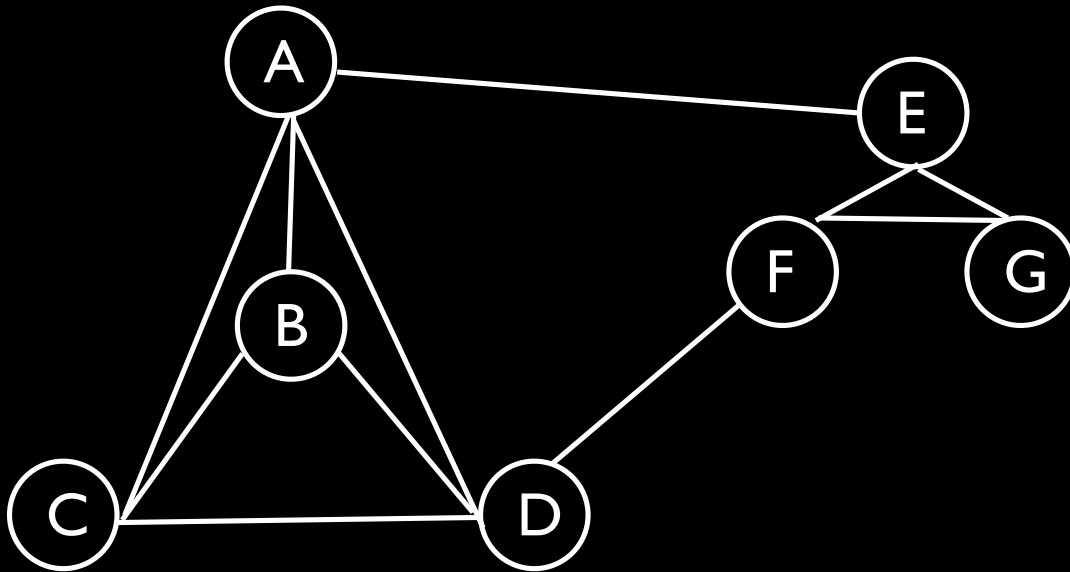
Clique

- A **clique** is a subset of vertices each of which is adjacent to all others.



- A,B,C,D
- E,F,G

Maximal Clique



A,B,C,D

E,F,G

Graph Isomorphism as Maximal Clique

A maximal isomorphism between two graphs G' and G'' corresponds to a maximal clique in their association graph G .

Motzkin-Straus Theorem

Consider a graph G with adjacency matrix A , a subset C of vertices of G , and a **characteristic vector** x^C (indicating membership in the subset C) defined as

$$x_i^C = \begin{cases} 1/|C| & \text{if } i \in C \\ 0 & \text{otherwise} \end{cases}$$

where $|C|$ is the cardinality of C .

Motzkin-Straus Theorem

It turns out that C is a maximum clique of G iff x^C maximizes the function $f(x) = x^T A x$, where x^T is the transpose of x , $x \in \mathbf{R}^N$, $\forall i x_i \geq 0$, and $\sum_{i=1}^N x_i = 1$.

So how do we obtain x ?

Replicator Equations

Starting at some initial state (typically just $x_i = 1/N$ corresponding to all x_i being equally supported as part of the solution), x can be obtained through iterative application of the following equation:

$$x_i(t + 1) = \frac{x_i(t)\pi_i(t)}{\sum_{j=1}^N x_j(t)\pi_j(t)}$$

where

$$\pi_i(t) = \sum_{j=1}^N w_{ij}x_j(t)$$

and w is a linear function of the adjacency matrix of the association graph (“evidence matrix”).

Evolutionary Game Theory

$$\pi_i(t) = \sum_{j=1}^N w_{ij} x_j(t)$$

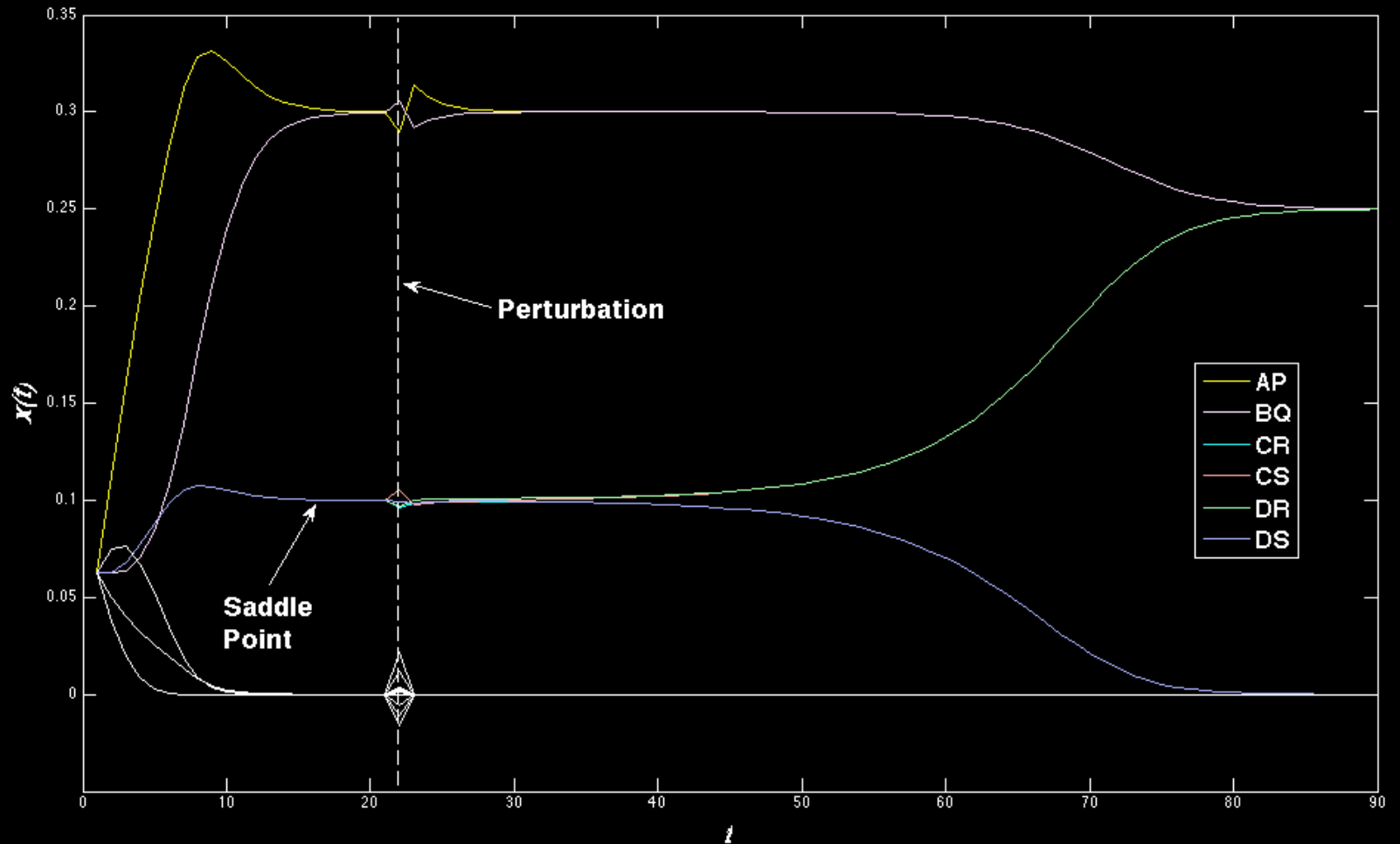
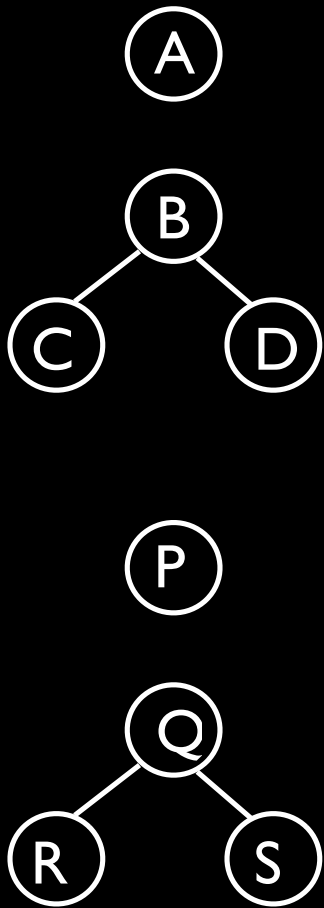
- Origins in Evolutionary Game Theory (Maynard Smith 1982)
- x_i is a strategy
- π_i is the overall payoff from that strategy
- w_{ij} is the utility of playing strategy i against strategy j

Evolutionary Game Theory

E.g. Prisoner's Dilemma

		Player B	
		<i>Cooperate</i>	<i>Defect</i>
Player A	<i>Cooperate</i>	A→3, B→3 Reward for mutual cooperation	A→0, B→5 Sucker's payoff and temptation to defect
	<i>Defect</i>	A→5, B→0 Temptation to defect and sucker's payoff	A→1, B→1 Punishment for mutual defection

Sample Run



Part II

Hyperdimensional Noise Vectors

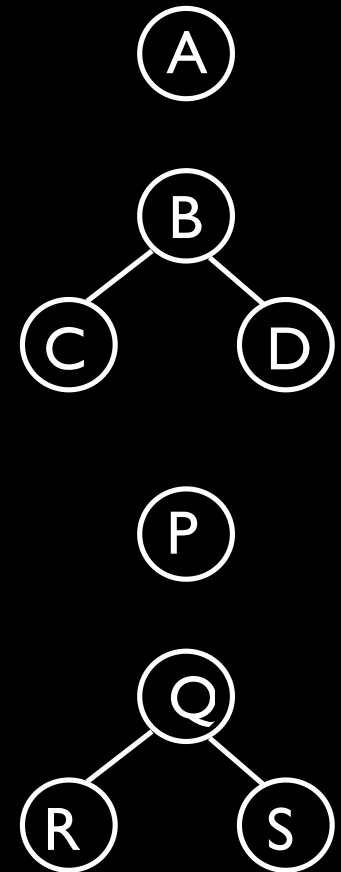
- Replicator equations are biologically motivated (cf. Hull 1989 on General Selection)
- But high-precision, low-dimensional coding (*a la* Motzkin-Straus) is biologically implausible

Hyperdimensional Noise Vectors

- Consider high-dimensional vectors (10,000 or more elements) randomly chosen from $\{+1, -1\}$.
- Nice properties
 - Lots of mutually orthogonal vectors, astronomical number of nearly-orthogonal
 - Highly robust to degradation
 - Each vector is its own multiplicative inverse (elementwise)

Hyperdimensional Noise Vectors

- We represent each vertex as one such vector
- Edge between A and B: $A*B$
- Set of edges: $B*C + B*D$
- Set of mappings:
 $A*P + B*Q + C*R + D*S$
- A “distributed data structure”



Hyperdimensional Noise Vectors

- Set of mappings:

$$A^*P + B^*Q + C^*R + D^*S$$

- Who is associated with A?

$$A^*(A^*P + B^*Q + C^*R + D^*S)$$

$$= A^*A^*P + A^*B^*Q + A^*C^*R + A^*D^*S$$

$$= P + \text{“junk” (via distance metric)}$$

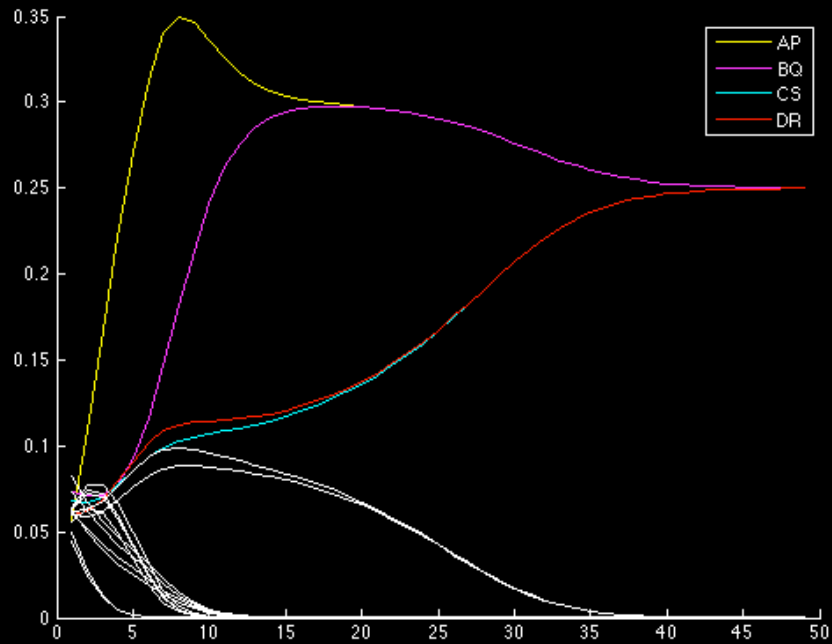
Replicator Equations with Hyperdimensional Vectors

- Possibilities $x: A*P + A*Q + A*R + A*S + \dots + D*S$
- Evidence $w: A*B*P*Q + A*B*P*R + \dots + B*C*Q*R + \dots + C*D*R*S$

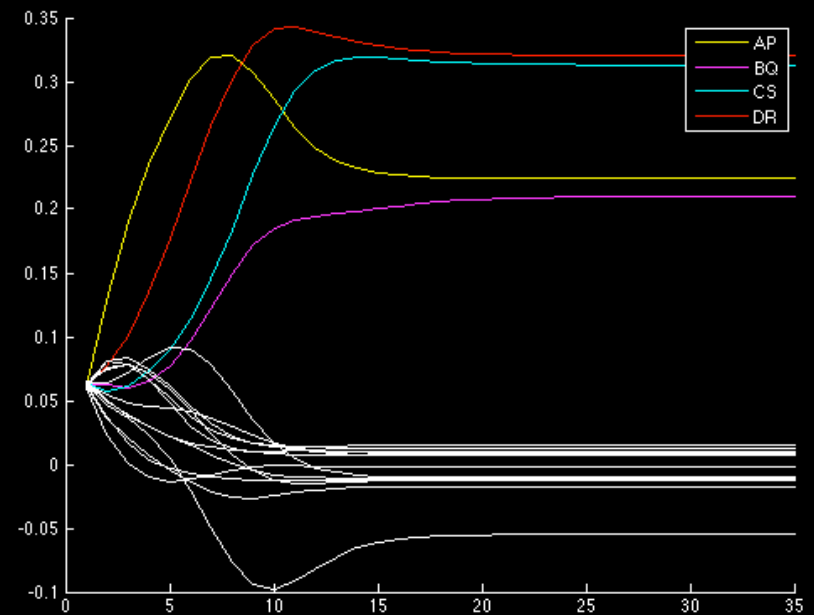
$$x*w = A*Q + B*R + \dots + A*P + \dots + D*S$$

- NOTE: $x*w$ is a single “holistic” vector operation!
- Glossed over: $w*\pi$ should reinforce, not self-cancel

Results



Pelillo (1999)



Levy & Gayler
(submitted)

Conclusions

- Motivating question (P. Kanerva):
[W]hat kinds of things suggested by the architecture of the brain, if we modeled them mathematically, could give some properties that we associate with mind?
- Difficult, highly interdisciplinary work, best done at a place like W&L

Try It At Home!

tinyurl.com/gidemo