

Scaling Up Game Theory: Representation and Reasoning with Action Graph Games

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This talk is primarily based on papers with:

Albert Xin Jiang

Navin A.R. Bhat

[AAAI 2006]

[UAI 2004]

and a joint paper [GEB, to appear 2010]

and also touches on more recent joint work with

Albert Xin Jiang, David R.M. Thompson,
Avi Pfeffer, Damien Bargiacchi, and James Wright

The Kind of Games Often Studied

- e.g., Prisoner's Dilemma: you and an accomplice are arrested. Should you confess or stay silent?

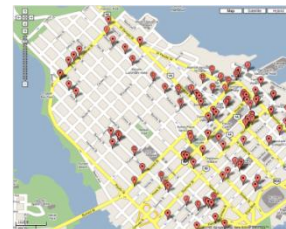
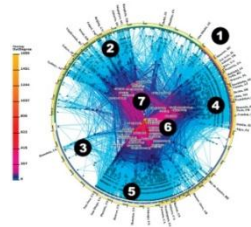
	C	D
C	$-5, -5$	$-20, 0$
D	$0, -20$	$-1, -1$

- The analysis of such 2×2 games has proven surprisingly interesting, and has had a profound impact both on our understanding of strategic situations and on popular culture



The Kind of Games We'd Like to Study

- In order to use game theory to **model real systems**, we need to consider games with more than two agents and two actions
- **Some examples** of the kinds of questions we would like to be able to answer:
 - How will heterogeneous users route their traffic in a network?
 - How will advertisers bid in a sponsored search auction?
 - Which job skills will students choose to pursue?
 - Where in a city will businesses choose to locate?
- Most GT work is **analytic, not computational**
- What's holding us back?
 - the size of classical game representations **grows exponentially** in the number of players
 - this makes all but the simplest games infeasible to write down
 - even when games can be represented, “fast” algorithms often have **worst-case performance exponential** in the game's size



Compact Representations

Research program for advancing the computational analysis of games:

1. find representations that can encode games of interest in **exponentially-less space** than the normal form
2. find **efficient algorithms** for working with these representations

Key representations from the literature:

- **Graphical Games** [Kearns, Littman, Singh, 2001]
 - utility functions exhibit strict independence
 - some pairs of agents have no (direct) effect on each other's payoff
 - many efficient algorithms
 - however, none of the games discussed above are compact as GGs
- **Congestion Games** [Rosenthal, 1973; Monderer & Shapley, 1996]
 - utility functions exhibit context-specific independence
 - whether agents affect each other's payoffs can depend on the action choices they each make
 - good theoretical properties; some algorithmic results
 - however, none of the games discussed above can be represented as CGs

Overview of This Talk

1. Basic AGGs: Definition and Examples
2. Analyzing and Extending the Representation
3. Computing Expected Utility
4. Recent Directions

The Coffee Shop Problem



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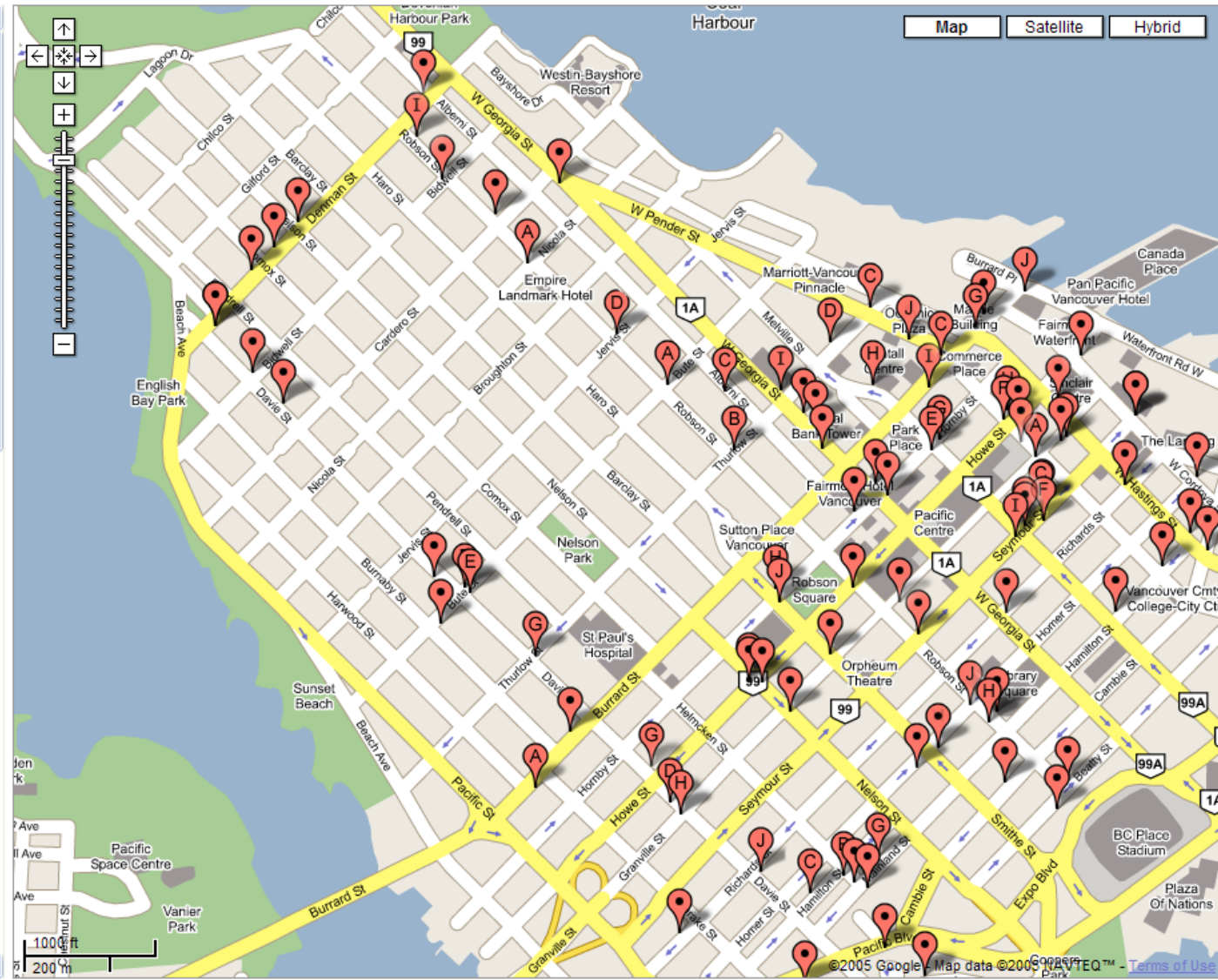
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Search results for **category: Coffee Houses** in this map

- A** [Connoisseurs' Coffee](#)
1075 Georgia Street West, Vancouver, BC V6E 3C9
(604) 683-1486
- B** [Melriches Coffeehouse](#)
1244 Davie Street, Vancouver, BC V6E 1N3
(604) 689-5282
- C** [Hole In The Wall Cappuccino Bar](#)
1030 Georgia Street West, Vancouver, BC V6E 2Y3
(604) 646-4653
- D** [Starbucks Coffee Co](#)
1055 W Georgia, Vancouver, BC V5K 1A1
(604) 685-5882
- E** [Five Roses Bakery Cafe](#)
1220 Bute Street, Vancouver, BC V6E 1Z8
(604) 669-8989
- F** [Starbucks Coffee Co](#)
1095 Howe Street, Vancouver, BC V6Z 1P6
(604) 685-7083
- G** [Uptown Espresso](#)
808 Nelson Street, Vancouver, BC V6Z 2H2
(604) 689-1920
- H** [Caffe Artigiano](#)
763 Hornby Street, Vancouver, BC V6Z 1S2
(604) 696-9222
- I** [Skyline Expresso](#)
900 Howe Street, Vancouver, BC V6Z 2M4
(604) 683-4234
- J** [Fahrenheit Celsius Coffee](#)
1225 Burrard Street, Vancouver, BC V6Z 1Z5
(604) 682-6675
- K** [Chicco Dall Oriente](#)
1504 Robson Street, Vancouver, BC V6G 1C2



Basic Action-Graph Games

- set of **players**: want to open coffee shops
- **actions**: choose a location for your shop, or choose not to enter the market
- **utility**: profitability of a location
 - some locations might have more customers, and so might be better *ex ante*
 - utility also depends on the number of other players who choose the same or an adjacent location



Formal Definitions

Definition 3 (neighborhood relation) *Given a graph having a set of nodes \mathcal{A} and edges E , define the **neighborhood relation** as $\nu : \mathcal{A} \rightarrow 2^{\mathcal{A}}$, with $\nu(i) = \{j | (j, i) \in E\}$.*

Define a **configuration over a node's neighborhood**, written as $c^{(\alpha)} \in C^{(\alpha)}$, as the elements of c that correspond to the actions $\nu(\alpha)$.

Definition 4 A **basic action-graph game (AGG- \emptyset)** is a tuple (N, A, G, u) :

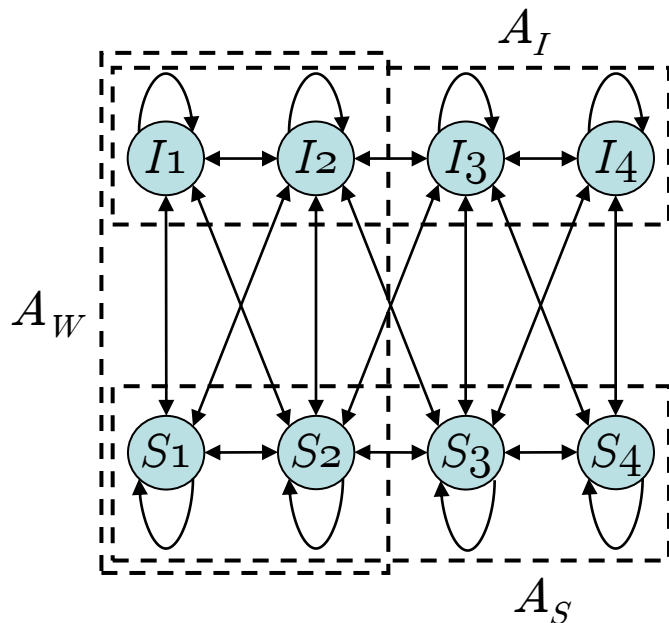
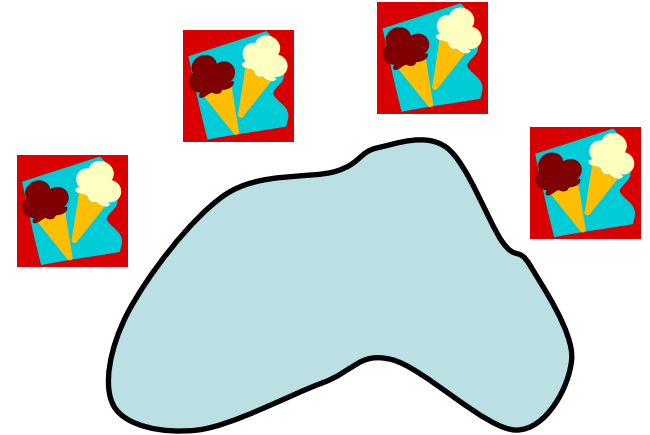
- N is the set of agents;
- $A = A_1 \times \dots \times A_n$, where A_i is the set of actions available to agent i ;
- $G = (\mathcal{A}, E)$ is an action graph, where $\mathcal{A} = \bigcup_{i \in N} A_i$ is the set of distinct actions;
- $u = (u^1, \dots, u^{|\mathcal{A}|})$, $u^\alpha : C^{(\alpha)} \rightarrow \mathbb{R}$.

Elaborated Ice Cream Vendor Problem

Inspired by [Hotelling, 1929]

n vendors sell either ice cream or strawberries at one of four stations along a beach

- n_I ice cream (I) vendors;
- n_S strawberry (S) vendors;
- n_W can sell I/S , but only on the west side.
- **competition** between nearby sellers of same type; **synergy** between nearby different types



Notes:

- graph structure independent of # agents
- overlapping action sets
- context-specific independence without strict independence



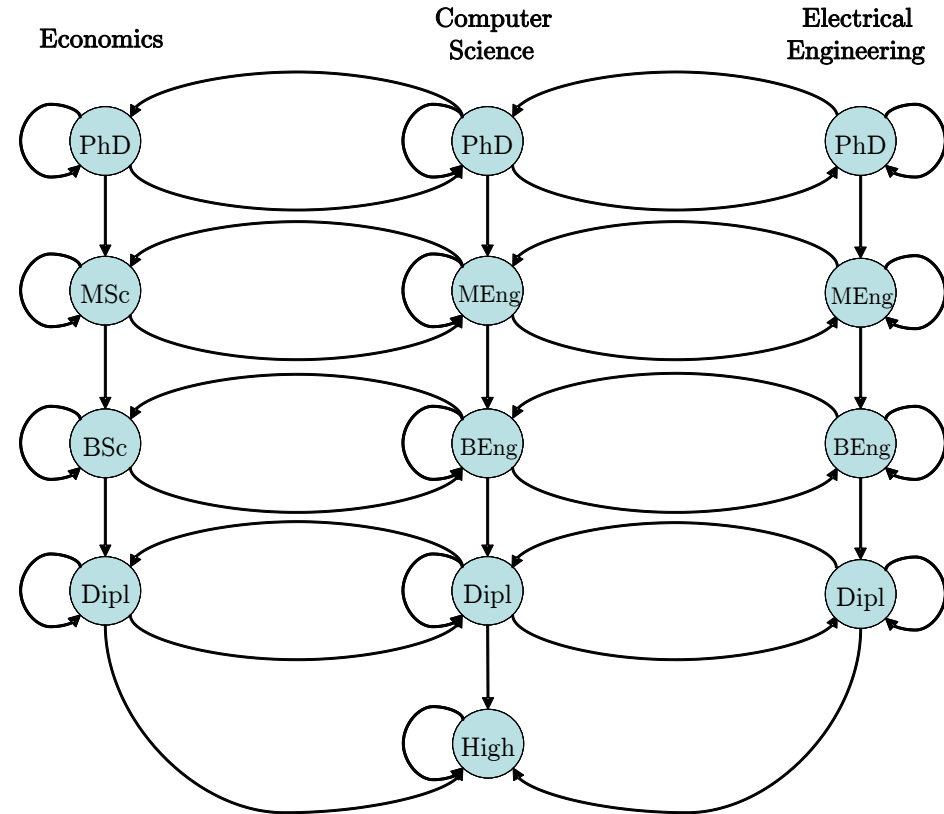
The Job Market Problem



Each player chooses a level of training

Players' utilities are the sum of:

- a constant cost:
 - difficulty; tuition; foregone wages
- a variable reward, depending on:
 - How many jobs prefer workers with this training, and how desirable are the jobs?
 - How many other jobs are willing to take such workers as a second choice, and how good are these jobs?
 - Employers will take workers who are overqualified, but only by one degree.
 - They will also interchange similar degrees, but only at the same level.
 - How many other graduates want the same jobs?



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Analyzing the AGG- \emptyset Representation

AGG- \emptyset s can represent **any game**.

Overall, AGG- \emptyset s are **more compact than the normal form** when the game exhibits either or both of the following properties:

1. Context-Specific Independence:

- pairs of agents can choose actions that are not neighbors in the action graph

2. Anonymity:

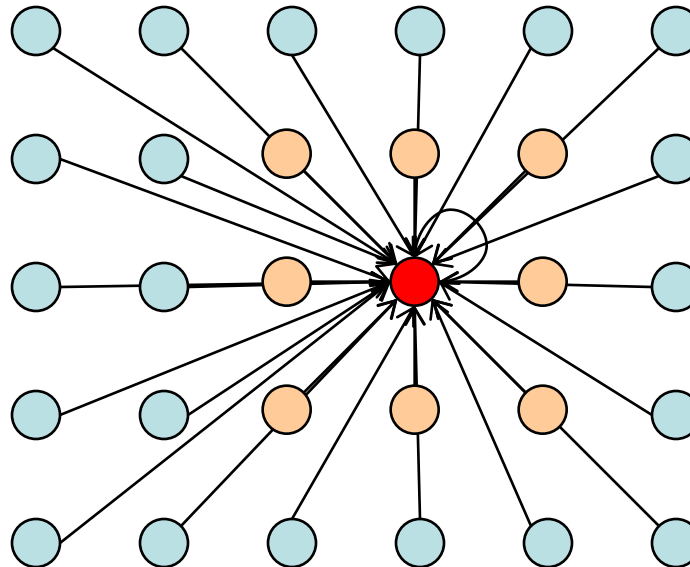
- multiple action profiles yield the same configuration

When max in-degree \mathcal{I} is bounded by a constant:

- **polynomial size:** $O(|A_{\max}|n^{\mathcal{I}})$
- in contrast, size of normal form is $O(n|A_{\max}|^n)$

The Coffee Shop Problem Revisited

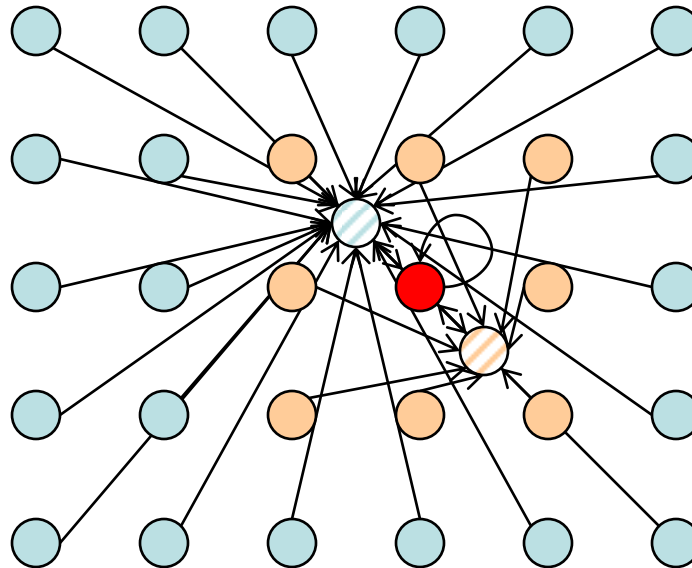
- What if utility also depends on total # shops?
- Now action graph has in-degree $|\mathcal{A}|$
 - NF & Graphical Game representations: $O(|\mathcal{A}|^N)$
 - AGG- \emptyset representation: $O(N^{|\mathcal{A}|})$
 - when $|\mathcal{A}|$ is held constant, the AGG- \emptyset representation is polynomial in N
 - but still doesn't effectively capture game structure
 - given i 's action, his payoff depends only on 3 quantities!



6 × 5 Coffee Shop Problem: projected action graph at the red node

AGG-FNs: Function Nodes

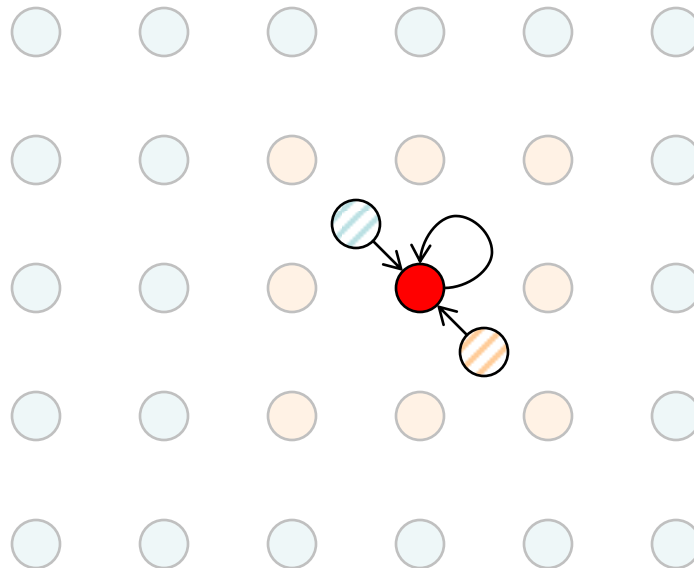
- To exploit this structure, introduce **function nodes**:
 - The “configuration” of a function node p is a (given) function of the configuration of its neighbors: $c[p] = f_p(c[\nu(p)])$
- **Coffee-shop example**: for each action node s , introduce:
 - a function node with adjacent actions as neighbors
 - $c[p'_s] = \text{total number of shops in surrounding nodes}$
 - similarly, a function node with non-adjacent actions as neighbors



6 × 5 Coffee Shop Problem: function nodes for the red node

The Coffee Shop Problem

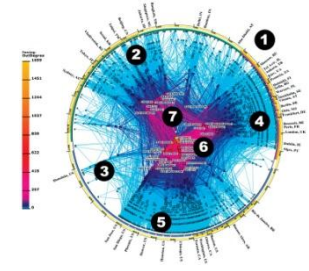
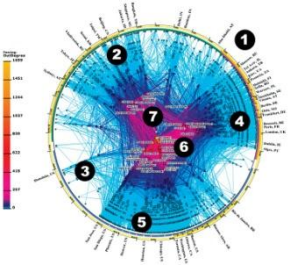
- Now the red node has only **three incoming edges**:
 - itself, the blue function node and the orange function node
 - so, the action-graph now has in-degree three
- Size of representation is now $O(N^3)$



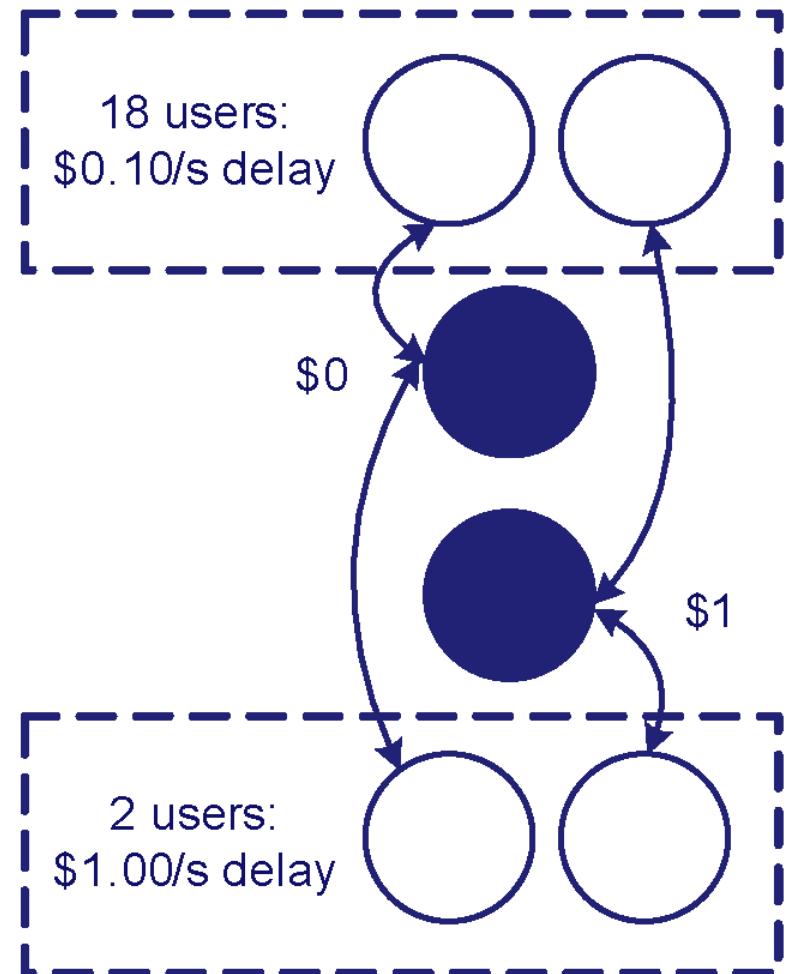
6 × 5 Coffee Shop Problem: projected action graph at the red node

Example: Parallel Edges

Based on [Thompson, Jiang & LB, 2007]; inspired by [Odlyzko, 1998]



- Network with one source, one sink, **two parallel edges**
 - both edges offer identical speed
 - one is free, one costs \$1
 - latency is an additive function of the number of users on an edge
- **Two classes of users**
 - 18 users pay \$0.10/unit of delay
 - 2 users pay \$1.00/unit of delay
- **Which edge should users choose?**
- Example scales to longer paths
 - not a congestion game because of player-specific utility



Further Representational Results

- Without loss of compactness, AGGs can also encode:
 - **Graphical** games (AGG- \emptyset)
 - **Symmetric** games (AGG- \emptyset)
 - **Anonymous** games (AGG-FN)
- One other extension to AGGs: explicit **additive structure**
- Enables compact encoding of still other game classes:
 - **Congestion** games (AGG-FNA)
 - **Polymatrix** games (AGG-FNA)
 - **Local-Effect** games (AGG-FNA)

Conclusion: AGGs compactly encode **all major compact classes** of simultaneous-move games, and also **many new games** that are compact in none of these representations.

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Computing Expected Utility

Expected utility of agent i for playing (pure) action a_i , if other agents play according to mixed-strategy profile s_{-i} :

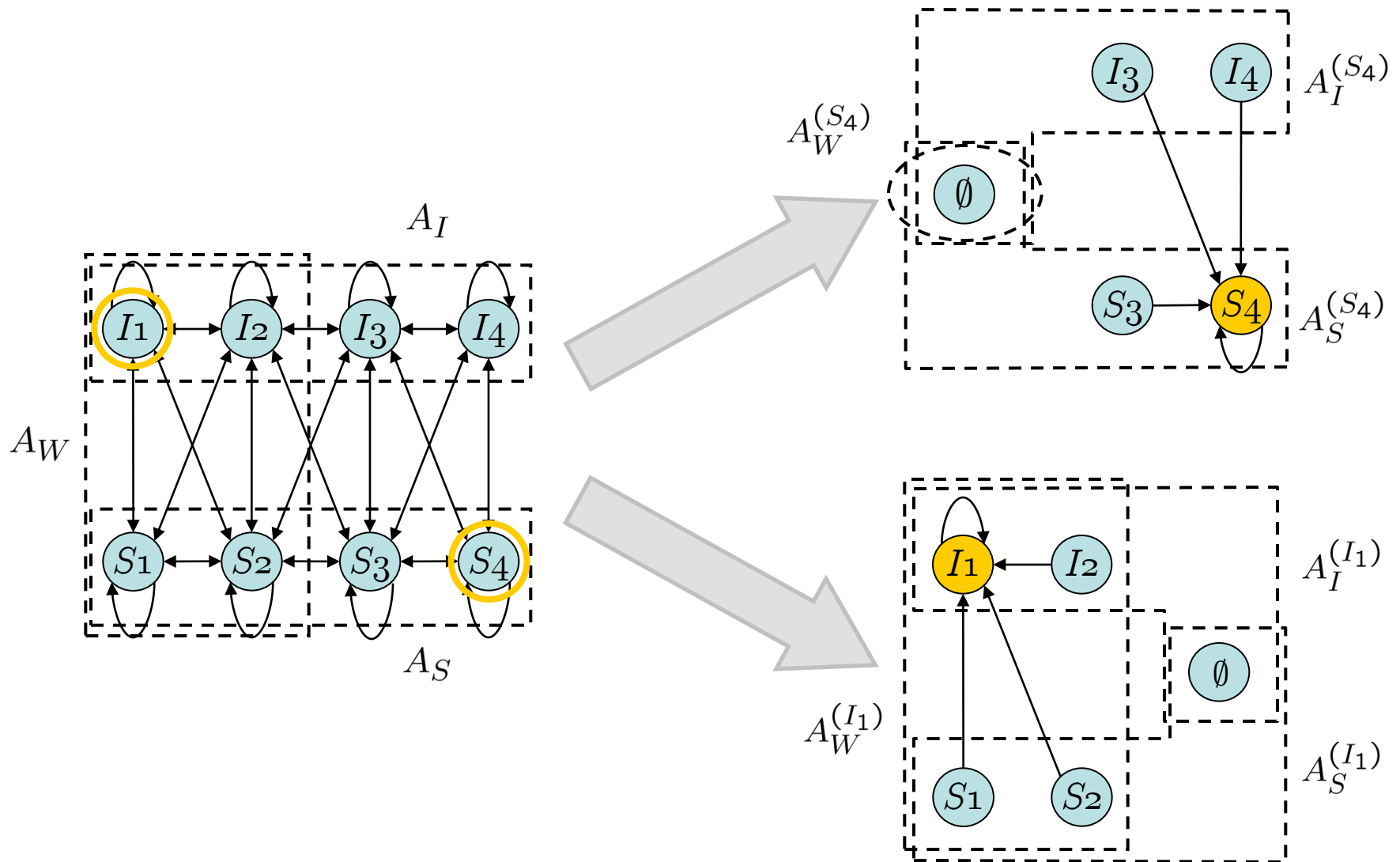
$$V_{a_i}^i(s_{-i}) \equiv \sum_{a_{-i} \in A_{-i}} u_i(a_i, a_{-i}) \Pr(a_{-i} | s_{-i})$$

Exponential-sized set: naive algorithm is $O(|A_{\max}|^{n-1})$

$V_{a_i}^i(s_{-i})$ is an inner-loop problem in many game-theoretic algorithms:

- **Best Response** (e.g., for multiagent reinforcement learning)
- **Govindan-Wilson** Algorithm (Nash equilibrium)
- **Simplicial Subdivision** Algorithm (Nash equilibrium)
- **Papadimitriou's** Algorithm (correlated Nash equilibrium)
- **Turocy's** Path Tracing Algorithm (quantal response equilibrium)
- **Predicted Action Distributions** under Level- k ; Cognitive Hierarchy

Computing with AGG- \emptyset s: Projection



Computing with AGG-0s: Projection

- Projection captures **context-specific independence** and strict independence

$$V_{a_i}^i(s_{-i}) = \sum_{a_{-i}^{(a_i)} \in A_{-i}^{(a_i)}} u^{a_i} \left(\mathcal{C}(a_i, a_{-i}^{(a_i)}) \right) Pr \left(a_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right)$$

Still exponential, but smaller than before

$$Pr \left(a_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right) = \prod_{j \in N \setminus \{i\}} s_j^{(a_i)}(a_j^{(a_i)}).$$

Linear-sized set

$*^{(\alpha)} \equiv$ projection with respect to action α

$\mathcal{C}(a_i, a_{-i}) \equiv$ configuration caused by a_i, a_{-i}

$\mathcal{S}(c) \equiv$ set of pure action profiles giving rise to c

Computing with AGG-0s: Anonymity

- Writing in terms of the configuration captures **anonymity**

$$V_{a_i}^i(s_{-i}) = \sum_{c_{-i}^{(a_i)} \in C_{-i}^{(a_i)}} u^{a_i} \left(\mathcal{C} \left(a_i, c_{-i}^{(a_i)} \right) \right) Pr \left(c_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right)$$

Polynomial-sized set

$$Pr \left(c_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right) = \sum_{a_{-i}^{(a_i)} \in \mathcal{S} \left(c_{-i}^{(a_i)} \right)} Pr \left(a_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right)$$

Exponential-sized set

$*^{(\alpha)} \equiv$ projection with respect to action α

$\mathcal{C}(a_i, c_{-i}) \equiv$ configuration caused by a_i, c_{-i}

$\mathcal{S}(c) \equiv$ set of pure action profiles giving rise to c

Dynamic Programming

- Can we **do better** computing $Pr \left(c_{-i}^{(a_i)} | s_{-i}^{(a_i)} \right)$? Note that
 - the players' mixed strategies are independent
 - s is a product probability distribution
 - each player affects a configuration c independently
- We can use **dynamic programming** to compute the probability of a configuration:
 - base case: zero agents and the mixed strategy s_0 :
 - $C_0 = \{c_0\}$
 - $c_0 = [0, \dots, 0]$
 - $P_0(c_0) = 1$
 - then add agents **one by one**:
 - C_k : the set of configurations that can be built by adding any action from the support of player k 's mixed strategy to any configuration from C_{k-1}
 - $$P_k(c_k) = \sum_{\substack{(c_{k-1}, a_k), \\ \mathcal{C}(c_{k-1}, a_k) = c_k}} s_k(a_k) \cdot P_{k-1}(c_{k-1})$$

Computing with AGGs: Complexity

Theorem 1 *Given an AGG- \emptyset representation of a game, i 's expected payoff $V_{a_i}^i(s_{-i})$ can be computed in time **polynomial in the size of the representation**. If \mathcal{I} , the maximum in-degree of the action graph, is bounded by a constant, $V_{a_i}^i(s_{-i})$ can be computed in time **polynomial in n** .*

- **Complexity** of our approach:
 $O\left(n^{\mathcal{I}} \text{poly}(n) \text{poly}(|A_{\max}|)\right)$
- **Exponential** speedup vs. standard approach:
 $O\left(|A_{\max}|^{n-1} \text{poly}(n) \text{poly}(|A_{\max}|)\right)$

In **AGG-FNs**, players are no longer guaranteed to affect c independently

- but **the DP algorithm still works** when function nodes can be expressed using some commutative, associative operator

Computing Expected Utility

$V_{a_i}^i(s_{-i})$ is an inner-loop problem in many game-theoretic algorithms:

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Because we compute $V_{a_i}^i(s_{-i})$ exactly, our expected utility algorithm yields an **exponential speedup** in every one of these algorithms, whenever the AGG is exponentially smaller than the normal form.

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1. computing pure strategy equilibria
2. analyzing sponsored search auctions
3. temporal AGGs
4. Bayesian AGGs
5. free software tools

(1) Computing Pure-Strategy Equilibrium

- **Pure Nash equilibrium** is often a more interesting solution concept than mixed Nash equilibrium
- It also presents a very **computationally different problem**
 - PSNE in normal form admits a very simple polytime algorithm
 - just check every action profile
 - For AGG- \emptyset s the representation can be exponentially smaller
 - thus, the same algorithm is exponential time

Theorem (Conitzer, personal communication; also proven independently in (Daskalakis et al. 2008)): The problem of determining whether a pure Nash equilibrium exists in an AGG- \emptyset is **NP-complete**, even when the AGG- \emptyset is symmetric and has max in-degree of three.

(1) Computing PSNEs in AGG- \emptyset s

[Jiang & LB, 2007]

We propose a **message passing algorithm**:

- partition action graph into subgraphs (via tree decomposition)
- construct equilibria of the game from equilibria of games played on subgraphs

This algorithm finds PSNE in polynomial time for every **symmetric AGG- \emptyset that has bounded treewidth**.

- it can also be applied to other bounded-treewidth settings

- Generalizes earlier algorithms

- finding pure equilibria in **graphical games**

[Gottlob, Greco, & Scarcello 2003; Daskalakis & Papadimitriou 2006]

- finding pure equilibria in **simple congestion games**

[Jeong, McGrew, Nudelman, Shoham, & Sun 2005]

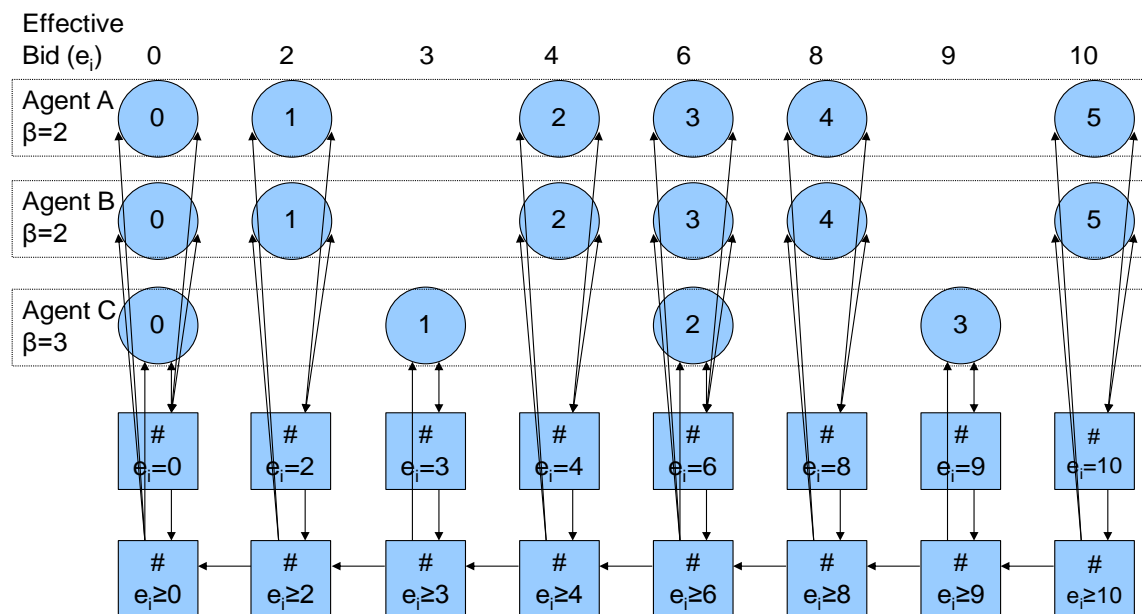


(2) Sponsored Search Auctions

[Thompson & LB, 2008; 2009]



- Position auctions are used to sell \$10Bs of keyword ads
- Some theoretical analysis, but **based on strong assumptions**
 - Unknown how different auctions compare in more general settings
- Idea: **analyze the auctions computationally**
 - Main hurdle: ad auction games are large; infeasible as normal form



AGG-FN representation of a Weighted, Generalized First-Price (GFP) Auction

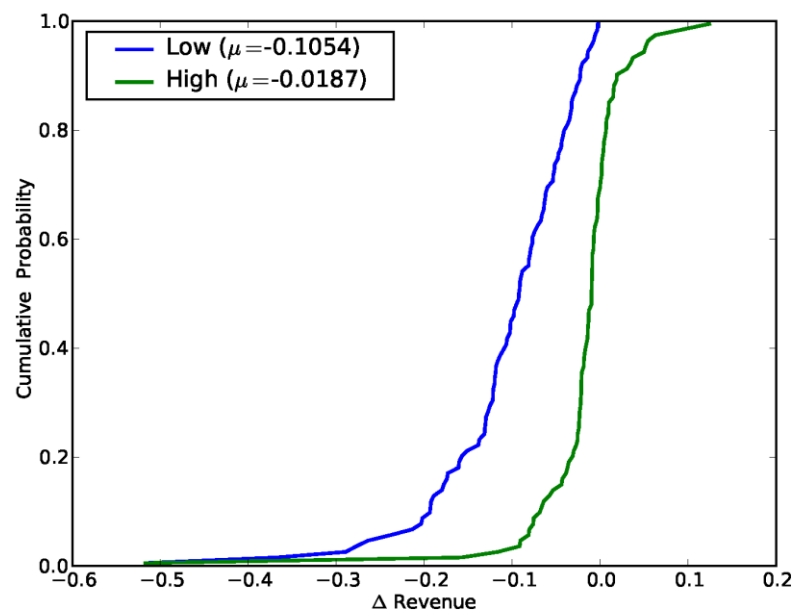
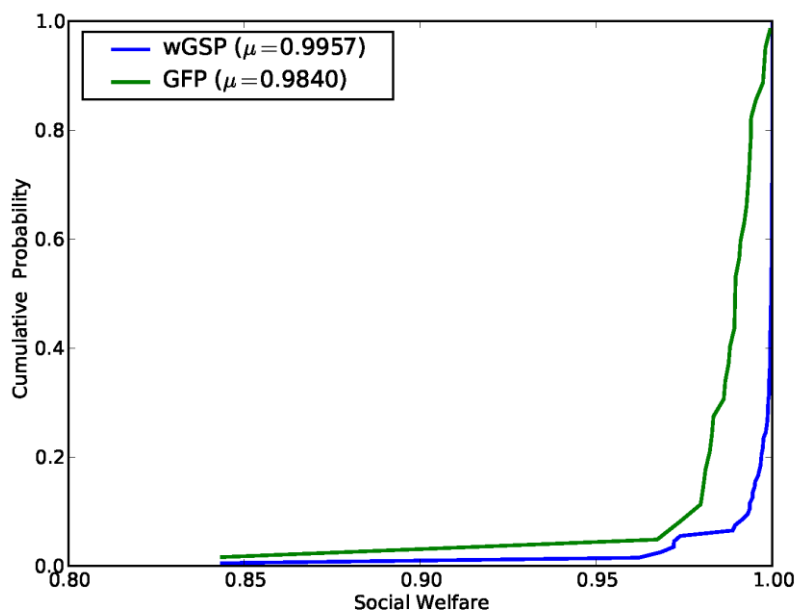


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Social welfare and revenue of EOS auction model

(3) Temporal Action Graph Games

[Jiang, LB & Pfeffer, 2009]

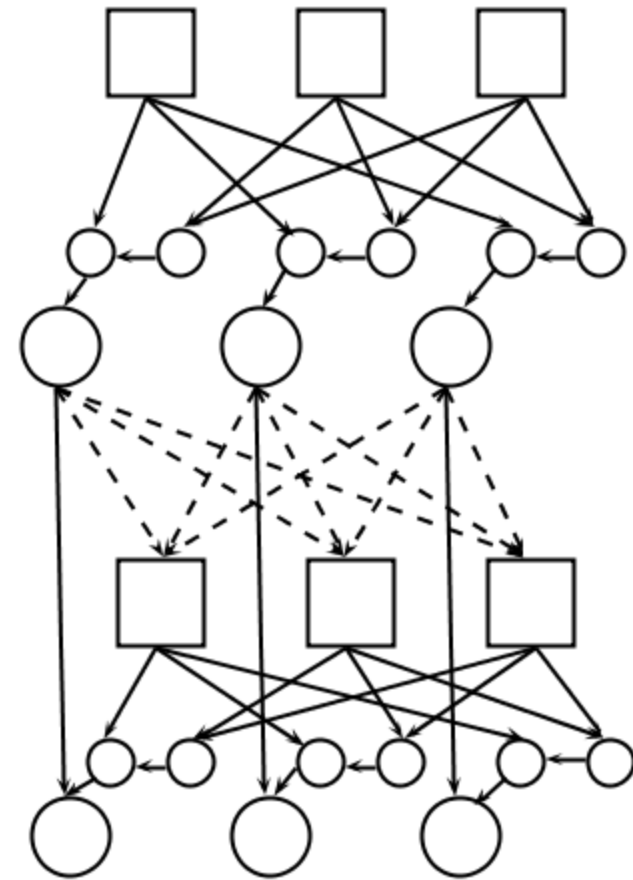
Goal: extend AGGs to **temporal settings**

- Model: An AGG-FN played over a series of **discrete time steps**
 - at each time step, a subset of players move
 - action counts on the action nodes grow over time
- Allow payoff uncertainty using **random variables** that are realized at a given time step
- Imperfect information: players may **condition their actions** on a given set of observed previous actions, chance variables and action counts
- Utility functions: action-specific and time-specific

(3) Properties of TAGGs

[Jiang, LB & Pfeffer, 2009]

- Can **compactly represent** a wide range of dynamic games, including:
 - arbitrary MAIDs [Milch & Koller, 2001]
 - games whose straightforward MAID representations are not compact
- Can be **efficiently encoded as MAIDs** by introducing deterministic chance nodes
- Efficient computation of **expected utility**
 - exploit anonymity and context-specific independence as in AGG- \emptyset s
 - also exploit the temporal structure
 - as with AGG- \emptyset s, can be leveraged to yield **exponential speedups in computation** (Nash equilibrium, etc.)



(4) Bayesian Games

- TAGGs aren't the most appropriate way of representing **simultaneous-move Bayesian games**
 - indeed, while such models are widely used (e.g., in auction theory), the setting has largely been neglected by the computational game theory community
- As far as we know, there are **no representations or algorithms** targeting general BNE computation
- This leaves two general approaches, both of which make use of complete-information Nash algorithms:
 1. **Induced normal form**
 - one action for each pure strategy (mapping from type to action)
 - set of players unchanged
 2. **Agent form**
 - one player for each type of each of the BG's players
 - action space unchanged

(4) Bayesian AGGs

[Jiang & LB, work under review 2010]

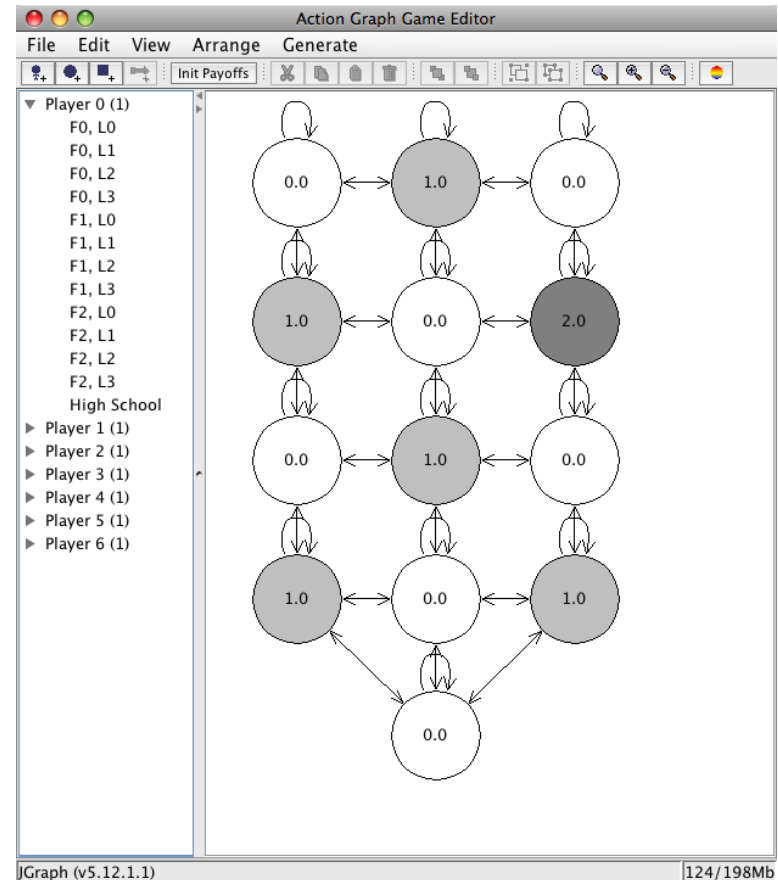
Bayesian AGG: an AGG-like representation of a Bayesian game's utility functions, which compactly encodes its agent form:

- **Bayesian network** for the joint type distribution
 - A (potentially separate) **action graph** for each type of each agent
 - A **utility function** that depends on which types are realized and on the actions taken by the other agents of the appropriate types
-
- **Representation size** grows polynomially in $|\Theta|$, $|A|$, n , when action graph has constant-bounded in-degree
 - Exponential savings over an unstructured Bayesian game
 - When types are independent, expected utility can be **computed in time polynomial in the size of the BAGG**
 - When types are not independent, expected utility can still be **computed in polynomial time** when an induced Bayesian network has bounded treewidth.

(5) Free Software Tools

[Jiang, Bargiacchi & LB, 2007–2010]

- Goal: make it **easier for other researchers** to use AGGs
- **Equilibrium computation** algorithms:
 - Govindan-Wilson (NE)
 - Simplicial Subdivision (NE)
 - Papadimitriou (CE) **in progress*
 - Turocy (QRE) **in progress*
- GAMUT:
 - extended to **support AGGs**
- Action Graph Game Editor:
 - **creates AGGs graphically**
 - facilitates entry of utility fns
 - supports “player classes”
 - auto creates game generators
 - visualizes eq. on the action graph



Conclusions

- **AGGs compactly represent games** exhibiting context-specific independence, anonymity and/or additive structure
- **Generalizes all major, existing compact representations** of simultaneous-move games
 - graphical games, congestion games, many others
- Recent directions:
 - Polytime algorithm for computing **pure strategy Nash equilibrium** (bounded treewidth; symmetric AGG- \emptyset)
 - modeling and comparing **sponsored search auctions**
 - extending AGGs to **temporal settings**
 - extending AGGs to **Bayesian games**
 - developing **free software tools**