Ordinal Preference Aggregation: Social Choice

A profile

Social choice mechanism
Ranking pictures [PGM+ AAAI-12]

A > B > C
Turker 1

B > A
Turker 2

B > C
Turker n
Social choice

$R_i, R_i^*$: full rankings over a set $A$ of alternatives
Social Choice and Computer Science

Computational thinking + optimization algorithms

Social Choice

Strategic thinking + methods/principles of aggregation

PLATO
4th C. B.C.

LULL
13th C.

BORDA
18th C.

CONDORCET
18th C.

TURING et al.
20th C.

ARROW
20th C.

21st Century
Applications: real world

- People/agents often have conflicting preferences, yet they have to make a joint decision
Applications: academic world

- Multi-agent systems [Ephrati and Rosenschein 91]
- Recommendation systems [Ghosh et al. 99]
- Meta-search engines [Dwork et al. 01]
- Belief merging [Everaere et al. 07]
- Human computation (crowdsourcing) [Mao et al. AAAI-13]
- etc.
How to design a good social choice mechanism?

What is being “good”?
Two goals for social choice mechanisms

GOAL1: democracy

GOAL2: truth

THIS TUTORIAL
Common voting rules
(what has been done in the past two centuries)

• Mathematically, a social choice mechanism (voting rule) is a mapping from \{All profiles\} to \{outcomes\}
  – an outcome is usually a winner, a set of winners, or a ranking
  – \(m\) : number of alternatives (candidates)
  – \(n\) : number of agents (voters)
  – \(D=(P_1,\ldots,P_n)\) a profile

• Positional scoring rules
  • A score vector \(s_1,\ldots,s_m\)
  – For each vote \(V\), the alternative ranked in the \(i\)-th position gets \(s_i\) points
  – The alternative with the most total points is the winner

  • Special cases
    • Borda, with score vector \((m-1, m-2, \ldots, 0)\)
    • Plurality, with score vector \((1,0,\ldots,0)\) [Used in the US]
An example

• Three alternatives \( \{c_1, c_2, c_3\} \)
• Score vector \((2,1,0)\) (Borda)
• 3 votes,

\[
\begin{array}{ccc}
2 & 1 & 0 \\
2 & 1 & 0 \\
2 & 1 & 0 \\
\end{array}
\]

\( c_1 \) gets \( 2+1+1=4 \), \( c_2 \) gets \( 1+2+0=3 \),
\( c_3 \) gets \( 0+0+2=2 \)

• The winner is \( c_1 \)
Single transferable vote (STV)

- Also called *instant run-off voting* or *alternative vote*
- The election has \(m-1\) rounds, in each round,
  - The alternative with the lowest plurality score drops out, and is removed from all votes
  - The last-remaining alternative is the winner
- [used in Australia and Ireland]

<table>
<thead>
<tr>
<th>a &gt; b &gt; c &gt; d</th>
<th>d &gt; a &gt; b &gt; c</th>
<th>c &gt; d &gt; a &gt; b</th>
<th>b &gt; c &gt; d &gt; a</th>
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<td>c &gt; d &gt; a</td>
</tr>
</tbody>
</table>

| 10 | 7 | 6 | 3 |
The Kemeny rule

- Kendall tau distance
  - \( K(V, W) = \# \{ \text{different pairwise comparisons} \} \)

- Kemeny rule
  - \( K(b > c > a, a > b > c) = ? \)
  - \( \text{Kemeny}(D) = \min_{W} K(D, W) = \min_{W} \sum_{P \in D} K(P, W) \)
  - For single winner, choose the top-ranked alternative in Kemeny\( (D) \)
  - [Has a statistical interpretation]
  - NP-Hard [Bartholdi, Tovey & Trick’89]
...and many others

- Approval, Baldwin, Black, Bucklin, Coombs, Copeland, Dodgson, maximin, Nanson, Range voting, Schulze, Slater, ranked pairs, etc…
• **Q:** How to evaluate rules in terms of achieving democracy?

• **A:** Axiomatic approach
Axiomatic approach
(what has been done in the past 50 years)

• **Anonymity**: names of the voters do not matter
  – Fairness for the voters
• **Non-dictatorship**: there is no dictator, whose top-ranked alternative is always the winner
  – Fairness for the voters
• **Neutrality**: names of the alternatives do not matter
  – Fairness for the alternatives
• **Consistency**: if \( r(D_1) \cap r(D_2) \neq \emptyset \), then \( r(D_1 \cup D_2) = r(D_1) \cap r(D_2) \)
• **Condorcet consistency**: if there exists a Condorcet winner, then it must win
  – A Condorcet winner beats all other alternatives in pairwise elections
• **Easy to compute**: winner determination is in \( P \) [Bartholdi, Tovey & Trick’89]
  – Computational efficiency of preference aggregation
• **Hard to manipulate**: computing a beneficial false vote is hard [Bartholdi, Tovey & Trick’89]
Which axiom is more important?

<table>
<thead>
<tr>
<th>Method</th>
<th>Condorcet consistency</th>
<th>Consistency</th>
<th>Easy to compute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positional scoring</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>rules</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kemeny</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Ranked pairs</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
</tbody>
</table>

- Some of these axiomatic properties are not compatible with others
- Food for thought: how to evaluate partial satisfaction of axioms?
An easy fact

• **Theorem.** For voting rules that selects a single winner, anonymity is not compatible with neutrality
  – proof:
Another easy fact
[Fishburn APSR-74]

• **Thm.** No positional scoring rule is Condorcet consistent:

  – suppose $s_1 > s_2 > s_3$

3 Voters

2 Voters

1 Voter

1 Voter

is the Condorcet winner

$3s_1 + 2s_2 + 1s_3$

$3s_1 + 3s_2 + 1s_3$
Not-So-Easy facts

• Arrow’s impossibility theorem
  – Google it!

• Gibbard-Satterthwaite theorem
  – Google it!

• Axiomatic characterization
  – Template: A voting rule satisfies axioms A1, A2, A2 ⇔ if it is rule X
  – If you believe in A1 A2 A3 are the most desirable properties then X is optimal
  – (anonymity+neutrality+consistency+continuity) ⇔ positional scoring rules [Young SIAMAM-75]
  – (neutrality+consistency+Condorcet consistency) ⇔ Kemeny [Young&Levenglick SIAMAM-78]
Statistical ideas

- Voters are imperfect
  - Nevertheless, we can argue that voting rules (asymptotically) reveal the ground truth
- Source of imperfection
  - A voter may have partial information
  - ...
Statistical ideas

• Condorcet’s Jury theorem
  – If Condorcet had been more hip, he’d have called it the “wisdom of crowds”

• MLE estimators
  – Kemeny and scoring rules
The Condorcet Jury theorem
[Condorcet 1785]

The Condorcet Jury theorem.

- Given
  - two alternatives \{a,b\}.
  - \(0.5 < p < 1\),

- Suppose
  - each agent’s preferences is generated i.i.d., such that
  - w/p \(p\), the same as the ground truth
  - w/p \(1-p\), different from the ground truth

- Then, as \(n \to \infty\), the majority of agents’ preferences converges in probability to the ground truth
The Condorcet Jury theorem
[Condorcet 1785]

The Condorcet Jury theorem.

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  – w/p \(1-p\), different from the ground truth

• Then, as \(n \to \infty\), the majority of agents’ preferences converges in probability to the ground truth
  – for \(p \approx 0.5\), prob grows as \(\sqrt{n}\)
The Condorcet Jury theorem
[Condorcet 1785]

Proof:
Assume \( n \) is odd (no tie-breaking needed)
Suppose \( m \) voters have voted correctly
Add 2 more voters (so keep odd number of voters)
Only time decision changes is when
  \( m \) is 1 vote short of majority and both new voters are correct
  \( m \) is equal to majority and both new voters are incorrect
The Condorcet Jury theorem
[Condorcet 1785]

Proof:
Assume \( n \) is odd (no tie-breaking needed)
Suppose \( m \) voters have voted correctly
Add 2 more voters (so keep odd number of voters)
Only time decision changes is when
\[
\begin{align*}
\text{m is 1 vote short of majority and both new voters are correct, } (1-p)p^2 \\
\text{m is equal to majority and both new voters are incorrect, } p(1-p)^2
\end{align*}
\]
Proof:
Assume \( n \) is odd (no tie-breaking needed)
Suppose \( m \) voters have voted correctly
Add 2 more voters (so keep odd number of voters)
Only time decision changes is when
\( m \) is 1 vote short of majority and both new voters are correct, \((1-p)p^2\) which is larger for \( p > 0.5 \)
\( m \) is equal to majority and both new voters are incorrect, \( p(1-p)^2 \)

The Condorcet Jury theorem
[Condorcet 1785]
The Condorcet Jury theorem
[Condorcet 1785]

Limitations of Condorcet Jury theorem

Only applies to choice between 2 alternatives
Supposes votes are uncorrelated
Ignores strategic voting (see above, only 2 alternatives)

...
Condorcet’s model

- Condorcet was not very clear how the Condorcet Jury theorem can be extended to m>2
- Young had an interpretation [Young APSR-1988]
- Parameter space
  - all combinations of opinions: an opinion is a pairwise comparison between candidates (can be cyclic)
    - $p<1$
- Sample space
  - all combinations of opinions
- Given “ground truth” opinions $W$ and $p<1$, generate opinions $V$ s.t. each opinion is i.i.d.
Mallows model [Mallows 1957]

- Parameter space
  - all rankings over candidates
  - $\varphi < 1$

- Sample space
  - all rankings over candidates

- Given a “ground truth” ranking $W$ and $\varphi < 1$, generate a ranking $V$ w.p.
  - $\Pr(V|W) \propto \varphi^{\text{Kendall}(V,W)}$

- MLE ranking is the Kemeny rule
Recent studies on Condorcet/Mallows model

- Learning [Lu and Boutilier ICML-11]
- Approximation by common voting rules [Caragiannis, Procaccia & Shah EC-13]
Classical voting rules as MLEs
[Conitzer&Sandholm UAI-05]

- When the outcomes are winning alternatives
  - MLE rules must satisfy consistency: if $r(D_1) \cap r(D_2) \neq \emptyset$, then $r(D_1 \cup D_2) = r(D_1) \cap r(D_2)$
  - All classical voting rules except positional scoring rules are NOT MLEs

- Positional scoring rules are MLEs

- This is NOT a coincidence!
  - All MLE rules that outputs winners satisfy anonymity and consistency
  - Positional scoring rules are the only voting rules that satisfy anonymity, neutrality, and consistency! [Young SIAMAM-75]
Classical voting rules as MLEs [Conitzer&Sandholm UAI-05]

• When the outcomes are winning rankings
  – MLE rules must satisfy reinforcement (the counterpart of consistency for rankings)
  – All classical voting rules except positional scoring rules and Kemeny are NOT MLEs

• This is not (completely) a coincidence!
  – Kemeny is the only preference function (that outputs rankings) that satisfies neutrality, reinforcement, and Condorcet consistency [Young&Levenglick SIAMAM-78]
2. Computational aspects

- Easy-to-compute axiom
- Hard-to-manipulate axiom
  - Computational thinking +
    game-theoretic analysis

3. Statistical approaches

- Condorcet Jury theorem
- Voting rules as MLEs

Computational thinking + optimization algorithms

Social Choice

Thank you!

Strategic thinking + methods/principles of aggregation
Social Choice in ACTION!

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\textsuperscript{3}University of New South Wales

May 4\textsuperscript{th}, 2015
Outline

1. Introduction
2. Diversity Models
   - Related Work
   - Diversity Beats Strength?
   - Give a Hard Problem to a Diverse Team
3. Aggregation of Opinions
4. Team Assessment
Multi-agent Teams

Machine Learning (Ensemble Systems)

Crowdsourcing

Forecasting Systems

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Multi-agent Teams

Machine Learning
(Ensemble Systems)

Crowdsourcing

Forecasting Systems
Multi-agent Teams

Why voting?
- Easy to implement
- Highly parallelizable
- Allows the (re-)use of existing agents
- Provides theoretical guarantees [Conitzer & Sandholm 2005, List01]
Problem Statement

Team Formation
Introduction

Problem Statement

Team Formation

- What is the best team of voting agents?
  - Novel predictions concerning the performance of different teams

[AAAI’2014]
[IJCAI’2013]
[AAAI’2014]
Problem Statement

Team Formation

- What is the best team of voting agents?
  - Novel predictions concerning the performance of different teams
- How to best aggregate their opinions?
  - Create new aggregation methodologies
Problem Statement

Team Formation

- What is the best team of voting agents?
  - Novel predictions concerning the performance of different teams
- How to best aggregate their opinions?
  - Create new aggregation methodologies
- How to assess their performance?
  - Create novel domain independent assessment methodologies
A diverse team of **weak agents** can outperform a uniform team (copies of **best agent**).

**Diverse teams get stronger as action space grows**

**Novel ranking extraction methodology**

**Aggregation for solving POMDPs**

**Predicting success of voting agents**
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Related Work

Social Choice

- Condorcet Jury Theorem [Condorcet’1785]

<table>
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<tr>
<th>Correct</th>
<th>Incorrect</th>
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<tr>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>0.9999</td>
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Social Choice

- Maximum Likelihood Approach [Young’1995, Conitzer and Sandholm’2005]

  "Correct Outcome"

  Agent 1  Agent 2  ...  Agent n
Social Choice

- Maximum Likelihood Approach [Young’1995, Conitzer and Sandholm’2005]
  - Identical and Independent Agents
Social Choice

- Maximum Likelihood Approach [Young’1995, Conitzer and Sandholm’2005]
  - Identical and Independent Agents

- Team Formation?
Diversity Models

Related Work

Ensemble Systems

- Ensemble Systems [Polikar’2012]

Training

Classifying

How to make the base classifiers “different”?
Ensemble Systems

- Ensemble Systems [Polikar’2012]

How to make the base classifiers “different”?
Ensemble Systems

Bagging

- Randomly choose samples to train a classifier

Cat  Cat  Dog

Dog  Cat  Cat

Dog  Dog  Dog
Ensemble Systems

Boosting

- Randomly choose samples to train a classifier

- Check which instances it misclassifies
Ensemble Systems

Boosting

- Train a new classifier
  - Half of the instances: correct classified
  - Second half: incorrect classified
Ensemble Systems

Boosting

- Train a new classifier
- Use samples that first 2 classifiers disagree
Ensemble Systems

AdaBoost

- Every sample starts with uniform probability
Ensemble Systems

AdaBoost

- Increases probability of misclassified samples
Ensemble Systems

Random Forests

- Another common approach: random forests
Ensemble Systems

Random Forests

- Tree classifier
Ensemble Systems
Random Forests

- Each tree is trained with a random sample of the data
Diversity Models

Related Work

Ensemble Systems

Random Forests

Training a Tree

Choose a random subset to evaluate

X₁  X₂  X₃  X₄  X₅  X₆

Dog  Cat  Cat  Dog  Cat  Dog  Cat  Dog

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Social Choice in ACTION!

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Diversity

- All these methods are trying to make the base classifiers *different*, but...
- ... why Diversity is so important?
The "evil" side of the Condorcet Jury Theorem...
## Diversity Models

### Related Work

The “evil” side of the Condorcet Jury Theorem...

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Social Choice in ACTION!

May 4th, 2015
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Diversity Beats Strength?

Strongest agent

VS

[IJCAI’2013]
What is diversity?

Teams composed by different agents

IJCAI’2013
Diversity Models

Diversity Beats Strength?

Model

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Diversity Beats Strength?

Simple Example

1 0 1 1

Strength
0.75

1 = Plays best action
Diversity Beats Strength?

Simple Example

1 0 1 1 0.75

1 = Plays best action
Diversity Beats Strength?

Simple Example

1 = Plays best action

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Social Choice in ACTION!

May 4th, 2015
Diversity Beats Strength?

Simple Example

```
1 0 1 1
0 1 1 0
1 1 0 0
1 1 0 1
0 0 1 1
1 1 1 0
1 1 1 1
```

Strength

- 0.75
- 0.50
- 1.00

1 = Plays best action

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Diversity Beats Strength?

Simple Example

```
0.99 0 0.99 0.99 0.74
0 0.99 0.99 0 0.49
0.99 0.99 0 0 0.49
0.99 0.99 0 0.99 0.74
0 0 0.99 0.99 0.49
0.999 0 0.999 0.999 0.749
0.999 0.999 0.999 0.999 0.999
```

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Give a Hard Problem to a Diverse Team

For which problems?

[AAAI’2014]
Give a Hard Problem to a Diverse Team

For which problems?

Diverse team gets stronger as action space increases

[AAAI’2014]
Our Model
Give a Hard Problem to a Diverse Team

- Focus on team of weak agents (diverse) vs team of strong agents (uniform)
- Study how the performance of different teams change as the action space increases
Our Model

Agent

- Each agent has a probability distribution. E.g. choosing:
  - best action with prob 0.5,
  - 2nd best with prob 0.3,
  - 3rd best with prob 0.2
Our Model

Coordination Mechanism

- Plurality Voting

World State

Team takes action B2
Our Model

Agent Types

- **Spreading Tail (ST) Agents**
  - Set of actions with nonzero probabilities increases
  - Probability of choosing best action unchanged (verified later in our experiments)
Best Agent

- Assumption: best agent “spreads tail” at slower rate

- Verified in our experiments
Theorem

[Informal] Performance of diverse team improves when the size of the action space grows
A Hard Problem to a Diverse Team

Proof — Intuition

- Set of actions with nonzero probabilities increases as the action space gets larger

![Bar chart showing the increase in probability with more actions](chart)

- Fewer actions
- More actions
A Hard Problem to a Diverse Team

Proof — Intuition

- In the limit, the probability of voting for each suboptimal action converges to 0
A Hard Problem to a Diverse Team

Proof — Intuition

- The agents will only agree in the optimal choice!

Optimal

Action 23489123

Action 587234123

Action 458234560

Action 945345345
A Hard Problem to a Diverse Team

Theorem 2

- Performance of Diverse team improves, but...
- Does it converge to a high value?
A Hard Problem to a Diverse Team

Theorem 2

Theorem

[Informal] Diverse team converges (exponentially fast) to optimal performance as the number of agents goes to infinity
Uniform Team

- Assumption: best agent “spreads tail” at slower rate
Diversity Models

Give a Hard Problem to a Diverse Team

Uniform Team

- Assumption: best agent “spreads tail” at slower rate

- Teams where the agents “spread the tail” faster will converge faster
Experiments

Computer Go

- 6 Go playing agents: Fuego, GnuGo, Pachi, MoGo, FuegoΔ, FuegoΘ
6 Go playing agents: Fuego, GnuGo, Pachi, MoGo, Fuego\(\Delta\), Fuego\(\Theta\)
- Diverse: all agents
Experiments

Computer Go

- 6 Go playing agents: Fuego, GnuGo, Pachi, MoGo, FuegoΔ, FuegoΘ
- Uniform: Copies of Fuego (the best agent)
Experiments

Computer Go

- Winning rate against fixed adversary as board size increases

- Slopes:
  - Diverse: 0.010
  - Uniform: 0.005

- Influence of board size is higher on Diverse with $p = 0.0797$
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Diverse teams get stronger as action space grows

**Novel ranking extraction methodology**

Aggregation for solving POMDPs
Aggregation of Opinions

- Ranked Voting

- But... Where do the rankings come from?
Ranking

- From the agent’s search tree?
  - Is that accurate?
- The “evil” side of ranked voting rules...
Performance of Classical Voting Rules

- Computer Go Experiments of Classical Voting Rules

![Graph showing the performance of classical voting rules with varying number of agents.](chart.png)
“Real” agents have noisy rankings

**New approach: Ranking by Sampling**

\[ A > B > D > C \]
By sampling, Borda significantly outperforms plurality voting.
Social Networks

Which nodes to pick for HIV prevention interventions?

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Social Networks

Which nodes to pick for HIV prevention interventions?

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Social Choice in ACTION!
Social Networks

Which nodes to pick for HIV prevention interventions?
Social Networks

Each agent works in a different instantiation

![Diagram of social networks with arrows connecting nodes A, B, C, D, E in different configurations](image)
Social Networks

Each agent works in a different instantiation

Weighted by how likely each network is.
Social Networks

Homeless Youth Social Network
Results

Influence Spread

Baseline  Simple Plurality  Weighted Plurality  Copeland
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**Novel ranking extraction methodology**

**Aggregation for solving POMDPs**

**Predicting success of voting agents**
Objective

- Predict the final outcome at any step of the problem solving process

Success?  
Failure?
Motivation

- Allows an operator to take remedy procedures **online**
  - Dynamically change the team
  - Dynamically change the voting rule
  - Increase allocation of resources
  - ...
Logistic Regression

After learned, can be executed at ANY TIME

$$\hat{f}(\vec{x}) = \frac{1}{1 + e^{-(\alpha + \vec{\beta}^T \vec{x})}}$$

Model learned with voting patterns of full games.
Full Feature Vector

Iteration 0: $A_0 \ A_0 \ A_1$

\[\begin{align*}
0 & \ 0 & \ 0 & \ 0 & \ 1 & \ 0 & \ 0
\end{align*}\]
Full Feature Vector

Iteration 0:

\[ \begin{array}{ccc}
  A0 & A0 & A1 \\
  \end{array} \]

\[ \begin{array}{cccccc}
  0 & 0 & 0 & 0 & 1 & 0 & 0 \\
  \end{array} \]

Iteration 1:

\[ \begin{array}{ccc}
  A1 & A1 & A0 \\
  \end{array} \]

\[ \begin{array}{cccccc}
  0 & 0 & 0 & 1 & 0 & 0 \\
  \end{array} \]
## Full Feature Vector

<table>
<thead>
<tr>
<th>Iteration 0:</th>
<th>A0</th>
<th>A0</th>
<th>A1</th>
</tr>
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<tbody>
<tr>
<td>Iteration 1:</td>
<td>A1</td>
<td>A1</td>
<td>A0</td>
</tr>
<tr>
<td>Iteration 2:</td>
<td>A0</td>
<td>A1</td>
<td>A1</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>1</th>
<th>0</th>
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<td>$\frac{2}{3}$</td>
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</tbody>
</table>
Theoretical Explanation

- Model: Final outcome is a random variable (w) influenced by which subset of agents agreed (H_i)

Domain Independent Model
Experiments

- 691 games for each team
- Games played against a fixed adversary (Fuego)
- Performance evaluated using 5-fold cross validation
- On-line prediction compared with Fuego running 50× longer
  - ... and also with the actual final outcome
- Metrics: Accuracy, Precision, Recall
Results

High quality predictions for all teams!

Accuracy does not depend on the strength

S. Marcolino, Xia, Walsh (USC,RPI,UNSW) Social Choice in ACTION! May 4th, 2015 58 / 61
Every Team Deserves a Second Chance
An Interactive 9x9 Go Experience

AAMAS 2015 Demo
Thank you!

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