# Learning Models of Macrobehaviors in Complex Adaptive Systems

#### Andrew Fast

afast@cs.umass.edu http://www.cs.umass.edu/~afast

Knowledge Discovery Laboratory Department of Computer Science University of Massachusetts Amherst

Advisor: David Jensen





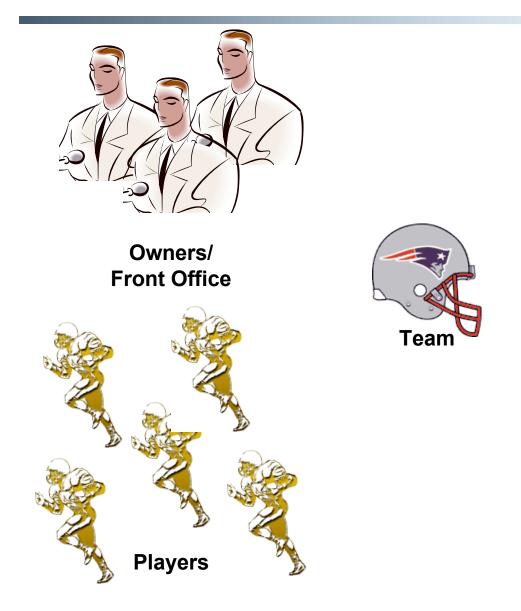
# **Complex Adaptive Systems**

# **Complex :** many diverse interconnected entities

# **Adaptive :**

capacity to learn from experience and change over time

# **Example: The NFL**



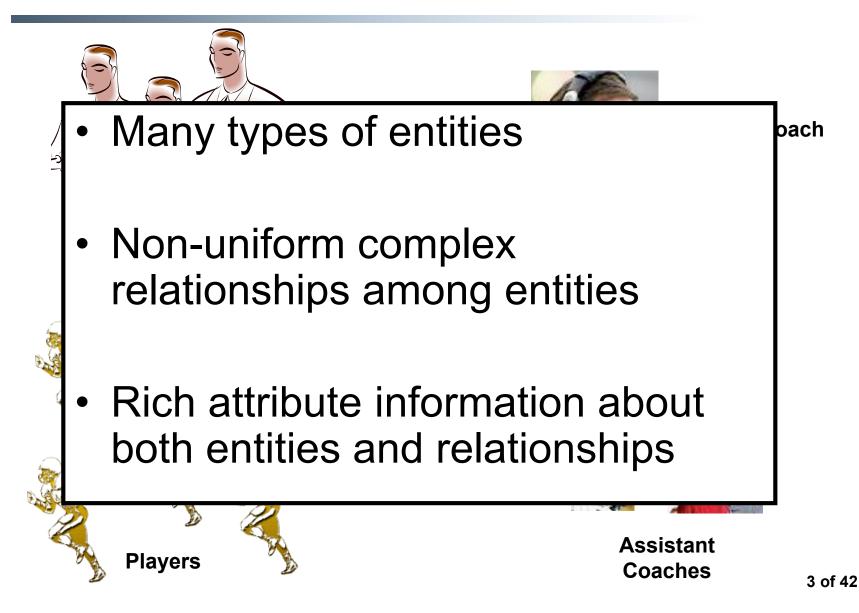


Head Coach



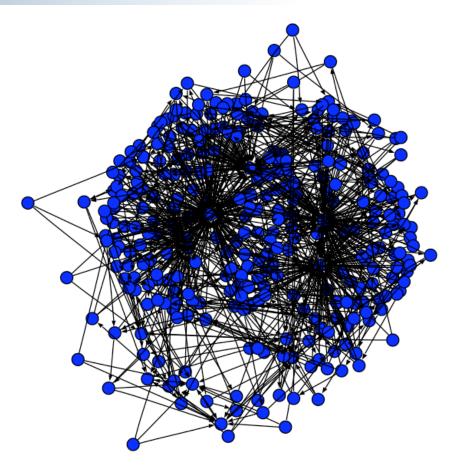
Assistant Coaches

# **Example: The NFL**



## **More Examples**

- Social Network Among Fraudulent Stock Brokers
- A multi-agent UAV system for monitoring ground targets
- Citation patterns in academic fields
- Usage patterns of networked computers and users



(Fast, Jensen, and Levine 2005)

# Outline

- 1. Overview of Complex Adaptive Systems
- 2. The Challenge of Macrobehaviors
- 3. Objective: Empirical Methods for Modeling Macrobehaviors
  - 1. Choosing the Proper Representation
  - 2. Flexible Models of Temporal Phenomena
  - 3. Flexible Models of Group Structure
- 4. Potential Pitfalls
- 5. Conclusions

#### **Macrobehaviors**

- Characteristics or behaviors of aggregated entities that arise over time, often unexpectedly, from interactions among the individuals and their attributes (Schelling 1978).
- Macrobehaviors can be either beneficial or pathological

#### **Beneficial**

- Wisdom of Crowds (Suroweicki 2004)
- "Invisible Hand" (Smith 1776)

#### Pathological

- Tragedy of the Commons (Turner 1993)
- Arms Race (Etcheson 1989)
- Monopolies (Arthur 1990)

## The Challenge Of Macrobehaviors

Due to the complexity of the systems, macrobehaviors are difficult to **identify** and **predict** in real systems...

...but, the success or failure of these systems often depend on **timely understanding** of these behaviors

Macrobehaviors occur:

- At differing time scales and intervals
- Within different size groups of entities

... but,

- the correct time scale
- the correct group size

are not known a priori.

# **The Challenge Of Macrobehaviors**

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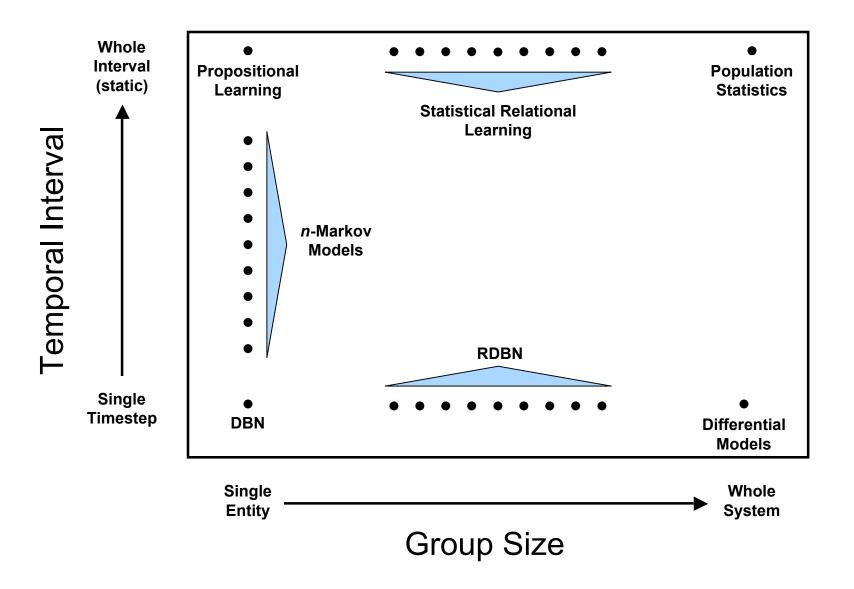
Hypoth	esis
Models of <sub>+</sub> Models of Time Groups	<ul> <li>Models of</li> <li>Macrobehaviors</li> </ul>

Macrobehaviors occur:

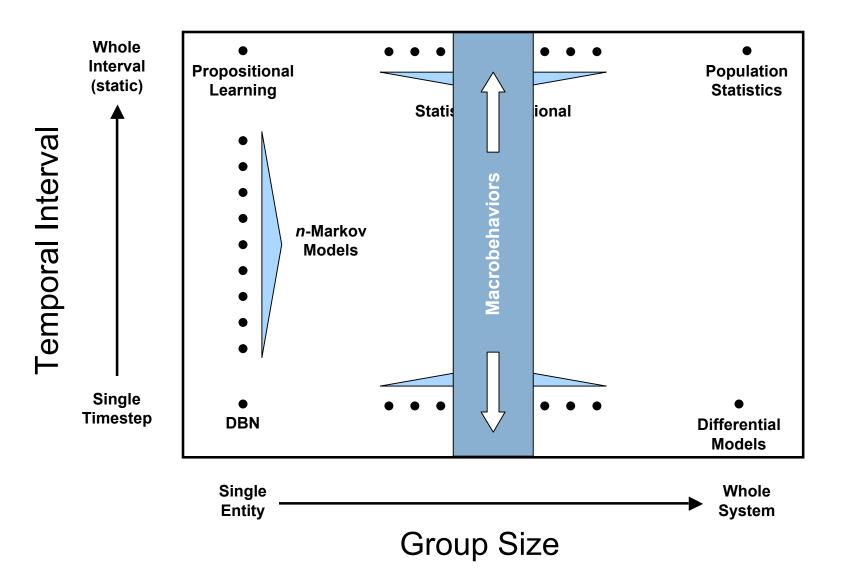
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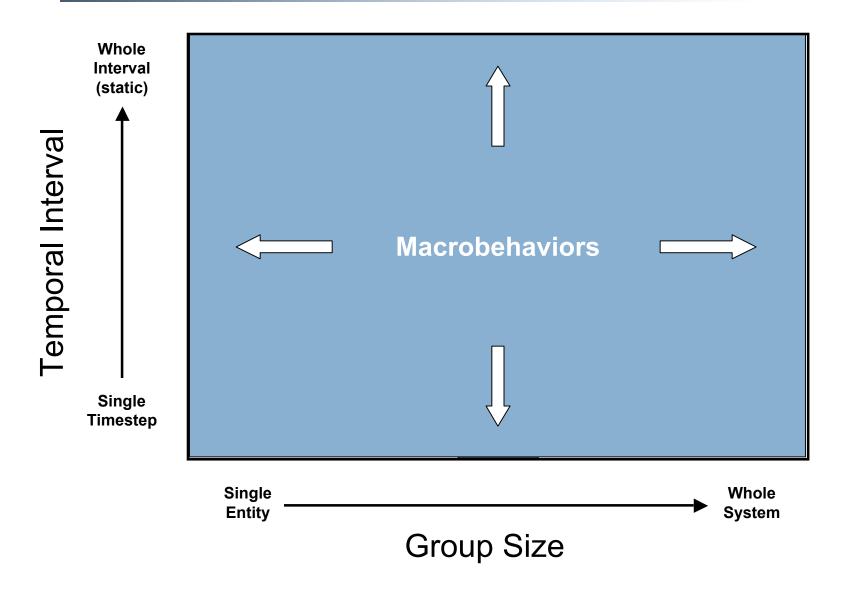
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## **Research Objectives**

Develop models of macrobehaviors that are:

#### Data Driven

–Automatically and efficiently learned from data

#### Understandable

-especially to human observers

#### Actionable

-Able to guide future decisions

#### Correct

–An accurate and unbiased representation of the true state of the world

# 1) Choosing the Proper Representation

# **Graph Representation**

- Neural Network of *C. Elegans*
- Power Grid
- Broadway musical teams (Guimera, Uzzi, Spiro and Amaral 2005)
- Spread of Influence (Kempe, Kleinberg, Tardös 2003)
- Stock Fraud
- Hollywood movie industry
- Scientific co-authorship (Guimera, Uzzi, Spiro and Amaral 2005)
- ...

# All can be represented as a graph with attributes on the vertices and edges.

(Watts and Strogatz 1998)

(Watts and Strogatz 1998)

(Neville et al. 2005)

(Neville et al. 2003)

# **Modeling Graphs**

- Statistical Relational Learning
  - Common representation is a graph with attributes
- Methods designed for data that :
  - Heterogeneous
  - Non-Independent
- Relational Dependency Networks (Neville and Jensen 2004)
  - Joint model of relational data
  - Able to learn cyclic dependencies
  - Allows for Collective Inference
  - Uses a relational decision tree model as a CPD (Neville et al. 2003)

# 2) Flexible Models of Temporal Phenomena

#### Will the Patriots win the Super Bowl in 2006?



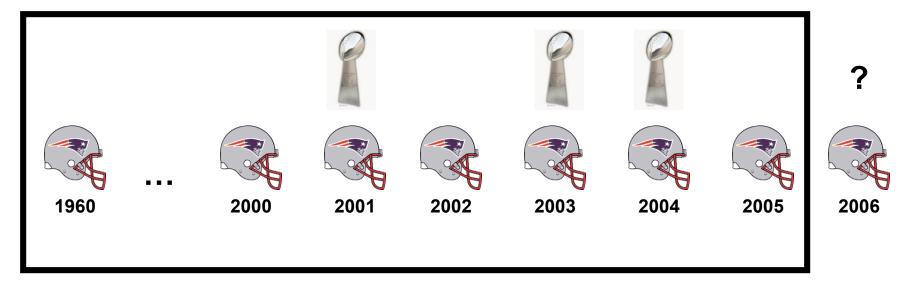
Goal: Use past information to predict future results.



#### But how much past information to use?



But how much past information to use?



P(Playoffs) = 3/45 = 0.67

#### But how much past information to use?



#### P(Playoffs) = 0/1 = 0.0

But how much past information to use?

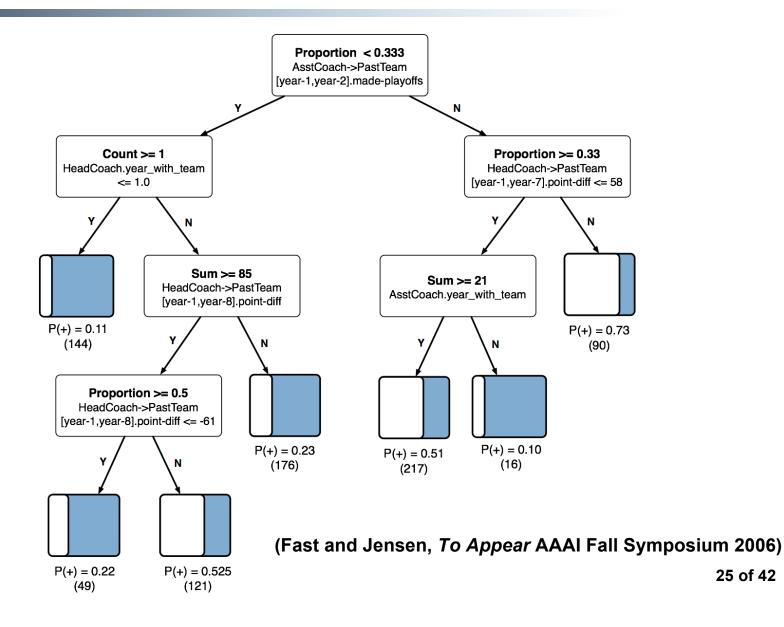


#### P(Playoffs) = 3/5 = 0.60



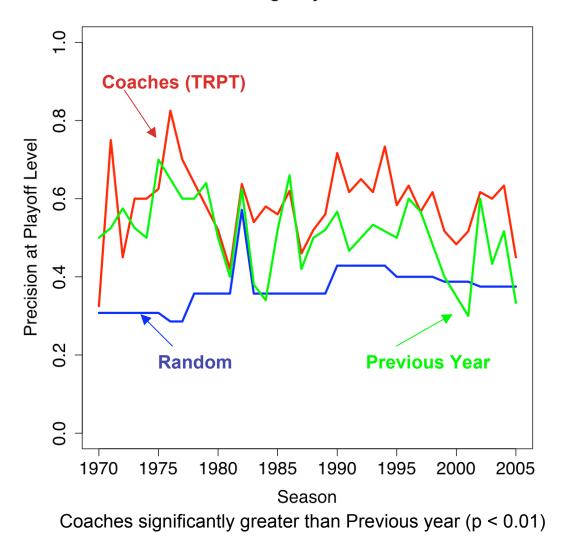
- Use a recursive partitioning algorithm for probability estimation
- Search over both aggregations of entities and temporal intervals.
- Incurs a large feature space expansion  $-\frac{n^2+n}{2}$  possible contiguous intervals

## **NFL Playoff Models**



## **Evaluating NFL Playoff Models**

**Predicting Playoff Success** 



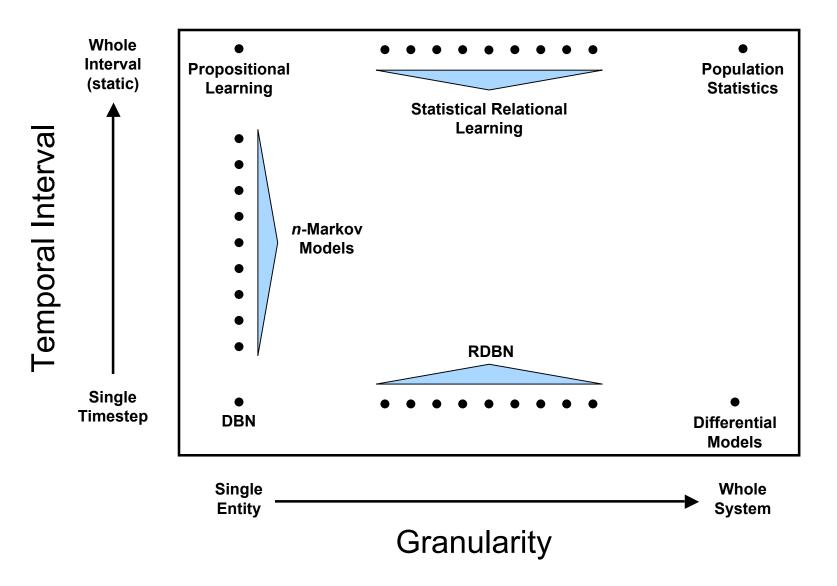
1982 - Player Strike

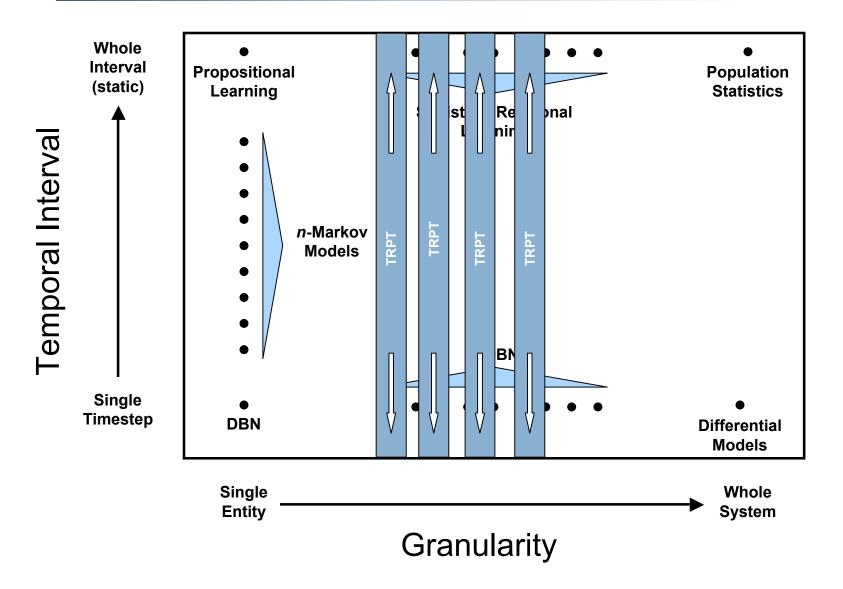
1990 - Playoffs Expanded to 12 teams

1992 - Salary Cap

1994 - Free Agency







# 3) Flexible Models of Group Structure

# **Not Group Finding**

- Many algorithms exist for finding groups in data.
  - Latent Dirichlet Allocation (Blei, Ng, and Jordan 2003)
  - Hierarchical Dirichlet Process(Teh, Jordan, Beal, and Blei 2004)

(See Fast, Jensen, and Levine 2005)

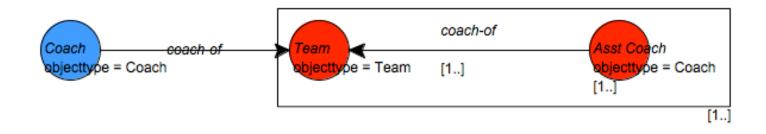
- Group Detection Algorithm (Kubica, Moore, Schneider and Yang 2002)
- **Community Finding Algorithm** (Girvan and Newman 2002)

— ...

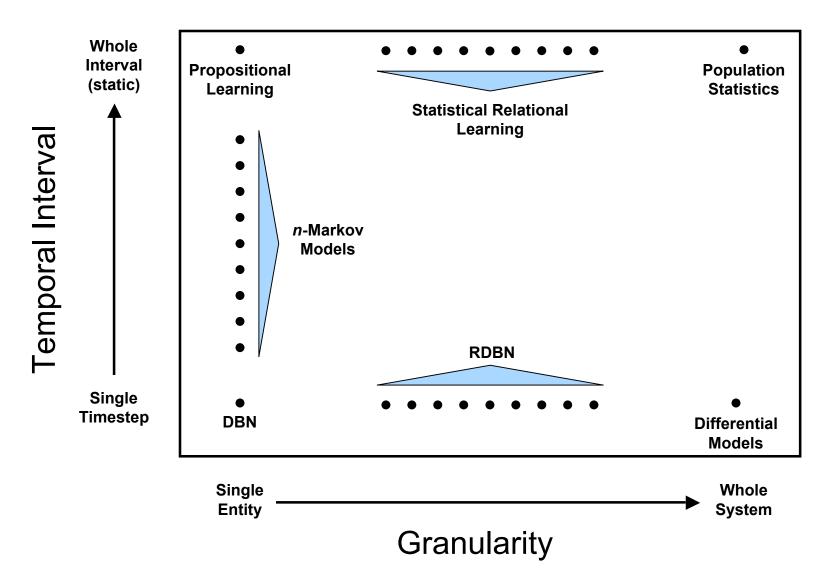
• Instead, learn which group structures are correlated with macrobehaviors.

# QGraph

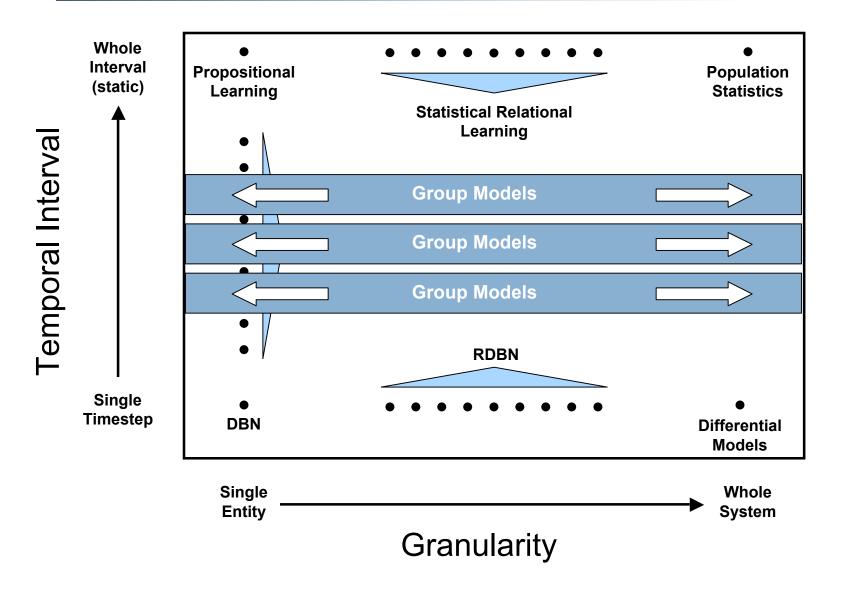
• Query language designed for relational data (Blau, Immerman, and Jensen 2002)

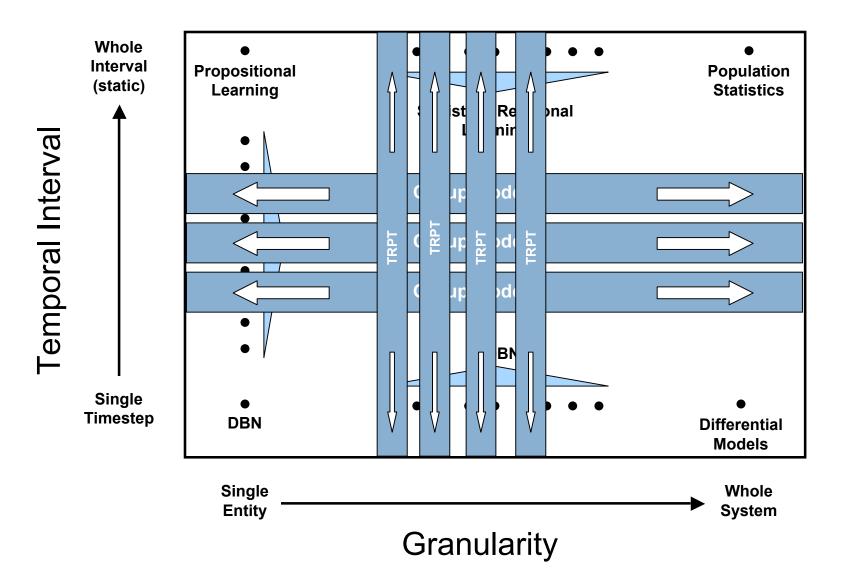


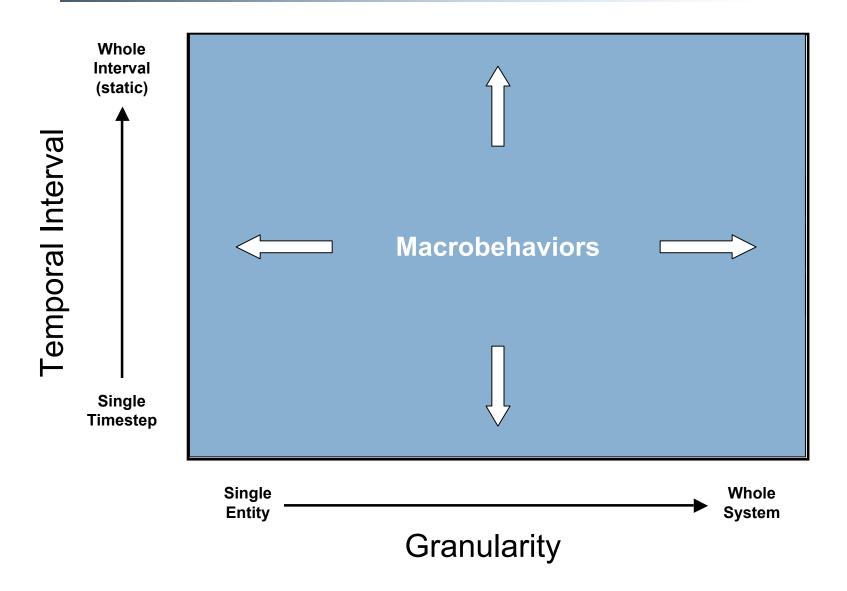
 Use QGraph to enumerate possible groups and calculate features based on those groups



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# **Drowning in Variance**

- Feature space expansion could lead to problems with high variance models
- Potential Solutions:
  - Collective Inference Use inferences on related entities and relations to constrain inferences on current entity
  - Large Data Sets Complex Adaptive Systems tend to generate VERY large data sets.
  - New Features Constrain Model Space -Temporal and Group Structure constrain the space of models, effectively limiting variance

# **Learning Incorrect Models**

- Expanded representation opens door for biases in structure learning.
  - Autocorrelation and Linkage
  - Degree Disparity
  - Some new bias?
- Multiple Comparisons Problem

## Solution is the same!

New randomization tests for relational data that are able to deal with both time and group structure

## Timeline

- Extend relational learning algorithms to search over all possible temporal intervals.
- Extend relational learning algorithms to search over possible group structure.
- Explore new learning algorithms for potential biases
- Explore options for improving initial models based in results of previous step

# **Thesis Contributions**

- New relational learning algorithms able to learn both the temporal and complex structural dependencies needed to detect macrobehaviors in complex adaptive systems.
- Development of novel computationally intensive methods for evaluating the bias and variance of those new models to determine if the models accurately represent the true state of the world

# **Remaining Concerns**

- Are these methods sufficient for modeling macrobehaviors?
  - Are there other dimensions I should consider?
- Other approaches for modeling groups?
- Other potential pitfalls?
- Contributions from other fields?

## **Questions?**

#### **Andrew Fast**

afast@cs.umass.edu http://www.cs.umass.edu/~afast

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