<table>
<thead>
<tr>
<th>Page #'s</th>
<th>Title</th>
<th>Name</th>
<th>Department</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-7</td>
<td>Isospectral Network Transformations</td>
<td>Ben Webb</td>
<td>Mathematics</td>
</tr>
<tr>
<td>8-13</td>
<td>BYU Math: ACME</td>
<td>Jared Webb</td>
<td>Mathematics</td>
</tr>
<tr>
<td>14-17</td>
<td>Applied Mathematics and Geophysical Fluid Dynamics</td>
<td>Jared Whitehead</td>
<td>Mathematics</td>
</tr>
<tr>
<td>18-32</td>
<td>Bayesian Nonparametrics for Flexible Inference</td>
<td>David Dahl</td>
<td>Statistics</td>
</tr>
</tbody>
</table>
Isospectral Network Transformations

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Areas of Interest:
Dynamics of Networks; Particle Dynamics on Lattices; Spectral Estimates & Dynamics
Isospectral Network Transformations

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Areas of Interest: Dynamical Systems & Applications
- Dynamics of Networks
- Particle Dynamics on Lattices
- Spectral Estimates & Dynamics
Isospectral Network Transformations

plant networks                     electrical networks                       neural networks                         computer networks

The Graph of a Network
Network Reductions that Preserve Network Spectrum

Original Network

Reduced Network
Reduction Properties

- **Existence and Uniqueness:** Any network can be uniquely reduced over any collection of its elements.

- **Flexibility:** Any reduction rule can be used to compare the reduced structure (topology) of two or more networks.

- **Ease of Computation:** Any isospectral transformation can be carried out using standard software.

The theory of Isospectral Transformations is found in:
Working on Networks?

**Goal:** Use these techniques to study the structure and/or statistics of reduced networks.

**What is missing?** The *technical expertise* from the biologist, physicist, engineer, etc. to know over which types of sets a network should be reduced.
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Mathematics  
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Areas of Interest:  
Rigorous Mathematics; Computer Programming;  
Mathematical and Statistical Modeling; Data Wrangling;  
Machine Learning
The Skill Set

- ACME students are competent in
  - Rigorous Mathematics
  - Computer Programming
  - Mathematical and Statistical Modeling
  - Data Wrangling
  - Machine Learning
The ACME Model

- Students choose an emphasis in another discipline

- Junior Year
  - Algorithms and Computation
  - Linear and Non-Linear Analysis

- Senior Year
  - Machine Learning and Advanced Computation
  - Probability Theory and Differential Equations
Probability and Data Science

- Python, MySQL, MPI, Hadoop
- Handwriting and Voice Recognition
- Bayesian and Markov Models

Differential and Integral Equations

- Finite Element Methods
- Stochastic Differential Equations
- Control Theory
- Compressed Sensing
Can ACME help me?

- Do you work with dirty or noisy data?
- Are off-the-shelf software models inadequate?
- Are your experiments expensive?
- Do your undergraduates need technical skills to excel in your field?

Then talk to ACME!
Applied Mathematics and Geophysical Fluid Dynamics

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Areas of Interest:
Applied Mathematics and Fluid Dynamics; Asymptotics and Multiple Scales
Applied Mathematics and Geophysical Fluid Dynamics

Jared P. Whitehead

Mathematics Department
Variational Bounds on Turbulent Quantities:

Rayleigh-Bénard Convection

Rayleigh number: \( Ra = \frac{g \alpha (T_{\text{hot}} - T_{\text{cold}}) h}{\nu \kappa} \)

Prandtl number: \( Pr = \frac{\nu}{\kappa} \)

Theorem:

\[
\begin{align*}
\text{T} + \text{u} &= \Delta \text{T} \\
\frac{1}{Pr} (\dot{\text{u}} + \text{u} \text{u}) &= p = \Delta \text{u} + Ra \hat{j} \text{T}
\end{align*}
\]

0 = u

Challenge: Determine how the transport of heat (non-dimensional Nusselt number) depends on Ra and Pr.

In 2 dimensions, with stress-free vertical boundaries we have the following **Theorem**:

\[
\text{Nu} \leq \frac{5^{7/12} \times 3^{3/4}}{2^{13/3}} \text{Ra}^{5/12} - \frac{1}{4} \approx 0.2891 \text{Ra}^{5/12}. \quad (29)
\]

Directly contradicting some wide-held theories.
Asymptotic limits of rapid rotation and strong stratification: climate and weather.

- A rotating, stratified earth produces rapid waves that do not affect the long-term (climate) dynamics.
- Appropriate filtering of these waves led to the 1\textsuperscript{st} accurate numerical weather prediction.
- Are these waves really important though?
- How do these waves affect the long-time asymptotic nature of the fluid flow?
- I use:
  - Multiple-scale asymptotics
  - Direct numerical simulations
  - Large-scale modeling assumptions
Bayesian Nonparametrics for Flexible Inference

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Statistics
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Areas of Interest:
Bayesian nonparametrics; Model-based clustering; Random partition models; Protein structure prediction; Bioinformatics
Statistical computing
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Speed Networking Event
August 25, 2014
Research Interests

In statistical speak:

- Bayesian nonparametrics
- Model-based clustering
- Random partition models
- Protein structure prediction
- Bioinformatics
- Statistical computing
Research Interests

In statistical speak:

- Bayesian nonparametrics
- Model-based clustering
- Random partition models
- Protein structure prediction
- Bioinformatics
- Statistical computing

In lay terms:

- Develop novel statistical methodology to solve hard problems in science using theory and computing.
- Methods to flexibly share information across groups.
- Incorporate data from different sources in an analysis.
- Assess uncertainly in inference.
Novel statistical methodology from the EPA distribution:

1. Cluster analysis:
   - Same input data as hierarchical clustering
   - Readily assess clustering uncertainty

2. Flexible Bayesian modeling in which pairwise distances influence from which observations to borrow strength \textit{a priori}.
Clustering the Iris Data

> iris[1:5,]
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1     5.1      3.5       1.4       0.2  setosa
2     4.9      3.0       1.4       0.2  setosa
3     4.7      3.2       1.3       0.2  setosa
4     4.6      3.1       1.5       0.2  setosa
5     5.0      3.6       1.4       0.2  setosa

> truth <- as.numeric(iris$Species)
> table(truth)

<table>
<thead>
<tr>
<th>truth</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
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<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>50</td>
<td>50</td>
</tr>
</tbody>
</table>

> data <- iris[,!(names(iris) %in% "Species")]
> distance <- dist(data)

> as.matrix(distance)[1:5,1:5]
  1     2     3     4     5
1 0.0000000 0.5385165 0.509902 0.6480741 0.1414214
2 0.5385165 0.0000000 0.300000 0.3316625 0.6082763
3 0.5099020 0.3000000 0.000000 0.2449490 0.5099020
4 0.6480741 0.3316625 0.244949 0.0000000 0.6480741
5 0.1414214 0.6082763 0.509902 0.6480741 0.0000000
> y <- hclust(distance, method="ward.D")
> adj.rand.index(cutree(y, 3), truth)
[1] 0.7311986
> y <- hclust(distance, method="ward.D")
> adj.rand.index(cutree(y, 3), truth)
[1] 0.7311986

> plot(y)
> x <- rpclust(distance,n.draws=10000, mass=1, discount=0.1)
> adj.rand.index(x$estimate, truth)
[1] 0.7370646

> data[x$exemplar,]
   Sepal.Length  Sepal.Width Petal.Length Petal.Width
   40        5.1         3.4       1.5       0.2
   140       6.9         3.1       5.4       2.1
   95        5.6         2.7       4.2       1.3
```r
> x <- rpclust(distance, n.draws=10000, mass=1, discount=0.1)
> adj.rand.index(x$estimate, truth)
[1] 0.7370646

> data[x$exemplar,]
   Sepal.Length Sepal.Width Petal.Length Petal.Width
  40        5.1        3.4        1.5       0.2
 140        6.9        3.1        5.4       2.1
  95        5.6        2.7        4.2       1.3

> plot(x); plot(x, data=data)
```

David B. Dahl — http://dahl.byu.edu
Bayesian Nonparametric Density Estimation

PDB ID 1ch4A: Ewens distribution
Bayesian Nonparametric Density Estimation

PDB ID 1azi: Ewens distribution
Bayesian Nonparametric Density Estimation

PDB ID 1azi: EPA distribution
Bayesian Nonparametric Density Estimation

PDB ID 1ch4A: EPA distribution
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