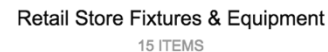
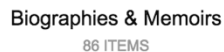
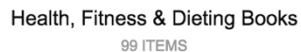
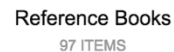
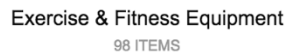
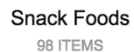


User Experience with Unsupervised Learning in Healthcare

Alli Gilmore | Healthcare Data Scientist | December 7, 2016



Machine learning algorithms have
distinct user experiences.



In healthcare, the stakes are higher.

What's stopping AI from being put to productive use in thousands of businesses around the world isn't some new learning algorithm. It's not the need for more programmers fluent in the mathematics of stochastic gradient descent and back propagation. It's not even the need for more accessible software libraries. What's needed for AI's wide adoption is an understanding of how to build interfaces that put the power of these systems in the hands of their human users.

- Greg Borenstein, game designer, technologist, teacher

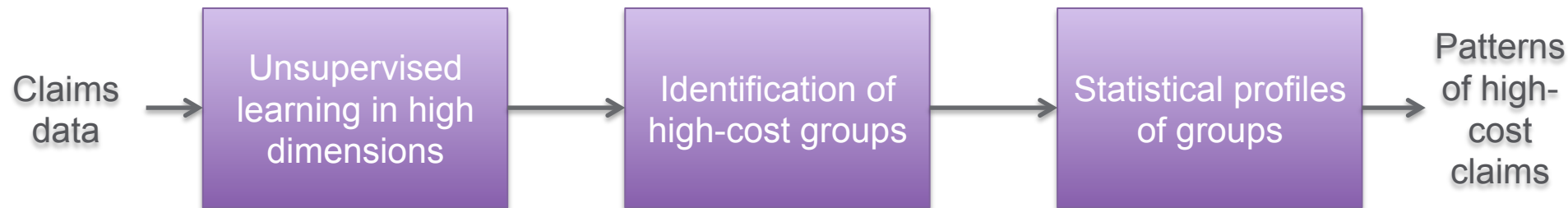
<https://medium.com/@atduskgreg/power-to-the-people-how-one-unknown-group-of-researchers-holds-the-key-to-using-ai-to-solve-real-cc9e75b1f334#.fdig21mhh>

- Power to the People: The Role of Humans in Interactive Machine Learning
Saleema Amershi, Maya Cakmak, W. Bradley Knox, Todd Kulesza
<http://bradknox.net/public/papers/AIMagazine2015-IML.pdf>
- Kahneman, Daniel. *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux, 2011

Disclaimer: details of systems have been masked to protect company confidential information of One Medical and others. User feedback is presented via composite characters.

Scenario

Finding patterns of high-cost claims



Features included:

- Patient demographics
- Facility information
- Billing codes (revenue codes, CPT, HCPCS)
- Diagnosis codes
- Payer information
- Summarized claims processing information

Improved feature set would include:

- Clinical history data extracted from EMR
- Clinical outcomes data extracted from EMR

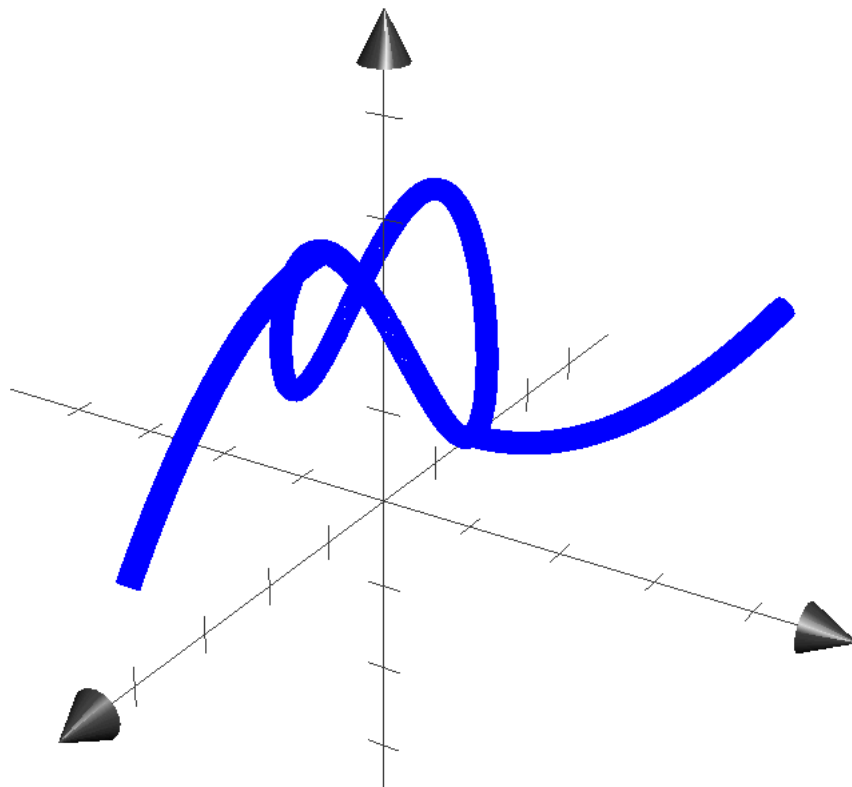
- Principles of topological and geometric data analysis
 - Metrics matter; coordinates (usually) don't
 - Shape matters, often qualitatively more than quantitatively
- Techniques
 - Persistent Homology: direct measurements of shape
 - Mapper: dimensionality reduction without projection

Gunnar Carlsson, "Topology and data," *Bulletin of the American Mathematical Society*, vol 46, 2009. [full-text pdf](#)

[Open source persistent homology \(Dionysus\)](#)

[Open source Mapper \(pymapper\)](#)

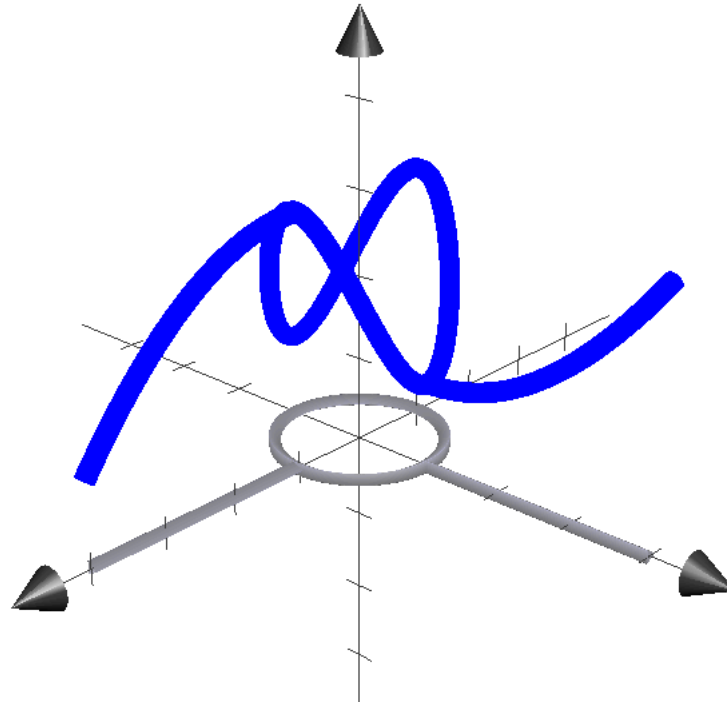
The Mapper Algorithm: Toy Example



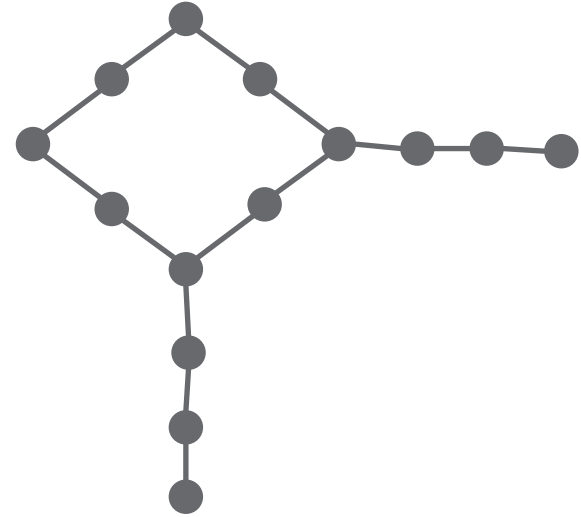
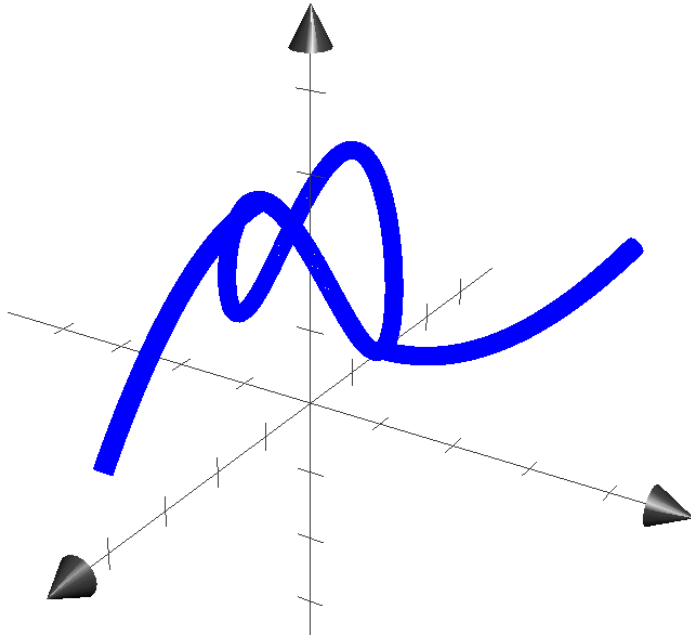
Gunnar Carlsson, Facundo Memoli, and Gurjeet Singh, “Data Sets and 3D Object Recognition,” *Eurographics Symposium on Point-Based Graphics*, 2007. [full-text pdf](#)

[Open source Mapper \(pymapper\)](#)

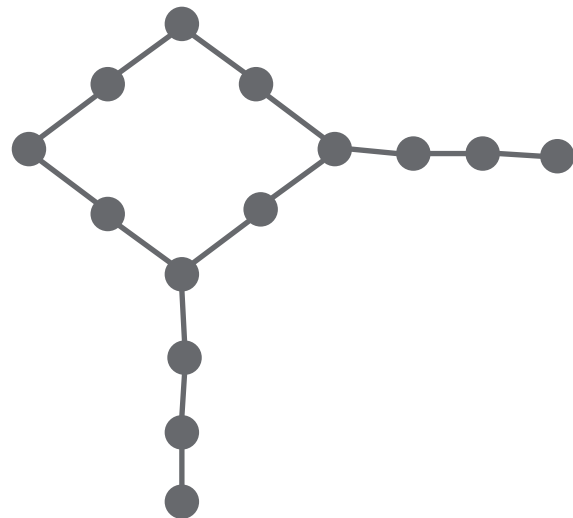
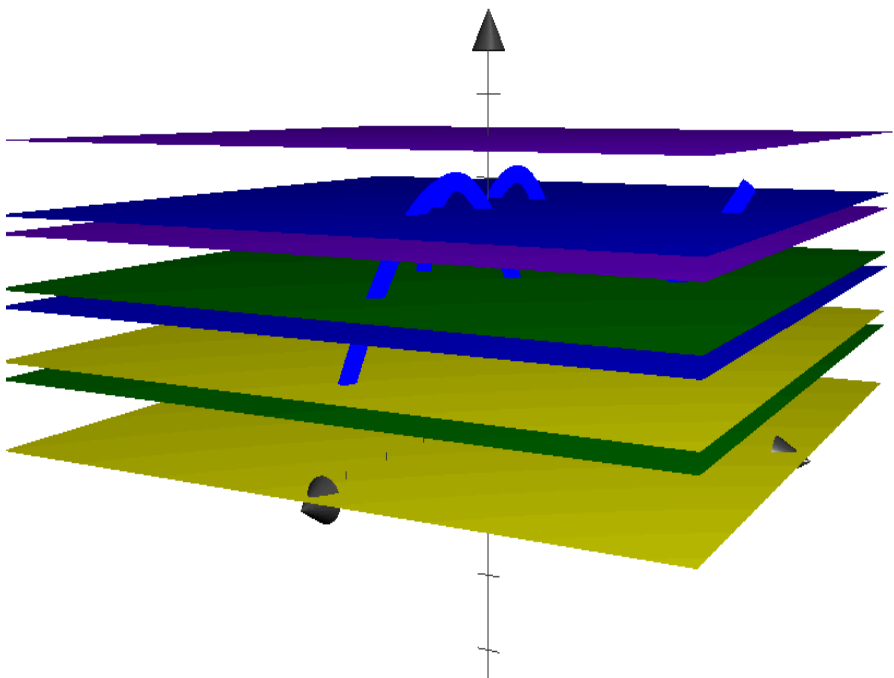
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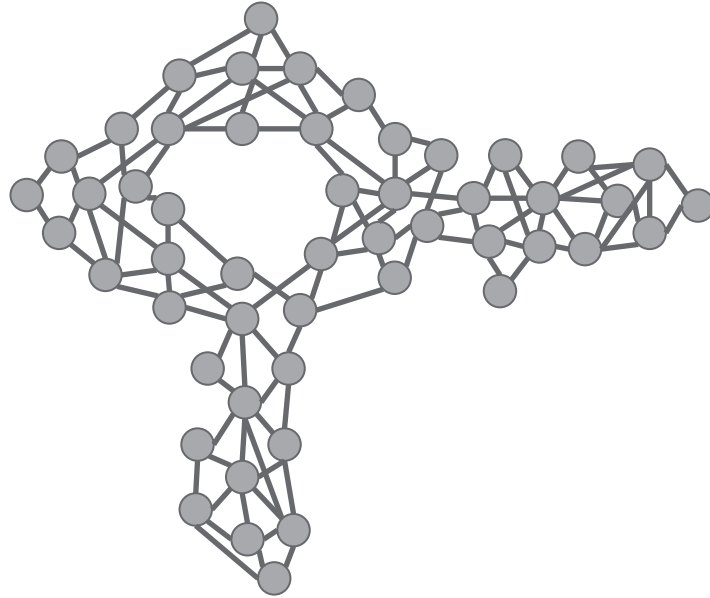
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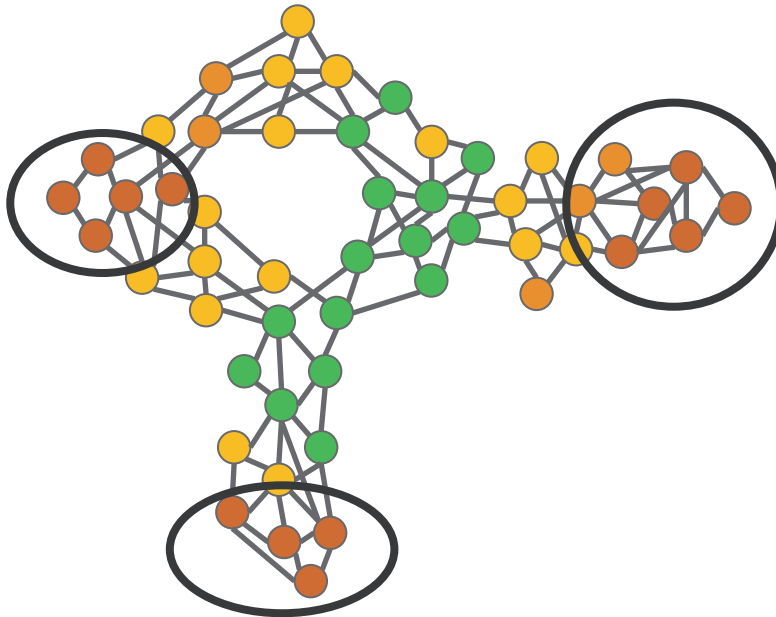
The Mapper Algorithm: Toy Example



The Mapper Algorithm: Realistic Output



The Mapper Algorithm: Identifying “Clusters”



Finding patterns of high-cost claims

	Feature	Claims in group	Claims out of group
Group 1 Total cost: \$xx Patients: 45	173 Nursery, Newborn, Level III	35%	8%
	174 Nursery, Newborn, Level IV	23%	5%
	9946b Inpatient neonatal intensive and pediatric neonatal...		
	Facility ABC	71%	28%
	Attending provider NPI 123456789	18%	2%
	P07 Disorders of newborn related to short gestation and ...	60%	8%
Group 2 Total cost: \$xx Patients: 248	612 MRI – Spinal cord / spine	70%	19%
	72xxx – MRI spine	68%	15%
	70xxx – MRI brain	5%	1%
	Referring provider NPI 234567890	22%	< 1%
	M54x Dorsalgia	43%	14%
Group 3 Total cost: \$xx Patients: 61	173 Nursery, Newborn, Level III	35%	8%
	174 Nursery, Newborn, Level IV	23%	5%
	9946b Inpatient neonatal intensive and pediatric neonatal...	39%	8%
	Facility XYZ	71%	28%
	Attending provider NPI 345678901	18%	2%

Finding patterns of high-cost claims

	Feature	Claims in group	Claims out of group
Group 3 Total cost: \$xx Patients: 104	636 Drugs Requiring Detailed Coding	57%	31%
	J7040 Infusion, normal saline solution, sterile	97%	23%
	Z51 Encounter for other aftercare and medical care	89%	15%
	Facility DEF	34%	8%
Group 5 Total cost: \$xx Patients: 1252	110 Room and Board – Private	40%	20%
	120 Room and Board – Semi-Private – Two Beds	40%	30%
	301 Lab - Chemistry	74%	48%
	302 Lab - Immunology	67%	32%
	272 Medical/Surgical Supplies and Devices – Sterile..	92%	68%

User Feedback

- “Some of these groups are obvious.”
- “Some of these groups don’t make sense.”
- “It looks like there are duplicates.”
- “I knew imaging would come up! So, this group is the imaging claims?”
- “This makes me want to dig into the data!”

Interpreting user feedback

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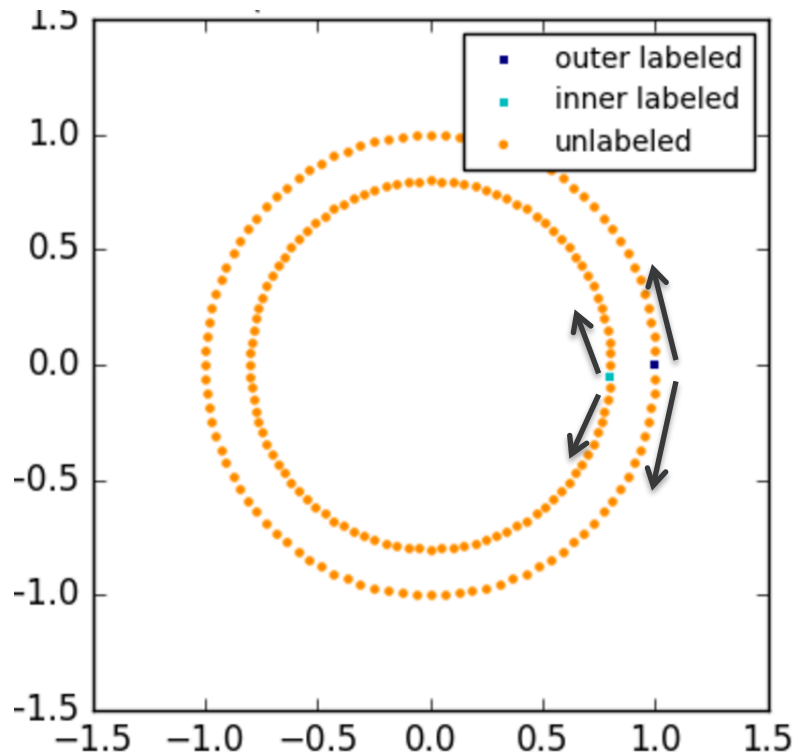
“Some of these groups don’t make sense.”

“This makes me want to dig into the data!”

- Groups arising from unsupervised methods pose an interpretability challenge for many users
 - Automatic pattern recognition feels “black box” compared to querying
 - Similarity is hard to judge at the group level
 - Interpreting groups feels like a guessing game
- Users want to engage in the process
 - contributing expertise
 - validating results

Putting a human in the loop

A new approach: Interactive Label Propagation



Users can confidently provide:

- Archetypal examples
- Features likely to be relevant

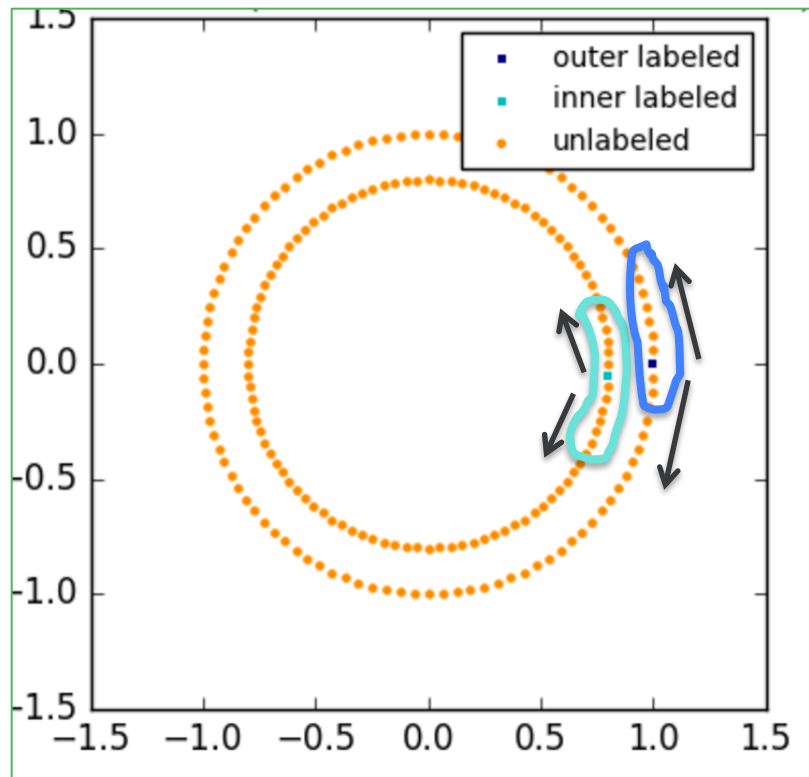
Users can confidently evaluate:

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Work in progress: Interactive label propagation

- Grow groups from archetypes
- Incorporate user feedback to identify group boundaries

A new approach: Interactive Label Propagation



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Work in progress: Interactive label propagation

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Concluding Themes

- employs human and machine expertise symbiotically
- makes the black box transparent
- enables users to understand, and validate, the algorithm's conclusions
- earns users' trust



Thanks!

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