Dependency diagnostic: Visually understanding pairwise variable relationships

Kevin Lin
Carnegie Mellon University,
Department of Statistics and Data Science
@linnylin92

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1	0.92833370	3.8042839
2	-0.30295657	-1.0313626
3	-0.45507998	-2.0610312
4	1.44913302	6.9135100
5	0.96801747	4.5033052
6	0.31809710	1.3910063
7	-0.07636837	-0.0629351
8	-1.51404029	-6.9245794
9	0.70839776	4.2499442
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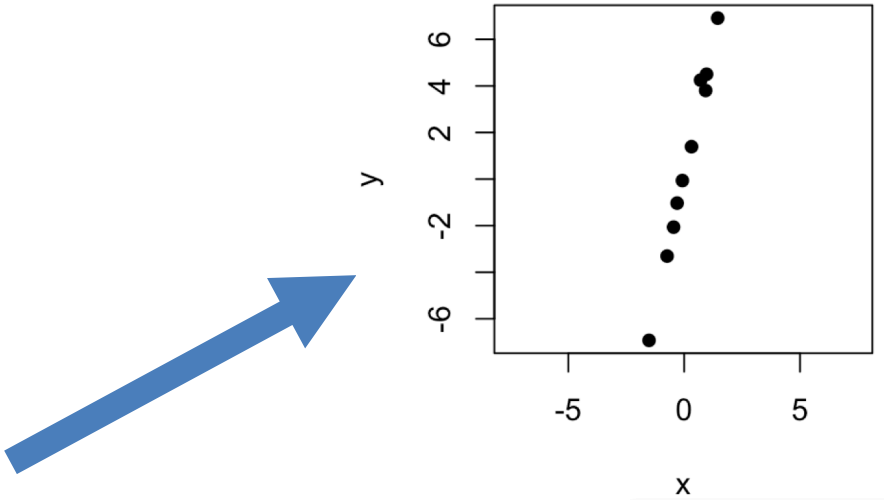

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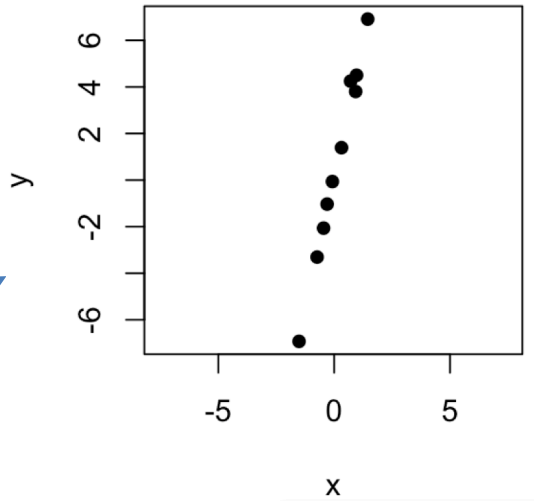


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> cor.test(x,y)

        Pearson's product-moment correlation

data:  x and y
t = 32.026, df = 8, p-value = 9.84e-10
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
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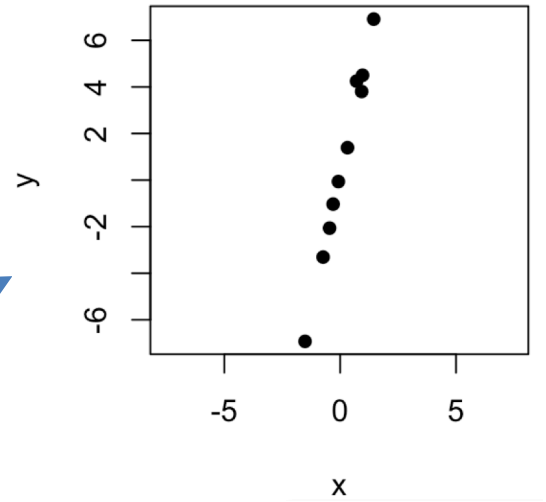

Visual

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Numerical

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- Numerical methods seem more appealing for large data analyses
  - Give a principled way to do multivariate analyses
  - More concrete; not based on opinions
  - Not affected by the plotting illusions

… but no numerical method can serve as a general-purpose tool for any situation.

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- However, there are often too many things to plot naively

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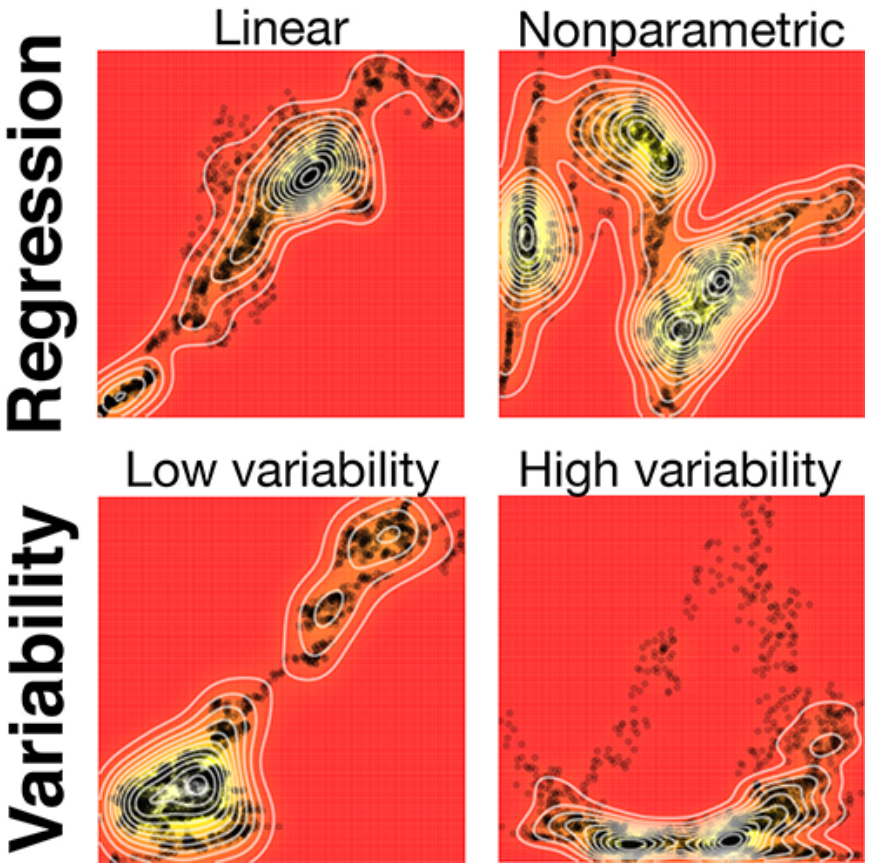
- However, we want to use visualizations to diagnose this numerical method.
- But if there are too many variables, there are too many scatterplots to visualize.
- Solution: A system to learn what kind of patterns we're looking for.

There are many types of patterns that can describe a scatterplot.



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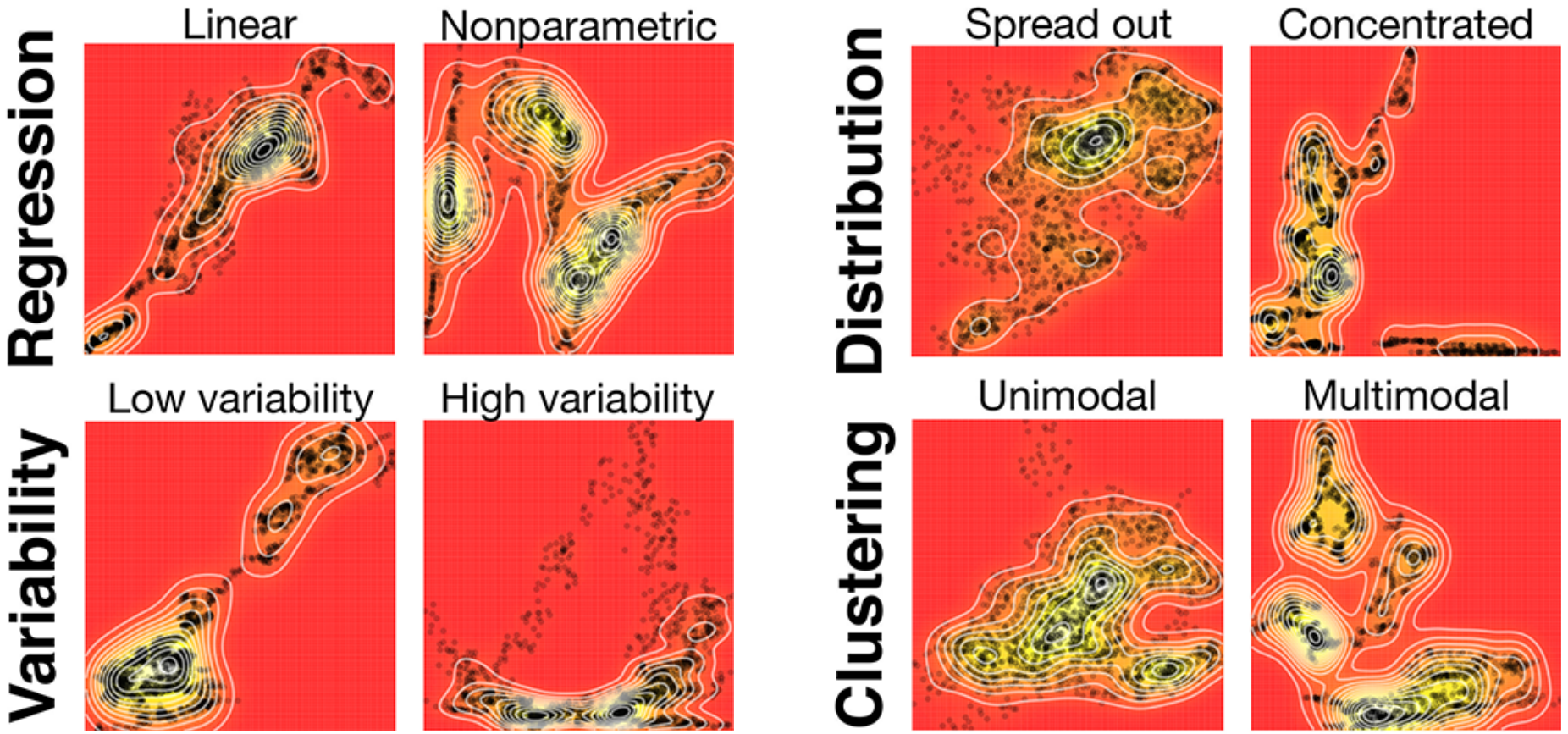
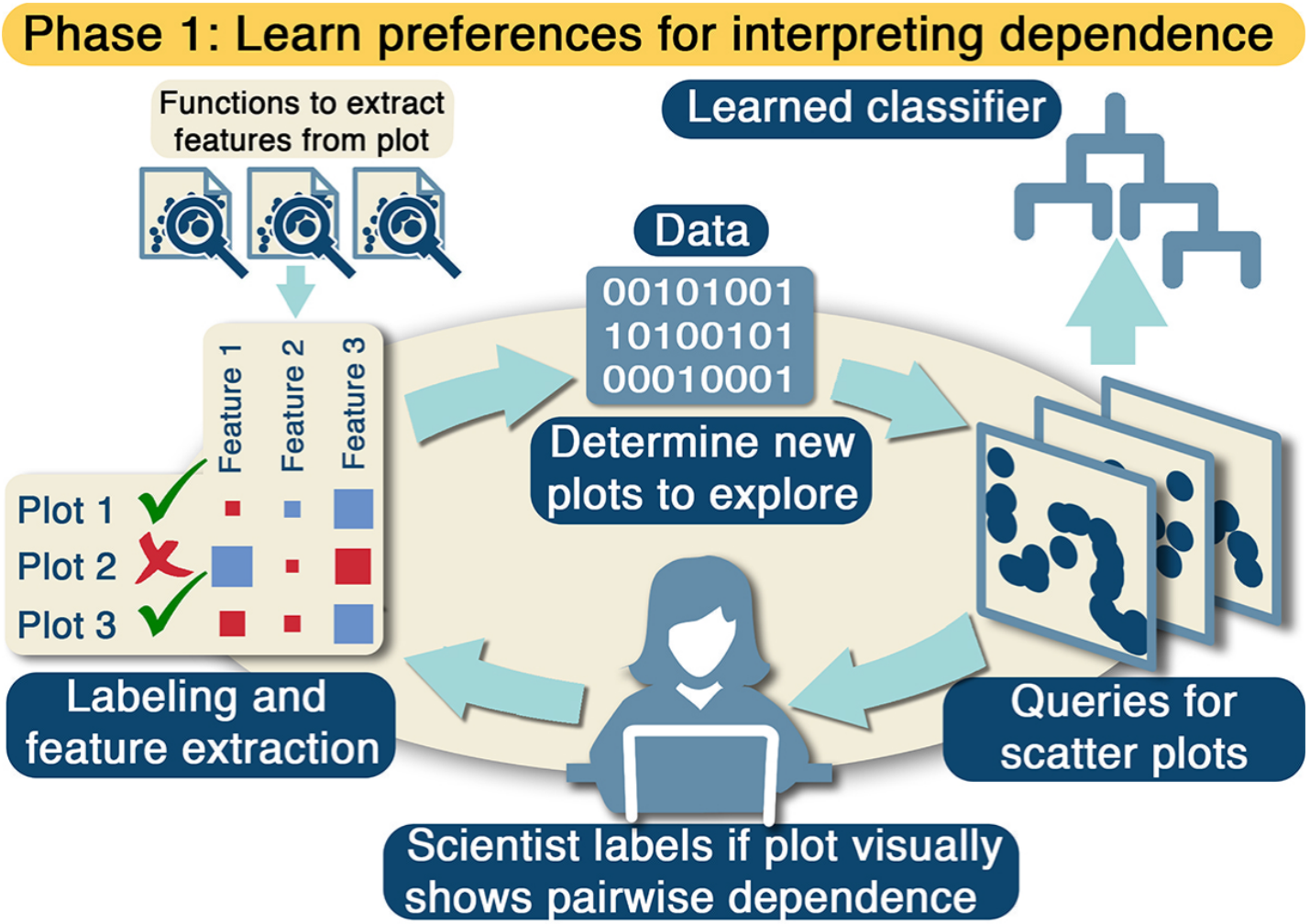


Flowchart of system



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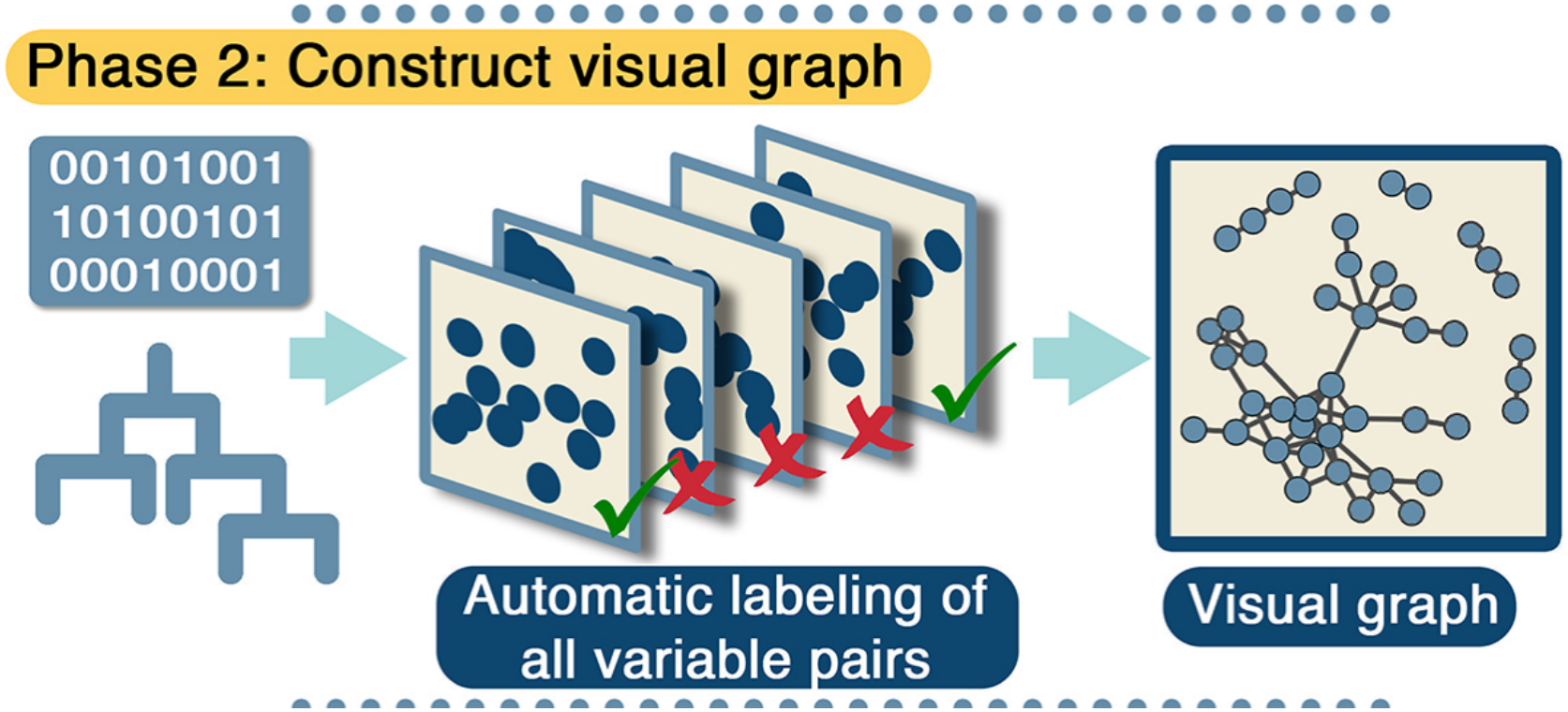
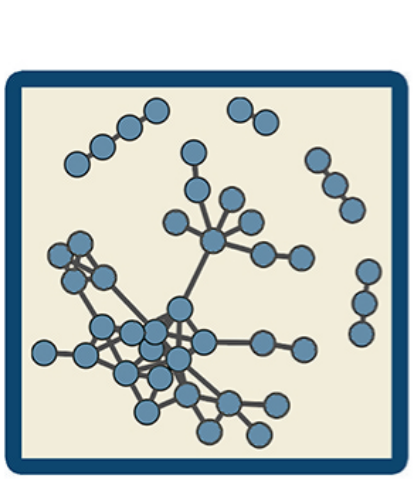
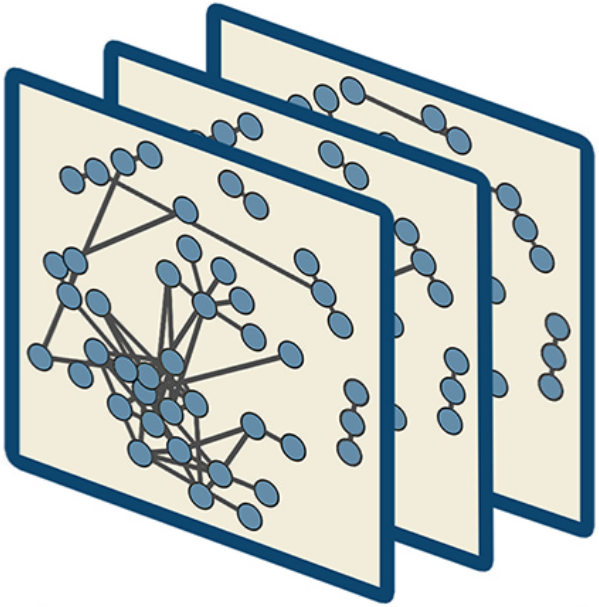


Flowchart of system

Phase 3: Compare visual and numerical graphs



vs.



Graphs estimated via numerical methods

The system advocates using Method 3 as the appropriate method for this dataset.

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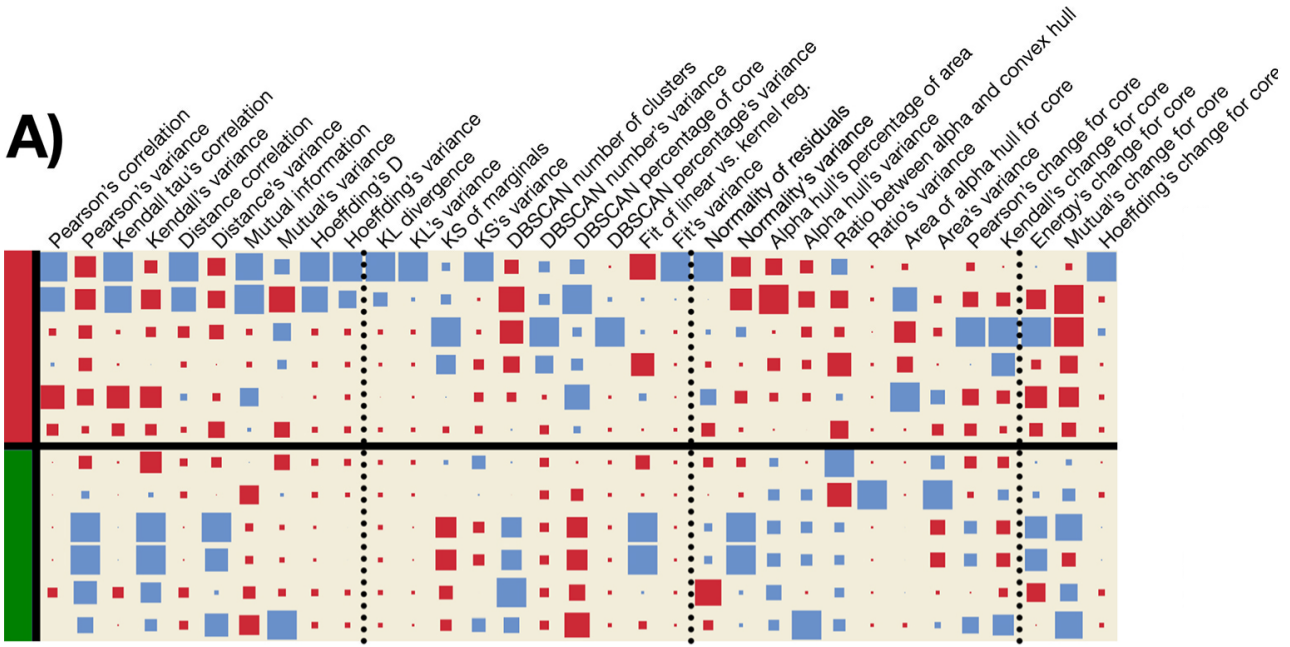
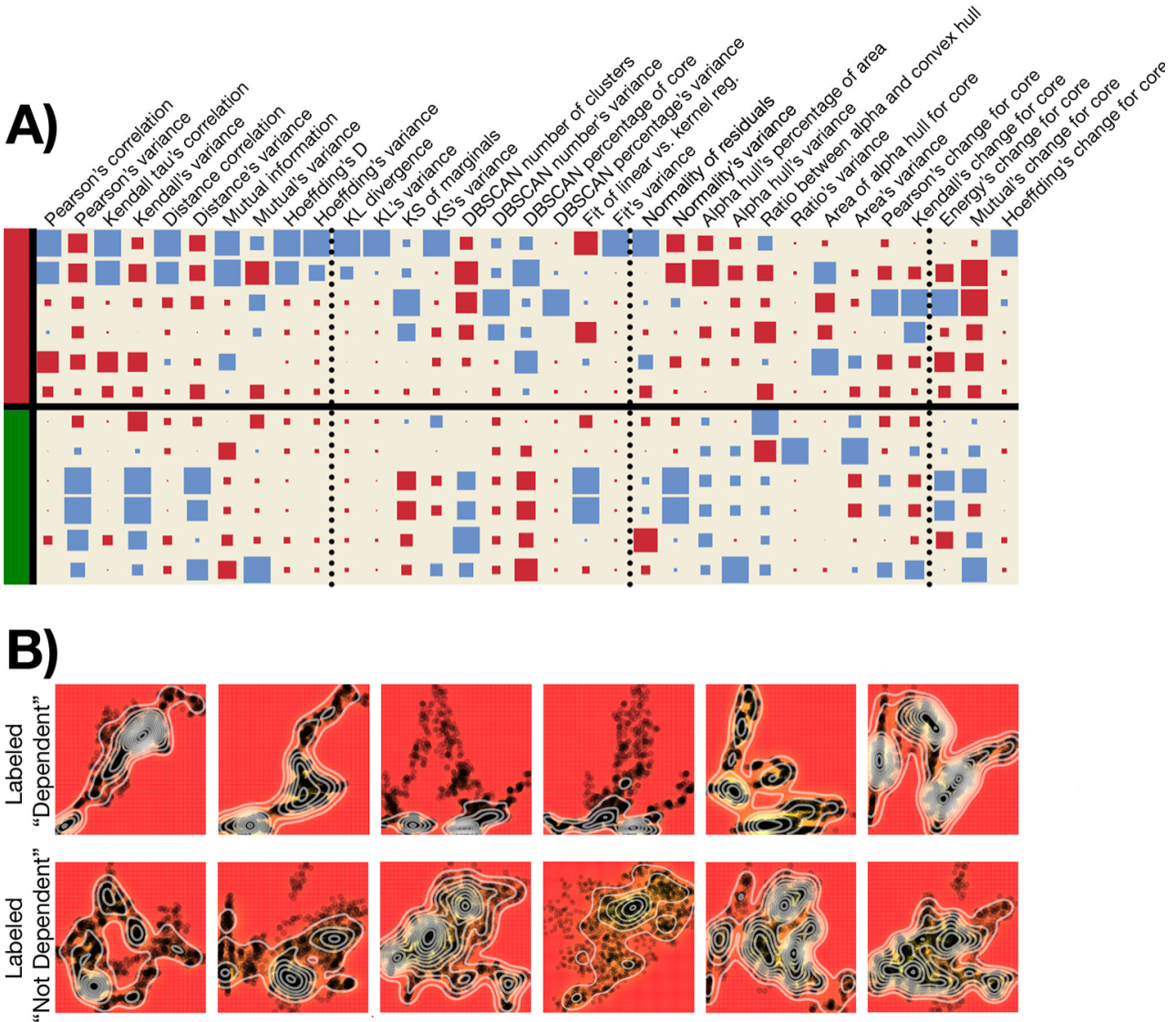
- Numerical features: Many numerical ways to quantify different aspects of a scatter plot
- Active learning: System to ensure that as few scatter plot as possible need to be manually labeled

We can make other plots to assess the quality of the learned classifier.



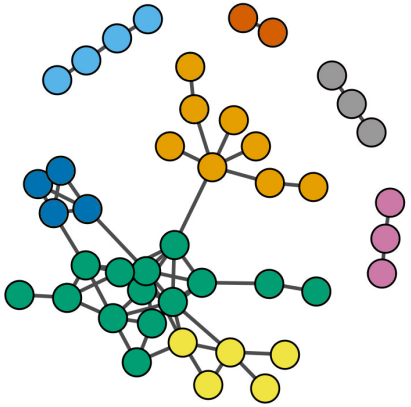
Avenue 3: Image recognition software to learn what patterns the user is interested in.



We apply our method for building a stock portfolio from 43 different healthcare companies.

- Data from 1998 to 2006

Visual graph



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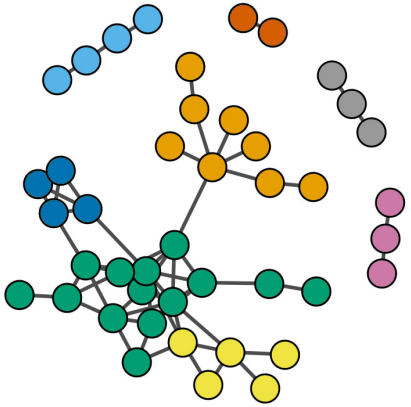

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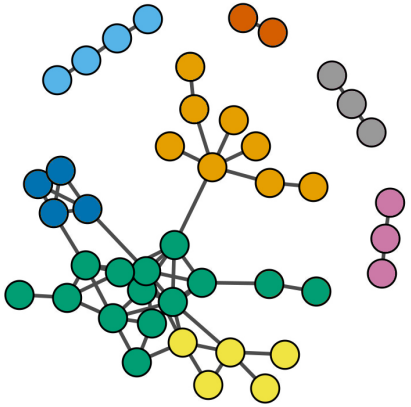

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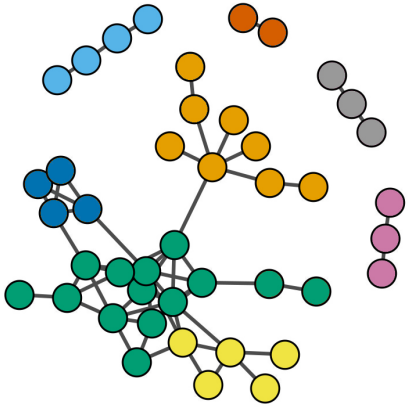
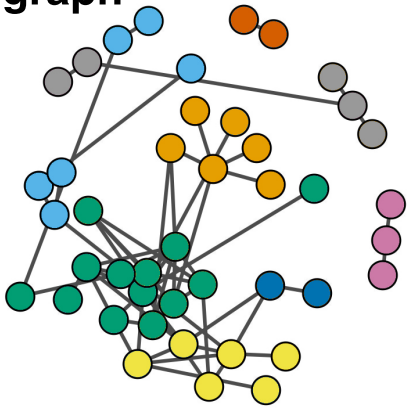
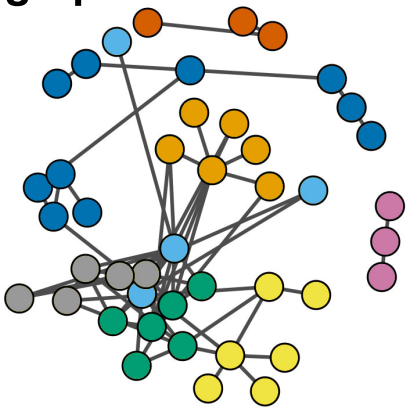


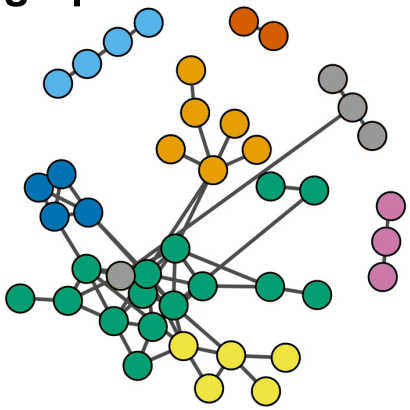
Pearson correlation graph



Distance correlation graph



Mutual information graph



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