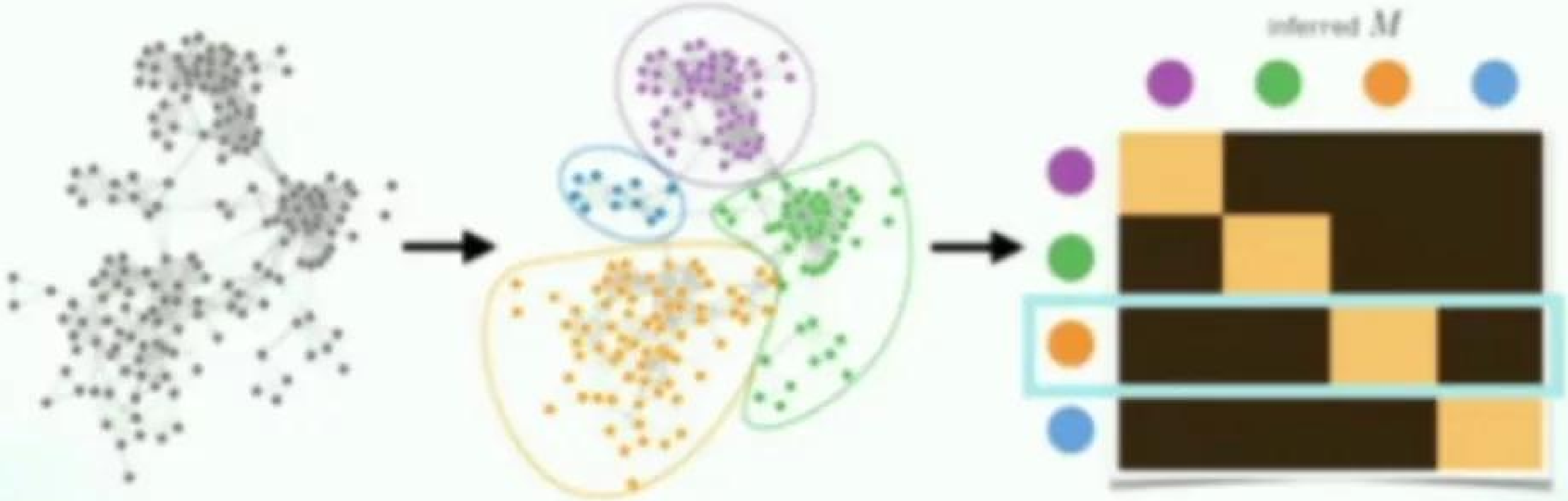
http://tuvalu.santafe.edu/~aaronc/datacode.htm

the stochastic block model

- each vertex i has type $z_i \in \{1, \ldots, k\}$ (k vertex types or groups)
- stochastic block matrix M of group-level connection probabilities
- probability that i, j are connected = M_{z_i, z_j}

community = vertices with same pattern of inter-community connections



1
00:00:12,020 --> 00:00:09,200
I'm Cole Mathis I'm a PhD student at

2
00:00:13,610 --> 00:00:12,030
Arizona State University I'm a

3
00:00:15,049 --> 00:00:13,620
theoretical physicist I study the

4
00:00:17,599 --> 00:00:15,059
original life and I just got back from

5
00:00:20,689 --> 00:00:17,609
10 days of field work with geochemists

6
00:00:22,099 --> 00:00:20,699
in Yellowstone I already mentioned the

7
00:00:23,540 --> 00:00:22,109
title of my talk before I get started I

8
00:00:25,400 --> 00:00:23,550
want to thank a few people everyone for

9
00:00:28,269 --> 00:00:25,410
me life is awesome a research lab

10
00:00:30,380 --> 00:00:28,279
they're great these two smokes a

11
00:00:31,970 --> 00:00:30,390
constant sounding board for me they're

12
00:00:33,500 --> 00:00:31,980
both here I appreciate their input on

13
00:00:35,840 --> 00:00:33,510

all these crazy and half warm thoughts

14
00:00:39,200 --> 00:00:35,850
that come out of my head some people

15
00:00:40,910 --> 00:00:39,210
that aren't here vim deck Vito

16
00:00:44,180 --> 00:00:40,920
peel for introducing me to generative

17
00:00:46,160 --> 00:00:44,190
models and Niles layman who does auto

18
00:00:49,520 --> 00:00:46,170
catalytic sets in RNA chemistry has had

19
00:00:52,160 --> 00:00:49,530
some interesting input my advisor Sarah

20
00:00:54,889 --> 00:00:52,170
Walker she's spectacular she's super

21
00:00:56,840 --> 00:00:54,899
awesome oh and the snake river for

22
00:00:59,450 --> 00:00:56,850
nucleating the idea behind this talk in

23
00:01:01,580 --> 00:00:59,460
my head somehow also if you're wondering

24
00:01:05,450 --> 00:01:01,590
what a theoretical physicist ads for

25
00:01:07,910 --> 00:01:05,460
field work that's that's about it it's

26
00:01:10,850 --> 00:01:07,920
very theoretical all right here's a

27
00:01:11,929 --> 00:01:10,860
slightly better name for my talk so I'm

28
00:01:14,240 --> 00:01:11,939
going to talk about the emergence of

29
00:01:17,420 --> 00:01:14,250
dynamic community structure and maybe

30
00:01:18,800 --> 00:01:17,430
autocatalytic network so hopefully I can

31
00:01:21,859 --> 00:01:18,810
unpack what that means by the end of

32
00:01:24,410 --> 00:01:21,869
this talk it's a complicated idea but I

33
00:01:26,480 --> 00:01:24,420
think with excellent introductions from

34
00:01:27,950 --> 00:01:26,490
Harrison and then it'll be easier for

35
00:01:31,550 --> 00:01:27,960
you swallow and hopefully I'll

36
00:01:32,749 --> 00:01:31,560
understand what I'm saying all right so

37
00:01:34,160 --> 00:01:32,759
if you study the original life

38
00:01:36,319 --> 00:01:34,170

eventually you ask yourself this

39
00:01:37,730 --> 00:01:36,329
question right and Tessa touched on this

40
00:01:39,649 --> 00:01:37,740
earlier what is life we don't have a

41
00:01:40,880 --> 00:01:39,659
good answer but there's some features

42
00:01:43,130 --> 00:01:40,890
right it's a one feature of life that

43
00:01:44,840 --> 00:01:43,140
you might want to try to explain is all

44
00:01:46,999 --> 00:01:44,850
the diversity we find in the biosphere

45
00:01:48,980 --> 00:01:47,009
right that's one thing that's like wow

46
00:01:51,080 --> 00:01:48,990
how do we explain this diversity thats

47
00:01:54,050 --> 00:01:51,090
everywhere how can we come up with a

48
00:01:55,340 --> 00:01:54,060
mechanism to really handle that another

49
00:01:57,109 --> 00:01:55,350
thing you might be curious about is like

50
00:01:59,870 --> 00:01:57,119
life is actually this very ordered and

51
00:02:00,980 --> 00:01:59,880
structured sort of set of chemical

52
00:02:03,249 --> 00:02:00,990
reactions that have a particular

53
00:02:04,700 --> 00:02:03,259
function and operate in particular way

54
00:02:06,590 --> 00:02:04,710
so these are two different

55
00:02:08,809 --> 00:02:06,600
interpretations to this question they're

56
00:02:09,919 --> 00:02:08,819
both obviously valid answers but

57
00:02:11,360 --> 00:02:09,929
depending on what you think is more

58
00:02:13,040 --> 00:02:11,370
interesting more important you might go

59
00:02:13,670 --> 00:02:13,050
different ways right so if you're

60
00:02:15,830 --> 00:02:13,680
interested in

61
00:02:17,449 --> 00:02:15,840
diversity you know our friend Darwin

62
00:02:19,009 --> 00:02:17,459
told us there's a way to explain this

63
00:02:20,420 --> 00:02:19,019

diversity it involves things that make

64
00:02:22,160 --> 00:02:20,430
copies of themselves and a few other

65
00:02:24,380 --> 00:02:22,170
features you might study things that do

66
00:02:25,849 --> 00:02:24,390
this in this talk I'm going to focus on

67
00:02:27,589 --> 00:02:25,859
the kinds of things Ben was talking

68
00:02:30,379 --> 00:02:27,599
about which are autocatalytic sets which

69
00:02:32,330 --> 00:02:30,389
are coupled reactions that form networks

70
00:02:34,849 --> 00:02:32,340
and sometimes these networks have auto

71
00:02:36,259 --> 00:02:34,859
catalytic features where they can make

72
00:02:38,990 --> 00:02:36,269
more of themselves and everything in it

73
00:02:41,509 --> 00:02:39,000
grows exponentially so that's what I'm

74
00:02:43,729 --> 00:02:41,519
going to focus on today so here's a

75
00:02:45,199 --> 00:02:43,739
brief outline I'm going to describe my

76
00:02:47,839 --> 00:02:45,209
model which is very similar to the one

77
00:02:49,129 --> 00:02:47,849
been described and then I'm going to

78
00:02:51,229 --> 00:02:49,139
talk about some background in auto

79
00:02:54,080 --> 00:02:51,239
catalytic sets some results from the

80
00:02:55,309 --> 00:02:54,090
early 70s and some later refinements I'm

81
00:02:56,149 --> 00:02:55,319
going to mention networks and in

82
00:02:58,280 --> 00:02:56,159
particular i'm going to talk about

83
00:03:00,709 --> 00:02:58,290
stochastic block models as a type of

84
00:03:02,360 --> 00:03:00,719
generative model then i'm going to talk

85
00:03:03,920 --> 00:03:02,370
about a little bit of information theory

86
00:03:07,399 --> 00:03:03,930
describe mutual information it's easy

87
00:03:09,470 --> 00:03:07,409
don't freak out and then I'm going to

88
00:03:11,360 --> 00:03:09,480

show how to identify structure in the

89
00:03:13,339 --> 00:03:11,370
dynamics of these autocatalytic sets and

90
00:03:14,929 --> 00:03:13,349
maybe some hints that there's a phase

91
00:03:17,449 --> 00:03:14,939
transition to dynamic order in these

92
00:03:20,089 --> 00:03:17,459
things which is rampantly speculative

93
00:03:22,580 --> 00:03:20,099
but I think I can justify all right so

94
00:03:23,509 --> 00:03:22,590
my model is really similar to Ben's so

95
00:03:25,580 --> 00:03:23,519
there's this sort of background

96
00:03:27,110 --> 00:03:25,590
chemistry going on right there's great

97
00:03:28,640 --> 00:03:27,120
squares and blue squares and they can

98
00:03:30,199 --> 00:03:28,650
come together they can form these

99
00:03:31,640 --> 00:03:30,209
sequences grain blue could be one and

100
00:03:33,770 --> 00:03:31,650
zero they could be a and B whatever you

101
00:03:35,330 --> 00:03:33,780
like so there's ligation when they come

102
00:03:37,969 --> 00:03:35,340
together there's Association when they

103
00:03:40,490 --> 00:03:37,979
fall apart in my model in contrast to

104
00:03:43,099 --> 00:03:40,500
Ben's it's close mass and i explicitly

105
00:03:44,689 --> 00:03:43,109
model the degradation so that has some

106
00:03:47,780 --> 00:03:44,699
interesting feedbacks but it's very

107
00:03:49,670 --> 00:03:47,790
similar so all of these reactions for

108
00:03:52,009 --> 00:03:49,680
all possible combinations of sequences

109
00:03:53,929 --> 00:03:52,019
are possible in mind and then there are

110
00:03:56,539 --> 00:03:53,939
some catalyzed reactions so this is an

111
00:03:58,369 --> 00:03:56,549
example of the formation of this gray

112
00:04:00,199 --> 00:03:58,379
dimer could be catalyzed by the great

113
00:04:02,210 --> 00:04:00,209

rhymer right there's lots of different

114
00:04:03,439 --> 00:04:02,220
ones you could do I'm going to spend the

115
00:04:06,589 --> 00:04:03,449
entire talk talking about this

116
00:04:08,270 --> 00:04:06,599
particular network of reactions it's

117
00:04:12,080 --> 00:04:08,280
sort of obvious when you look at it it's

118
00:04:14,929 --> 00:04:12,090
a mirror image make dimers make trimers

119
00:04:18,620 --> 00:04:14,939
trimers make these trimers help things

120
00:04:22,009 --> 00:04:18,630
that go astray right so pretty simple is

121
00:04:23,839 --> 00:04:22,019
anybody confused by this yet cool all

122
00:04:26,420 --> 00:04:23,849
right it's a background on our kind of

123
00:04:26,890 --> 00:04:26,430
like set theory so if you take all of

124
00:04:28,749 --> 00:04:26,900
these

125
00:04:30,460 --> 00:04:28,759
reactions and you randomly sprinkle

126
00:04:32,920 --> 00:04:30,470
catalysts you say this molecule

127
00:04:36,760 --> 00:04:32,930
catalyzes this reaction you're

128
00:04:39,490 --> 00:04:36,770
guaranteed to get auto catalytic sets if

129
00:04:40,719 --> 00:04:39,500
the random you're guaranteed to get auto

130
00:04:42,400 --> 00:04:40,729
catalytic sets as long as the

131
00:04:44,800 --> 00:04:42,410
probability is high enough and as long

132
00:04:47,110 --> 00:04:44,810
as the polymers are long enough this is

133
00:04:48,939 --> 00:04:47,120
a result from 1970 a lot of chemists got

134
00:04:52,029 --> 00:04:48,949
really mad about it there's been a lot

135
00:04:54,550 --> 00:04:52,039
of refinements it's held up for 40 years

136
00:04:55,900 --> 00:04:54,560
at this point here's a great reference

137
00:04:57,219 --> 00:04:55,910
if you're curious about these kind of

138
00:04:59,110 --> 00:04:57,229

things didn't port act studies I'm

139
00:05:02,020 --> 00:04:59,120
extensively and he's really good at at

140
00:05:04,300 --> 00:05:02,030
handling them so now let's take a step

141
00:05:05,830 --> 00:05:04,310
back so keep this in your head keep this

142
00:05:06,790 --> 00:05:05,840
in your head here's another thing to

143
00:05:07,960 --> 00:05:06,800
keep in your head all right what are

144
00:05:09,700 --> 00:05:07,970
networks Harrison did a good job

145
00:05:11,260 --> 00:05:09,710
describing these things here's some

146
00:05:13,510 --> 00:05:11,270
example of networks right nodes and

147
00:05:15,730 --> 00:05:13,520
edges an entity and a link between

148
00:05:17,980 --> 00:05:15,740
entities right how do we describe them

149
00:05:19,570 --> 00:05:17,990
one way to describe networks is with

150
00:05:21,820 --> 00:05:19,580
what's called an adjacency matrix right

151
00:05:23,980 --> 00:05:21,830
so like this network you have one two

152
00:05:26,980 --> 00:05:23,990
three and four here right we could label

153
00:05:29,230 --> 00:05:26,990
1234 1234 we could put a zero if there's

154
00:05:32,320 --> 00:05:29,240
a no link and one if there is a link

155
00:05:33,730 --> 00:05:32,330
right simple description and then you

156
00:05:35,050 --> 00:05:33,740
could get different combinations of

157
00:05:37,240 --> 00:05:35,060
these to form different different

158
00:05:39,240 --> 00:05:37,250
matrices right so these these are two

159
00:05:41,920 --> 00:05:39,250
representations of the same thing

160
00:05:43,420 --> 00:05:41,930
similarly we could wait the edges right

161
00:05:46,629 --> 00:05:43,430
so this is a slightly different kind of

162
00:05:48,430 --> 00:05:46,639
network but all we've done is instead of

163
00:05:51,790 --> 00:05:48,440

ones and zeros on this adjacency matrix

164
00:05:54,640 --> 00:05:51,800
we've put real value numbers right the

165
00:05:56,260 --> 00:05:54,650
slight generalization ok so now that's

166
00:05:58,750 --> 00:05:56,270
in your head how do we describe networks

167
00:06:00,700 --> 00:05:58,760
one way to describe networks is with a

168
00:06:01,990 --> 00:06:00,710
thing called a generative model there's

169
00:06:04,089 --> 00:06:02,000
lots of different kinds of generative

170
00:06:06,219 --> 00:06:04,099
models and the idea here is you have a

171
00:06:08,110 --> 00:06:06,229
statistical representation of the

172
00:06:11,290 --> 00:06:08,120
network you define a set of parameters

173
00:06:12,969 --> 00:06:11,300
that you can use to generate networks

174
00:06:14,740 --> 00:06:12,979
which are statistically similar to the

175
00:06:18,129 --> 00:06:14,750
one you're interested in so for example

176
00:06:19,689 --> 00:06:18,139
here we've got three different networks

177
00:06:24,100 --> 00:06:19,699
they all have four nodes and they all

178
00:06:27,760 --> 00:06:24,110
have what four edges yeah maybe boy I

179
00:06:29,020 --> 00:06:27,770
can't count so the idea here is these

180
00:06:30,370 --> 00:06:29,030
are all equivalent they all have the

181
00:06:31,930 --> 00:06:30,380
same number of nodes at the same number

182
00:06:34,210 --> 00:06:31,940
of edges so I could make a generative

183
00:06:35,620 --> 00:06:34,220
model that says I'm going to describe my

184
00:06:37,600 --> 00:06:35,630
network by the number of nodes and the

185
00:06:39,459 --> 00:06:37,610
number of edges you can refine that a

186
00:06:40,480 --> 00:06:39,469
lot further right so generative models

187
00:06:42,809 --> 00:06:40,490
described structure

188
00:06:46,180 --> 00:06:42,819

in a statistical sense it's key point

189
00:06:48,939 --> 00:06:46,190
all right I stole these slides from a

190
00:06:51,279 --> 00:06:48,949
professor here at cu-boulder Erin closet

191
00:06:53,680 --> 00:06:51,289
he's pretty rad he put them online for

192
00:06:56,760 --> 00:06:53,690
free I don't think he'll mind they're

193
00:06:58,779 --> 00:06:56,770
great right a particular class of

194
00:07:00,339 --> 00:06:58,789
generative models for networks that have

195
00:07:02,980 --> 00:07:00,349
become very very popular are called

196
00:07:05,050 --> 00:07:02,990
stochastic block models stochastic block

197
00:07:07,930 --> 00:07:05,060
models look for community structure in

198
00:07:09,040 --> 00:07:07,940
networks so computer scientists mostly

199
00:07:10,450 --> 00:07:09,050
worried about these kinds of things and

200
00:07:12,400 --> 00:07:10,460
computer scientists like well-formed

201
00:07:15,159 --> 00:07:12,410
problems right so here's a well-formed

202
00:07:17,050 --> 00:07:15,169
problem I'm gonna give you guys a social

203
00:07:18,790 --> 00:07:17,060
network for everyone in this room right

204
00:07:20,860 --> 00:07:18,800
and then you're going to tell me if

205
00:07:22,689 --> 00:07:20,870
there's community structure in it and

206
00:07:23,800 --> 00:07:22,699
what that is right and so we know

207
00:07:25,270 --> 00:07:23,810
there's community structure in here

208
00:07:26,950 --> 00:07:25,280
right there's like a bunch of us from

209
00:07:29,260 --> 00:07:26,960
ASU there's all these see you people

210
00:07:31,029 --> 00:07:29,270
right so this might be our social

211
00:07:32,469 --> 00:07:31,039
network lots of us know each other but

212
00:07:34,059 --> 00:07:32,479
these might be the communities within it

213
00:07:35,830 --> 00:07:34,069

right this might be a su this might be

214
00:07:37,899 --> 00:07:35,840
bolder this might be somewhere else this

215
00:07:39,370 --> 00:07:37,909
might be everybody else right so you

216
00:07:43,210 --> 00:07:39,380
want to break you want to break the

217
00:07:44,890 --> 00:07:43,220
network into structures where within the

218
00:07:46,749 --> 00:07:44,900
community their links are their

219
00:07:48,700 --> 00:07:46,759
properties are similar and without the

220
00:07:51,610 --> 00:07:48,710
community their properties are different

221
00:07:53,140 --> 00:07:51,620
right it's a simple idea there's a lot

222
00:07:55,959 --> 00:07:53,150
of different ways to do with it do it

223
00:07:57,760 --> 00:07:55,969
this is a associative network right so

224
00:07:59,499 --> 00:07:57,770
where things that are similar associate

225
00:08:01,510 --> 00:07:59,509
with each other starts to look like this

226
00:08:02,830 --> 00:08:01,520
this is the inverse of that dissociative

227
00:08:04,240 --> 00:08:02,840
you don't hang out with anybody that's

228
00:08:05,800 --> 00:08:04,250
like you right this is what you should

229
00:08:07,089 --> 00:08:05,810
do at a conference right don't hang out

230
00:08:09,909 --> 00:08:07,099
with the people from your lab go meet

231
00:08:11,260 --> 00:08:09,919
other people there's ordered ones where

232
00:08:12,879 --> 00:08:11,270
it's kind of in between and then there's

233
00:08:16,330 --> 00:08:12,889
these core periphery ones which are a

234
00:08:18,430 --> 00:08:16,340
particular interest to metabolisms all

235
00:08:20,670 --> 00:08:18,440
right so what have I told you I told you

236
00:08:23,379 --> 00:08:20,680
about my model I've told you about a

237
00:08:24,850 --> 00:08:23,389
generative model for networks right I we

238
00:08:26,890 --> 00:08:24,860

can describe the structure of networks

239
00:08:28,990 --> 00:08:26,900
and statistical sense by creating a

240
00:08:31,059 --> 00:08:29,000
model that makes things like it right

241
00:08:33,010 --> 00:08:31,069
all right everybody got all this in

242
00:08:35,019 --> 00:08:33,020
their head I'm gonna add another piece

243
00:08:37,510 --> 00:08:35,029
here's information theory this is like

244
00:08:38,709 --> 00:08:37,520
page 2 of an information theory textbook

245
00:08:40,899 --> 00:08:38,719
it's not stare it's called mutual

246
00:08:43,120 --> 00:08:40,909
information if you have two variables x

247
00:08:45,790 --> 00:08:43,130
and y the mutual information between x

248
00:08:48,100 --> 00:08:45,800
and y is how much do I learn about why

249
00:08:49,720 --> 00:08:48,110
given that I know X or how much do I

250
00:08:52,000 --> 00:08:49,730
learn about x given that I know why it's

251
00:08:53,750 --> 00:08:52,010
symmetric it's totally correlation

252
00:08:54,800 --> 00:08:53,760
there's no causal anything

253
00:08:56,360 --> 00:08:54,810
you can think of it like a linear

254
00:08:57,380 --> 00:08:56,370
correlation except super generalized

255
00:08:59,060 --> 00:08:57,390
right so it's kind of like a nard

256
00:09:01,100 --> 00:08:59,070
squared value for things that are like

257
00:09:04,340 --> 00:09:01,110
so far away from linear you couldn't

258
00:09:05,990 --> 00:09:04,350
even couldn't even fathom all right so

259
00:09:08,030 --> 00:09:06,000
remember my model this is why my model

260
00:09:10,580 --> 00:09:08,040
looks right like right so what are my

261
00:09:11,870 --> 00:09:10,590
variables I've got lots of the different

262
00:09:14,270 --> 00:09:11,880
concentrations of these different

263
00:09:15,590 --> 00:09:14,280

polymers floating around right so I

264
00:09:17,780 --> 00:09:15,600
could look at a time series of these

265
00:09:19,820 --> 00:09:17,790
concentrations which is what these are

266
00:09:21,860 --> 00:09:19,830
right darker colors means there was more

267
00:09:25,010 --> 00:09:21,870
at a given time lighter colors means

268
00:09:27,560 --> 00:09:25,020
there was fewer time goes that way that

269
00:09:29,000 --> 00:09:27,570
direction okay and I could say all right

270
00:09:31,490 --> 00:09:29,010
this is one sequence and this is another

271
00:09:32,960 --> 00:09:31,500
sequence how correlated are they what's

272
00:09:35,980 --> 00:09:32,970
the mutual information between these two

273
00:09:38,060 --> 00:09:35,990
sequences I get a number right great

274
00:09:40,190 --> 00:09:38,070
simple number throat in this equation

275
00:09:42,320 --> 00:09:40,200
comes out the other end I can do this

276
00:09:44,930 --> 00:09:42,330
for all possible pairs of sequences in

277
00:09:47,690 --> 00:09:44,940
my system right up to length 6 because I

278
00:09:48,950 --> 00:09:47,700
don't want to do it forever all right

279
00:09:52,010 --> 00:09:48,960
and I can build something like this

280
00:09:54,530 --> 00:09:52,020
right so this is all these numbers where

281
00:09:55,850 --> 00:09:54,540
I've calculated what would happen what

282
00:09:58,340 --> 00:09:55,860
the mutual information between them

283
00:10:00,170 --> 00:09:58,350
would be right so now I've got a

284
00:10:02,090 --> 00:10:00,180
weighted network right this is an

285
00:10:05,510 --> 00:10:02,100
adjacency matrix for a weighted network

286
00:10:07,040 --> 00:10:05,520
where the weights on the edges are the

287
00:10:08,870 --> 00:10:07,050
mutual information shared between those

288
00:10:12,280 --> 00:10:08,880

two sequences and the nodes are the

289
00:10:17,090 --> 00:10:12,290
sequences this is capturing the dynamic

290
00:10:20,450 --> 00:10:17,100
correlations in this complicated model

291
00:10:21,980 --> 00:10:20,460
right so this is what this model looks

292
00:10:24,530 --> 00:10:21,990
like this is what the correlations look

293
00:10:27,380 --> 00:10:24,540
like now I've got the stochastic block

294
00:10:28,910 --> 00:10:27,390
model so i can ask is this structured is

295
00:10:31,970 --> 00:10:28,920
their structure there is there a

296
00:10:36,260 --> 00:10:31,980
rigorous way to characterize it and the

297
00:10:38,780 --> 00:10:36,270
answer is yes sometimes so depending on

298
00:10:40,820 --> 00:10:38,790
how effective my catalysts are structure

299
00:10:42,650 --> 00:10:40,830
emerges or a dozen in this system right

300
00:10:44,030 --> 00:10:42,660
so this is I used a different color

301
00:10:47,990 --> 00:10:44,040
scheme I'm sorry I made all these slides

302
00:10:50,300 --> 00:10:48,000
yesterday so these are the same networks

303
00:10:52,490 --> 00:10:50,310
that I just showed you this is when the

304
00:10:54,770 --> 00:10:52,500
catalyst is increases the reaction rate

305
00:10:56,480 --> 00:10:54,780
by a factor of 10 and this is when the

306
00:10:59,720 --> 00:10:56,490
catalyst increases the reaction rate by

307
00:11:05,270 --> 00:10:59,730
a factor of 1.1 it's a zero but that's

308
00:11:07,490 --> 00:11:05,280
type of right so in this case if i use a

309
00:11:09,590 --> 00:11:07,500
bayesian inference method i can be

310
00:11:11,660 --> 00:11:09,600
confident my belief can be almost unity

311
00:11:13,280 --> 00:11:11,670
that there is structure here and it's

312
00:11:14,840 --> 00:11:13,290
the algorithm kind of breaks it up into

313
00:11:17,150 --> 00:11:14,850

this core periphery structure here which

314
00:11:20,510 --> 00:11:17,160
is nice the same thing for the low

315
00:11:22,880 --> 00:11:20,520
calluses rate my belief is like barely

316
00:11:24,740 --> 00:11:22,890
better than then fifty-fifty chance I'm

317
00:11:26,450 --> 00:11:24,750
like now this is just it's probably a

318
00:11:28,100 --> 00:11:26,460
mistake like there might not be

319
00:11:31,160 --> 00:11:28,110
structure there at all it's 5050 who

320
00:11:33,410 --> 00:11:31,170
knows right so these are two limits okay

321
00:11:35,360 --> 00:11:33,420
so now what I can do is swing between

322
00:11:36,530 --> 00:11:35,370
these different catalysis rates and

323
00:11:39,140 --> 00:11:36,540
figure out what the likelihood of

324
00:11:41,480 --> 00:11:39,150
structure being seen there is which is

325
00:11:45,290 --> 00:11:41,490
what you see here man that came out

326
00:11:47,690 --> 00:11:45,300
really bad okay all right so this is is

327
00:11:50,030 --> 00:11:47,700
basically relative belief how much

328
00:11:51,500 --> 00:11:50,040
stronger do I think how much more should

329
00:11:54,740 --> 00:11:51,510
I believe that there is structure there

330
00:11:57,710 --> 00:11:54,750
then I shouldn't believe so 5050 means

331
00:11:59,960 --> 00:11:57,720
like thats toss toss of a coin you can't

332
00:12:03,020 --> 00:11:59,970
really be sure here is the catalysis

333
00:12:05,810 --> 00:12:03,030
rate so i started at 0.1 here and then

334
00:12:07,580 --> 00:12:05,820
all the way to 10 you know dislike it

335
00:12:09,650 --> 00:12:07,590
stays pretty constant all the way till

336
00:12:12,470 --> 00:12:09,660
about five five and a half and then you

337
00:12:14,390 --> 00:12:12,480
get this sharp upswing here this is

338
00:12:16,010 --> 00:12:14,400

actually very well known in a very

339
00:12:17,570 --> 00:12:16,020
different context so people have seen

340
00:12:20,060 --> 00:12:17,580
phase transitions like this in icing

341
00:12:23,060 --> 00:12:20,070
models they've seen this in the

342
00:12:26,690 --> 00:12:23,070
community detection literature in

343
00:12:28,940 --> 00:12:26,700
network science so I can't be sure yet

344
00:12:30,170 --> 00:12:28,950
because I made this yesterday but I'm

345
00:12:31,910 --> 00:12:30,180
pretty sure this is a proper phase

346
00:12:33,440 --> 00:12:31,920
transition so what do I even mean by

347
00:12:34,940 --> 00:12:33,450
that what is this phase transition

348
00:12:37,550 --> 00:12:34,950
represent running out of time so I'll

349
00:12:38,480 --> 00:12:37,560
try it out quick what do I mean all

350
00:12:40,610 --> 00:12:38,490
right do you guys know what Bernard

351
00:12:42,800 --> 00:12:40,620
cells are like if you take a thin layer

352
00:12:44,600 --> 00:12:42,810
of fluid and you heat it on the bottom

353
00:12:46,100 --> 00:12:44,610
and like for a while nothing happens but

354
00:12:48,770 --> 00:12:46,110
you turn it way up and you start to make

355
00:12:52,460 --> 00:12:48,780
these like cycles right here right can

356
00:12:54,500 --> 00:12:52,470
it the onset of convection instead of

357
00:12:58,040 --> 00:12:54,510
just conduction that's what's happening

358
00:13:00,710 --> 00:12:58,050
here this is order on the scale of the

359
00:13:04,160 --> 00:13:00,720
dynamics in the system right this is

360
00:13:07,490 --> 00:13:04,170
disordered this is ordered this is the

361
00:13:09,890 --> 00:13:07,500
transition from disordered to ordered in

362
00:13:11,900 --> 00:13:09,900
the dynamics so it's an ordered phase

363
00:13:21,330 --> 00:13:11,910

transition in the dynamics and

364
00:13:27,070 --> 00:13:23,590
all right we got time for like one

365
00:13:29,440 --> 00:13:27,080
question if it's awesome anyone anyone

366
00:13:32,610 --> 00:13:29,450
nothing so I confuse that everyone got

367
00:13:36,640 --> 00:13:32,620
one oh man I just kind of noticed that

368
00:13:38,620 --> 00:13:36,650
this catalytic increasing factor that's

369
00:13:39,970 --> 00:13:38,630
something in this very abstract model

370
00:13:42,910 --> 00:13:39,980
that you could actually relate to the

371
00:13:44,830 --> 00:13:42,920
real world is so could you perhaps go

372
00:13:47,230 --> 00:13:44,840
through and say like you know this

373
00:13:49,420 --> 00:13:47,240
catalyst this enzyme is really efficient

374
00:13:52,060 --> 00:13:49,430
so that would be more likely to cause

375
00:13:53,830 --> 00:13:52,070
more order in the system right so so

376
00:13:54,910 --> 00:13:53,840
that's what's interesting right so even

377
00:13:56,170 --> 00:13:54,920
if you have catalysts if they're not

378
00:13:57,700 --> 00:13:56,180
very effective if you're in this regime

379
00:14:00,040 --> 00:13:57,710
you're not going to see this global

380
00:14:01,720 --> 00:14:00,050
scale change hmm but they don't have to

381
00:14:04,390 --> 00:14:01,730
be that effective right so the average

382
00:14:06,610 --> 00:14:04,400
effect of the catalyst is to speed up

383
00:14:08,500 --> 00:14:06,620
the like uncatalyzed reaction by a

384
00:14:10,000 --> 00:14:08,510
factor of five right here which like we

385
00:14:12,100 --> 00:14:10,010
care to the bios yeah that's not much

386
00:14:13,660 --> 00:14:12,110
for right and here where it was

387
00:14:16,900 --> 00:14:13,670
completely ordered it was only a factor

388
00:14:19,390 --> 00:14:16,910

of 10 Wow so yeah so Troy factor of a

389
00:14:23,230 --> 00:14:19,400
thousand right yeah million i did i did

390
00:14:27,220 --> 00:14:23,240
this asymptotes it goes yeah yeah yeah

391
00:14:29,020 --> 00:14:27,230
um so yeah it's a good question yeah

392
00:14:31,000 --> 00:14:29,030
that's awesome all right thank you very

393
00:14:32,740 --> 00:14:31,010
much oh I'm gonna plug one more thing if

394
00:14:34,420 --> 00:14:32,750
you think that scientific publishing can

395
00:14:35,950 --> 00:14:34,430
be done better and you think

396
00:14:37,510 --> 00:14:35,960
astrobiology can help do it you should

397
00:14:39,940 --> 00:14:37,520
talk to me before we leave because I'm

398
00:14:42,850 --> 00:14:39,950
really passionate about that are you

399
00:14:44,200 --> 00:14:42,860
starting your own journal I I'm open to

400
00:14:45,730 --> 00:14:44,210
anything I'm gonna try to get everybody

401
00:14:47,470 --> 00:14:45,740
on free prints first and then we could