Gender Dependent Structures of Dialogue Networks in Films

Termeh Shafie & Pete Jones
Mitchell Centre for Social Network Analysis
University of Manchester

female representation in films



the under- and misrepresentation of female characters in movies

- infrequent appearances of women in visual media
- gender role stereotyping



Alison Bechdel's "Dykes to Watch Out For" (1985)

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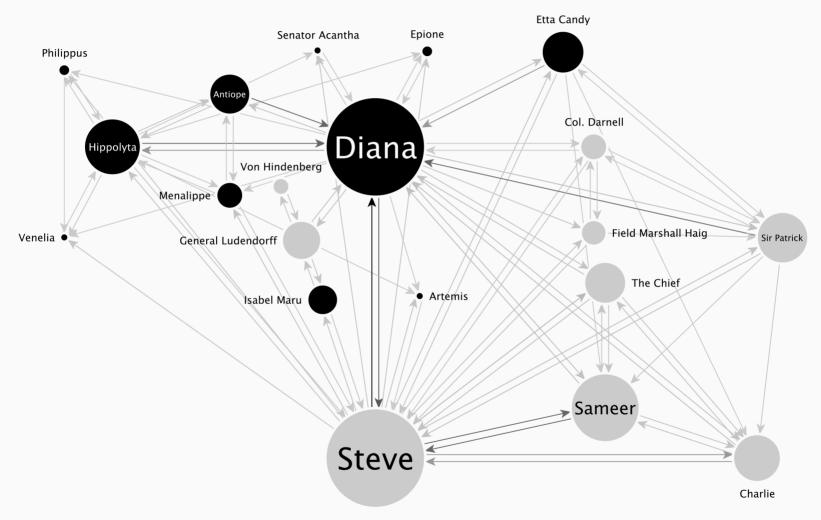
the bechdel test

- two named female characters
- who talk to each other...
- ...about something other than men

Alison Bechdel's "Dykes to Watch Out For" (1985)

data: wonder woman





Pete Jones (2018): Diana in the World of Men: a character network approach to analysing gendered vocal representation in Wonder Woman, Feminist Media Studies

data: wonder woman



no. scenes	no. lines	no. characters
61	769	20
% characters female	% lines out femal	e % lines in female

edge variables

- who talks to who?
- how many times?
- what do they say?

node variables

- character gender
- total number of lines
- total number of lines in

data: wonder woman



no. scenes	no. lines	no. characters
61	769	20
% characters female	% lines out femal	e % lines in female
55	43.0	4 49

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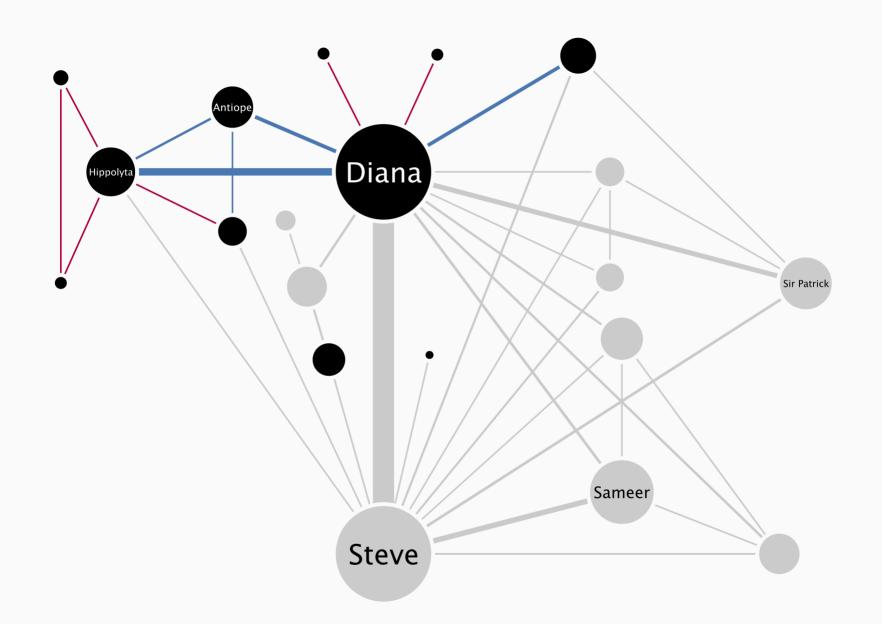
coding conversation topic

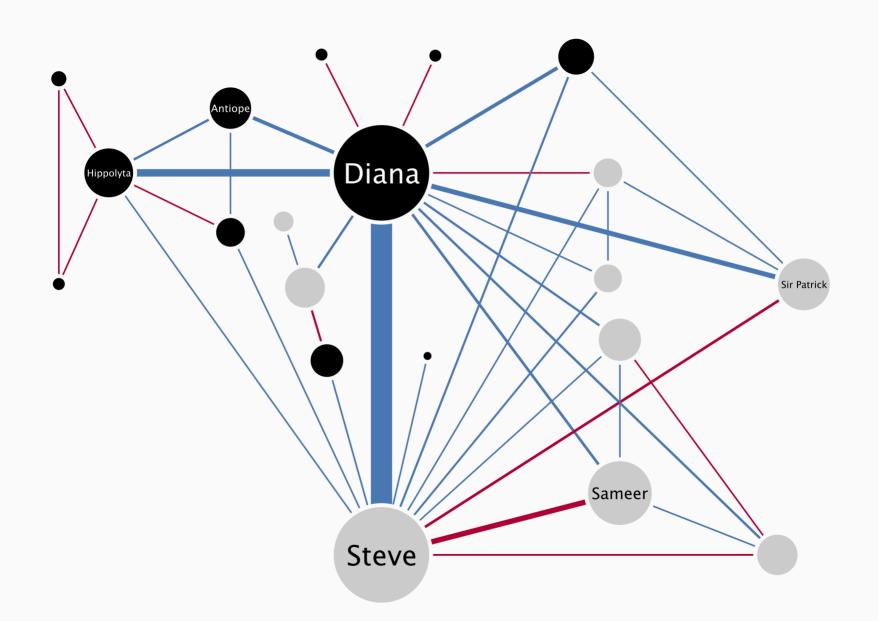


dialogues coded based on topic being about a man or not about a man

corpus of male referenced words: if a line between character u and v contains male referenced word he him himself his topic = 1 brother brothers son sons father man men boy boys guy guys steve sammy charlie general topic = 0 etc.

- ullet pass if <25% of all lines between character u and v are male referenced
- fail otherwise





analysis tools



statistical entropy analysis

- assess (conditional) dependencies
- association graphs
- prediction power plots

random multigraph models

- generate random multigraphs
- compare expected to observed
- infer significant differences

statistical entropy analysis



entropy is a measure of uncertainty of random variables

univariate entropy
$$H(X) = \sum_x p(x) \log_2 rac{1}{p(x)}$$

bivariate entropy
$$H(X,Y) = \sum_x p(x,y) \log_2 rac{1}{p(x,y)}$$

joint entropy

$$J(X,Y) = H(X) + H(Y) - H(X,Y)$$

non-negative and equal to 0 iff $X \perp Y$

expected conditional entropy

$$EH(Y|X) = H(X) + H(Y) - H(X,Y)$$

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association graphs

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prediction power plots

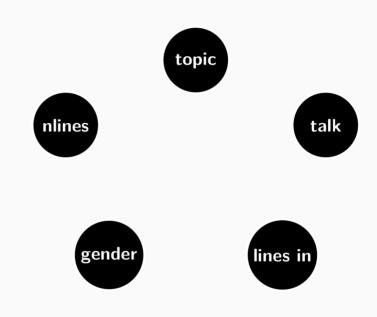
edge variables



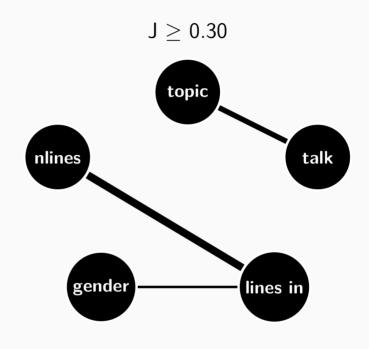
only consider variables with the same domain together

variable	observed/transformed	range
gender	node variable edge variable	r = 3
number of lines	node variable edge variable	r = 3
number of lines in	node variable edge variable	r = 3
talk (dialogue)	edge variable	r = 2
topic	edge variable	r = 2

j	#(J = j)	#(J ≥ j)
2.02	1	1
0.72	1	2
0.31	1	3
0.29	1	4
0.27	1	5
0.24	1	6
0.23	1	7
0.19	1	8
0.05	1	9
0.02	1	10



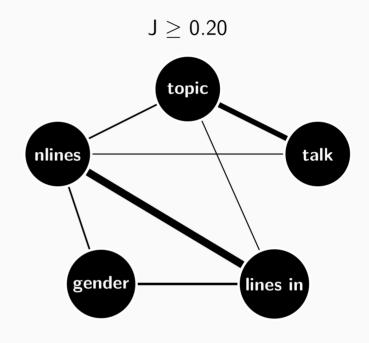
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strongest association between

- number of lines and number of times spoken to
- speaking and topic of conversation
- gender and number of times spoken to

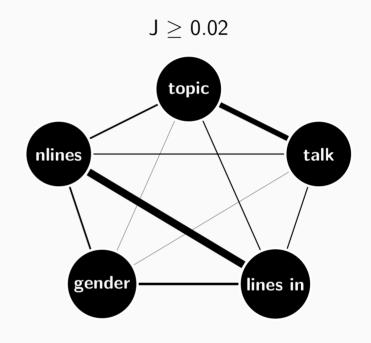
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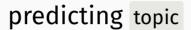


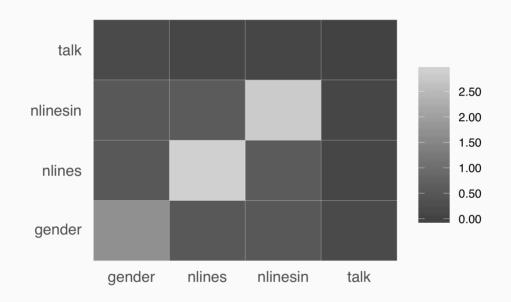
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prediction power plots







strongest predictions

- talk variable alone or in combination with any of the other variables (not surprising)
- gender in combination with number of lines

multigraphs



graphs where loops and multiple edges are permitted

- can appear directly in applications
- can be constructed by different kinds of aggregation in graphs



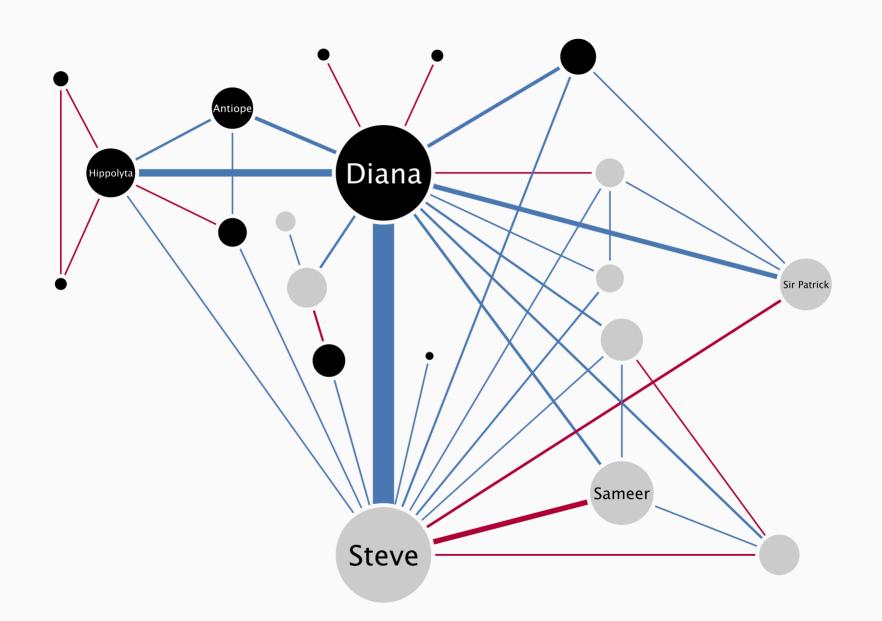
graphs where loops and multiple edges are permitted

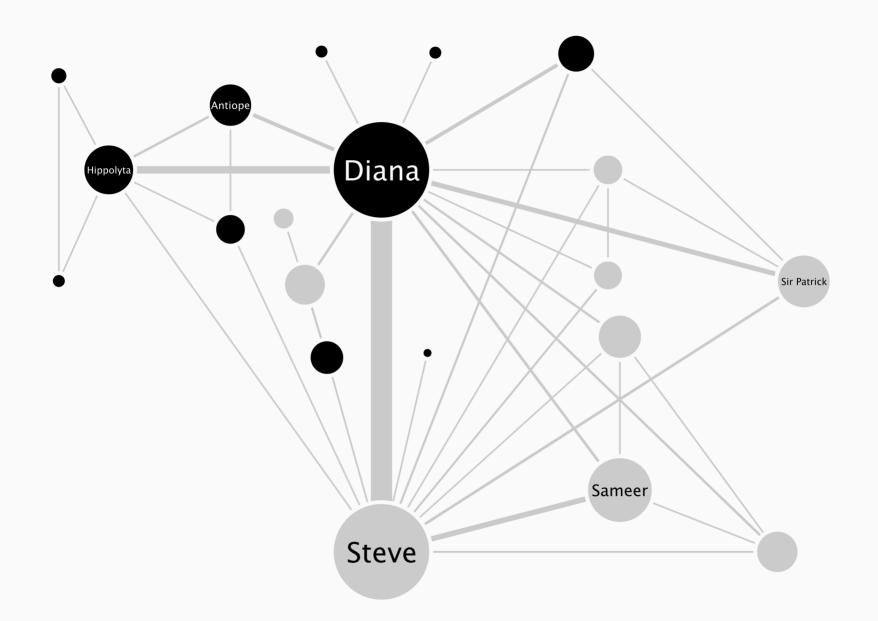
- can appear directly in applications
- can be constructed by different kinds of aggregation in graphs

aggregation can be based on single or multiple vertex attributes

- number of lines (low/high)
- gender (female/male)

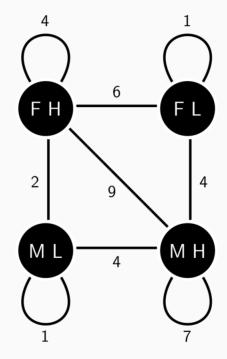
(disregard topic as a start)







aggregated by number of lines (L/H) and gender (F/M)

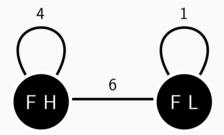


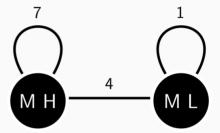
random multigraph model given fixed degree sequence used to compare

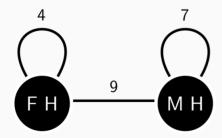
- observed to expected number of loops and non-loops
- convey structural dependencies and generative social processes

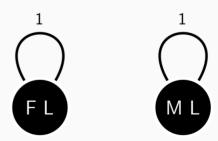
multigraphs

to make the interpretations meaningful we need to aggregate one step further...





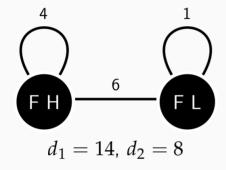


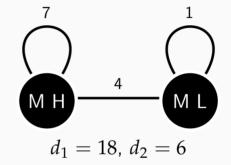


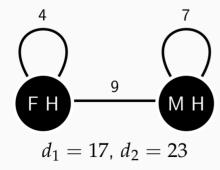
random multigraph model

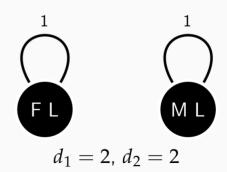


random stub matching given fixed degree sequence



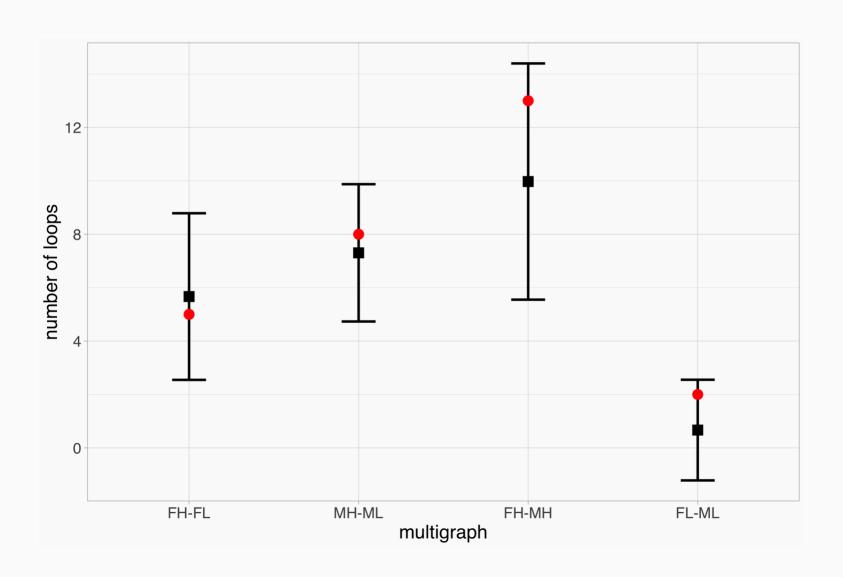






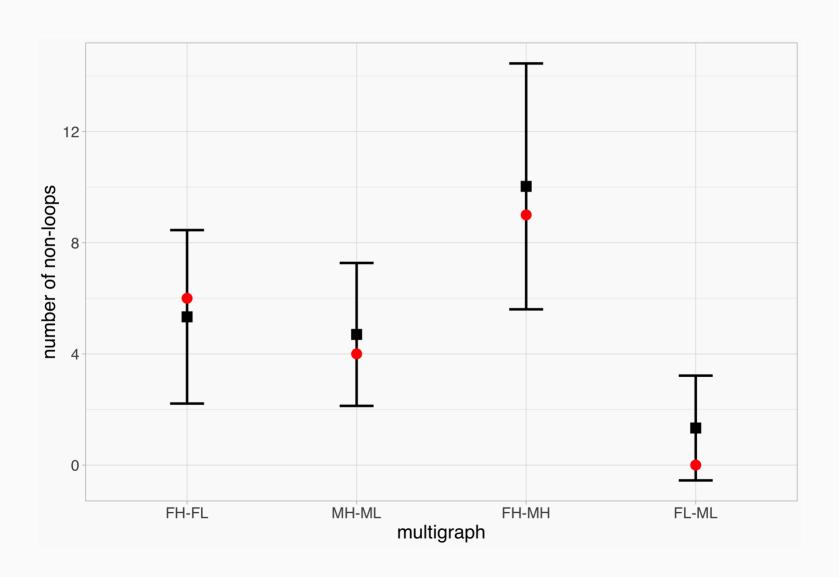
number of loops





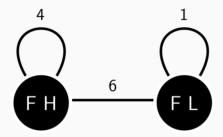
number of non-loops

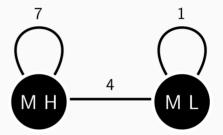


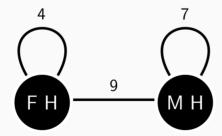


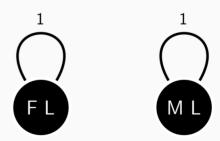


aggregated by number of lines (L/H) and gender (F/M)...



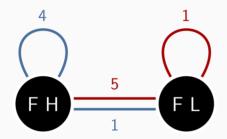


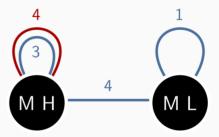


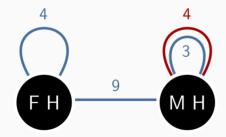


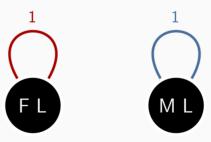


...but keep topic and model 8 multigraphs









improve and generalise the content analysis



- improve and generalise the content analysis (suggestions welcome)
- aggregate based on more vertex attributes
- apply other random multigraph models
- apply to corpus of movies



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some references:

- Termeh Shafie (2016): Analyzing local and global properties of multigraphs, The Journal of Mathematical Sociology, 40:4, 239-264
- Ove Frank and Termeh Shafie (2016): Multivariate entropy analysis of network data. Bulletin of Sociological Methodology/Bulletin de Méthodologie Sociologique, 129(1), 45-63.
- Termeh Shafie (2015): A Multigraph Approach to Social Network Analysis. Journal of Social Structure, 16.
- Pete Jones (2018): Diana in the World of Men: a character network approach to analysing gendered vocal representation in Wonder Woman, Feminist Media Studies