Contextual Effects in Hashtag Publics: Introducing Exponential Random Graph Modeling (ERGM) for Analyzing Locally Emerging Ad Hoc Publics

1. RESEARCH IDEA AND SIGNIFICANCE: THE DIGITAL CONDITION

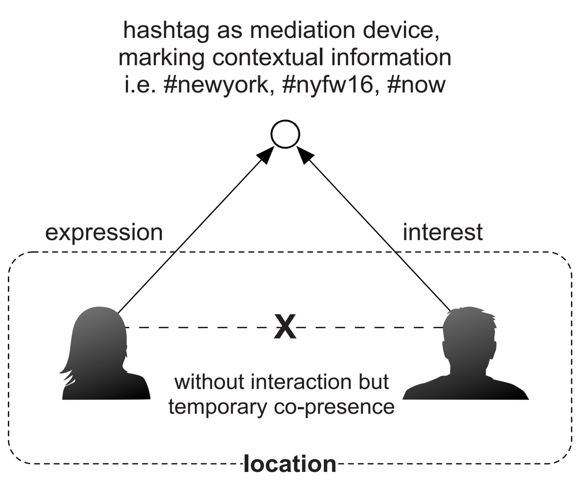
The capacities of complex communication infrastructures enable people to interact, engage and contribute to the public sphere (Stalder, 2017). It is a fact, that internet based technology enables social interaction and participation in the public sphere for people around the globe. This is the condition for some known real-world phenomena like „Phubbing", the „Displacement" the „Vacancy Problem", the creation of „Echo Chambers" or „Hashtag Hijacking".

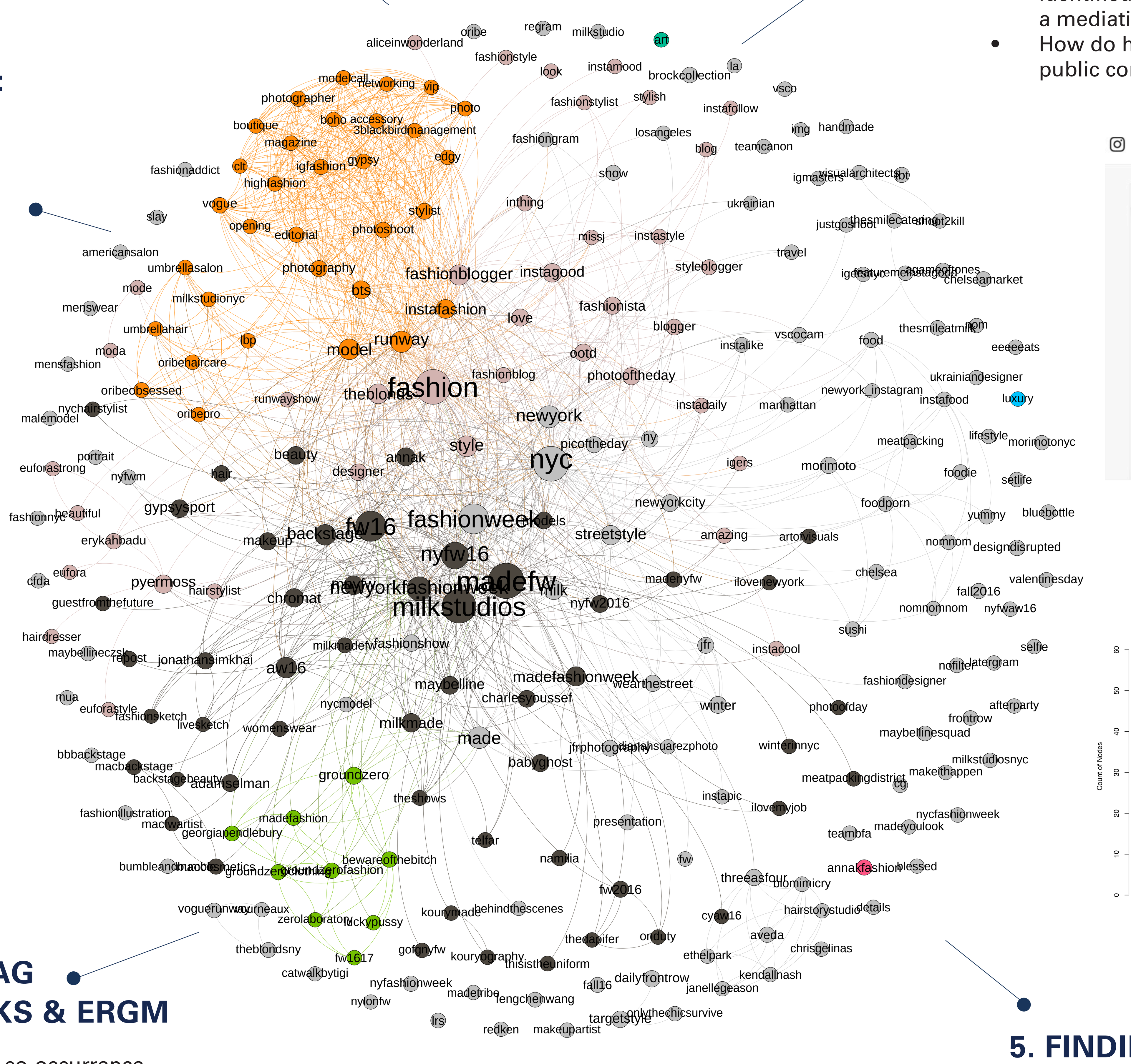
2. RESEARCH & WORKING QUESTIONS: HASHTAG FUNCTIONALITIES

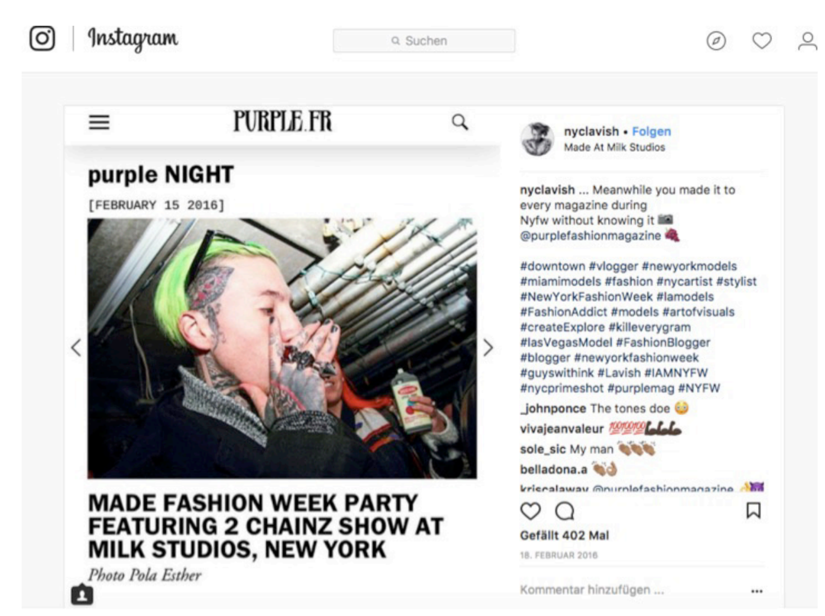
- What functions do hashtags and hashtag combinations serve in mediated ad hoc publics?
- Which effects between jointly used hashtags can be identified that affect the functionality of the hashtag as a mediation device?
- How do hashtag functions differ in a locally emerging public compared to a global public?

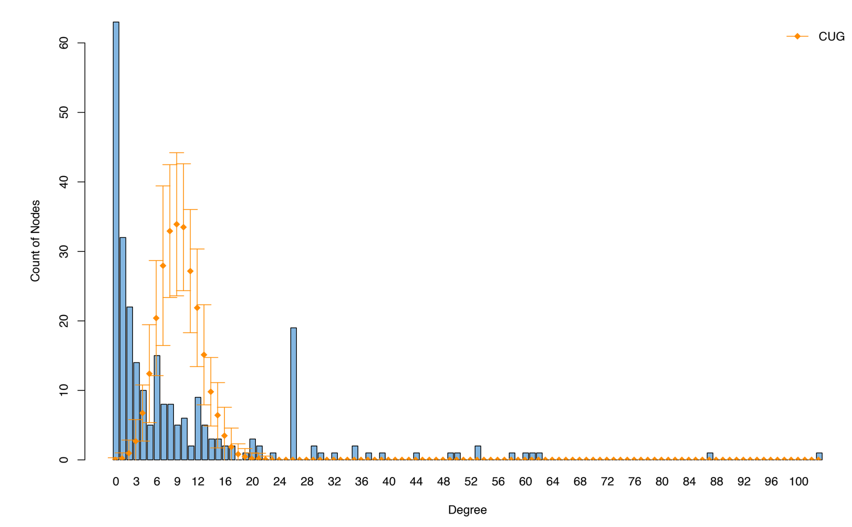
3. THEORETICAL FOUNDATION: THE HASHTAG AS DEVICE OF MEDIATION

The mediating function of the hashtag, leads to a characteristic of the public identified as „ambient affiliation" (Zappavigna, 2011). Bruns & Stiglitz identified stable communication patterns and developed a first hashtag typology (Bruns & Stiglitz, 2012). Arvidsson & Caliandro identified the aggregating and highlighting function of brand hashtags (Arvidsson & Caliandro, 2015). Only the consideration of blended spaces and the context enables the correct interpretation of a hashtag (Prazmo, 2018).









4. METHODOLOGY - HASHTAG CO-OCCURRENCE NETWORKS & ERGM

Based on network methodology, a hashtag co-occurrence network model was designed using observed Instagram data from the New York Fashion Week. In addition to descriptive social network analysis, stochastic network modeling was applied through exponential random graph modeling (ERGM).

Dependence Assumption	Configuration	Parameter in R (Statnet)
NODAL ATTRIBUTE EFFECTS		
Hashtag popularity attraction		`nodecov`: main effect of an attribute (numeric)
Hashtag popularity attraction		`absdiff`: absolute difference (numeric)
Impact of the hashtag category		`nodefactor`: attribute effects (categorical)
DYADIC INTERACTION TERMS		
Pairing of similar hashtag categories (Homophily)		`nodematch`: interaction (categorical)
Pairing of different hashtag categories, brand and context-related hashtags (Heterophily)		`nodemix`: interaction (categorical)
STRUCTURAL EFFECTS		
Density of the hashtag public		`edges`
Transitivity of jointly used hashtags		`gwesp`: geometrically weighted edgewise shared partner distribution
Transitivity of jointly used hashtags		`gwdsp`: geometrically weighted dyadwise shared partner distribution

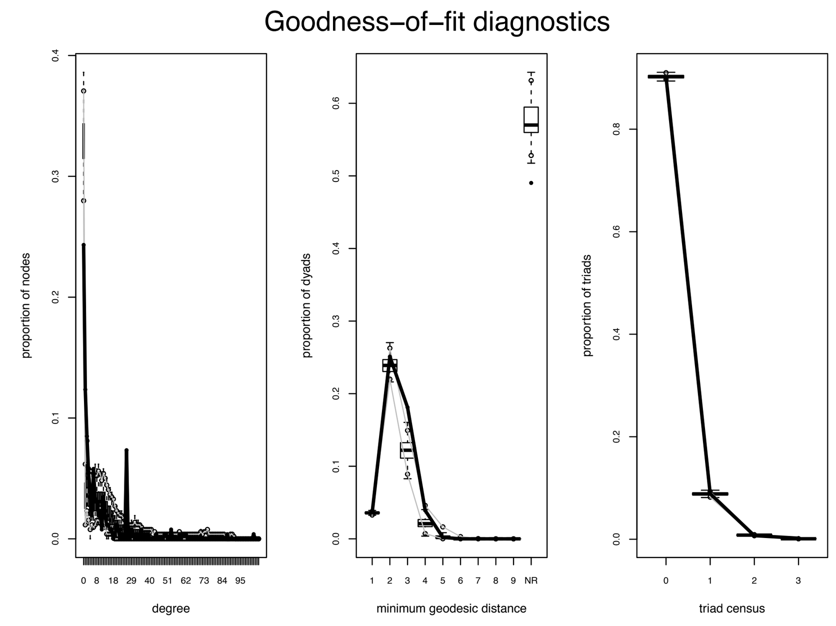
Hashtag

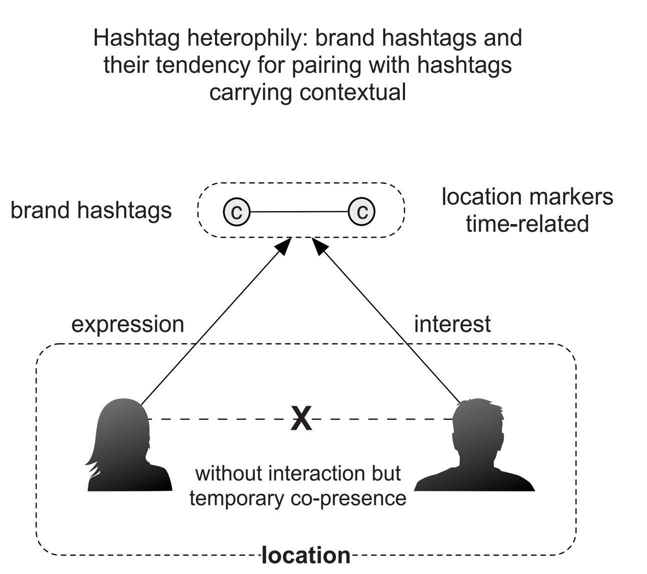
Hashtag with attributes

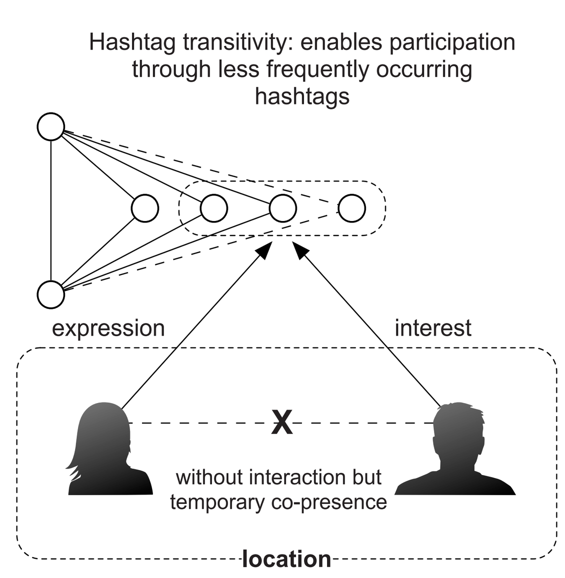
Hashtag with a categorical attributes

Binary edge: Representing the joint use of hashtags with a certain threshold

Goodness–of–fit diagnostics







5. FINDINGS

The final network model confirms specific hashtag functions and their role in the emergence of an ad hoc public in different ways:

1. There is a correlation between the popularity as well as the category of a hashtag and the likelihood of joint use.

2. The model shows a tendency for hashtags of the same category to be used jointly, reflecting an effect for uniform homophily.

3. Brand hashtags tend to connect with event and time-related hashtags that support also previous research (Arvidsson & Caliandro, 2015; Gillespie, 2014).

4. Hashtag transitivity has been identified through the application of higher-order terms in the model.

5. The model of a locally emerging public shows significant differences in terms of the structure compared to a global hashtag public, which can be seen as patterns of contextual effects.

	Model A	Model B	Model C
edges	$-7.52\ (0.66)^{***}$	$-8.98\ (1.02)^{***}$	$-9.92\ (0.91)^{***}$
nodecov.count	$0.03\ (0.00)^{***}$	$0.04\ (0.00)^{***}$	$0.02\ (0.00)^{***}$
absdiff.count	$-0.02\ (0.00)^{***}$	$-0.02\ (0.00)^{***}$	$-0.01\ (0.00)^{***}$
nodefactor.category.brand	$0.83\ (0.33)^{*}$	$1.40\ (0.51)^{**}$	$0.80\ (0.43)$
nodefactor.category.community	$1.68\ (0.33)^{***}$	$2.39\ (0.52)^{***}$	$1.28\ (0.43)^{**}$
nodefactor.category.event	$0.88\ (0.34)^{**}$	$1.45\ (0.52)^{**}$	$0.75\ (0.44)$
nodefactor.category.intention	$1.11\ (0.34)^{**}$	$1.86\ (0.52)^{***}$	$1.18\ (0.43)^{**}$
nodefactor.category.location	$0.94\ (0.34)^{**}$	$1.66\ (0.52)^{**}$	$0.99\ (0.44)^{*}$
nodefactor.category.person	$1.00\ (0.35)^{**}$	$1.78\ (0.52)^{***}$	$1.01\ (0.44)^{*}$
nodefactor.category.theme	$1.63\ (0.33)^{***}$	$2.22\ (0.51)^{***}$	$1.14\ (0.43)^{**}$
nodematch.category		$0.57\ (0.09)^{***}$	$0.51\ (0.08)^{***}$
mix.category.brand.event		$0.65\ (0.17)^{***}$	$0.71\ (0.17)^{***}$
mix.category.brand.intention		$0.10\ (0.27)$	$0.04\ (0.26)$
mix.category.brand.location		$0.09\ (0.20)$	$0.19\ (0.20)$
mix.category.brand.time		$2.25\ (0.66)^{***}$	$2.07\ (0.70)^{**}$
gwesp.fixed.0.25			$3.44\ (0.21)^{***}$
gwdsp.fixed.0.25			$-0.06\ (0.00)^{***}$
AIC	7586.09	7531.11	6382.67
BIC	7670.26	7657.36	6525.75
Log Likelihood	-3783.05	-3750.55	-3174.34

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

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