Check List for Co-Host Prior to Meeting

- Make everyone co-hosts
- Test chat function
- Test breakout rooms(?)
- Confirm with tech that we want move across breakout rooms
- We don't want to give the tech permission to leave
- Find out what the ADM person should be doing (David Woods?)
- Can we set the countdown for dissolution of breakout rooms?
- Can we send global announcements across breakout rooms?
- We need to lay out the protocol



If you like, along with this deck, you can check out the following resources in advance....

- Links for resources for the session
 - Hannigan, T. R., Haans, R. F., Vakili, K., Tchalian, H., Glaser, V. L., Wang, M. S., ... & Jennings, P. D. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals*, *13*(2), 586-632.
 - Schmiedel, T., Müller, D., & vom Brocke, J. (2019). Topic modeling as a strategy of inquiry in organizational research: A tutorial with an application example on organizational culture. *Organizational Research Methods*, 22(4), 941-968.
 - Other listed papers at the sites below.
- IDeaS general page: <u>http://www.interpretivedatascience.com/</u>
- GitHub: <u>https://ideas-repo.github.io</u>
- If you examine this this deck in advance, we suggest that you refrain from looking at the exercise answers until after we do them collectively. ③





Topic Modeling Advances

Curating Corpora, Using Structured Models, and Theorizing with Visuals





80th Annual Meeting of the Academy of Management

Hannigan, Haans, Glaser, Tchalian, Valadao, Jennings IDeaS August 7, 2020

Goals of Session



1. Build community

2. Extend your knowledge of advances in rendering with tmodeling.



Plan of the Session

Time (Mins)	Торіс	Presenters
5-7	Welcome, Goals, Plan, Protocols	Dev (or Tim)
5-7	Rendering with a Focus on Visuals	Vern
15+5	LDA & STM - Curation & Topic Modeling Methods for Visuals	Richard & Rodrigo Informational Questions Only Please
15+15	STM Exercise in Breakout Rooms (6) – Interactive (How to read output – 2 components)	Set Up- Random Assignment + General Discussion
15+5	hSBM & Hierarchical Models - Curation & Topic Modeling Methods for Visuals	Tim & Hovig Informational Questions Only Please
15 + 15	hSBM Exercise in Breakout Rooms (6) – Interactive (What to do with the outputs – 3 components)	Set Up- Random Assignment + + General Discussion
10	Back to Rendering Visuals, & Visualization Theory	Dev
5	Next IDeaS Workshop, Resources	Dev (but all please chime in $\textcircled{\odot}$)



Session Protocol



- Again, thanks for joining us; we look forward to your engagement.
- Please download the three key files on the AoM Web Page for this session (under the Files tab): this powerpoint (pdf form), two .xls exercise files.
- During the session, please raise your hand using the Zoom function and mute your mic until you're ready to ask questions.
- We'll use random assignment to breakout rooms of 5; if you leave a room, you'll have to request to be put back in manually.
- Sorry but no mid-point refresh, so please take the time when you have a moment (for standing, etc.).



How can we use topic modeling to generate new theoretical insights?

Topic Modeling Rendering in Theory-Building Spaces





Visualization: A key step in the rendering process

Topic 32															
Summary:															
	Words	major	rebellion	job	event	state	report	case	crime	level	related				
Raw Topic	Output:														
0.023*"majo	or" + 0.019	*"rebellio	on" + 0.018*"	job" + 0.0	17*"event"	+ 0.015*"s	tate" + 0.01	5*"report"	+ 0.014*"c	ase" + 0.013	3*"crime" +				
0.012*"leve	el" + 0.010*	"relate" +	- 0.010*"matt	er'' + 0.01	0*"capture"	+0.010*"	record" $+ 0$.010*"law"	+ 0.009*"u	nrest"					
Articles:															
weight: 0.5	57 title: Re	bellion, c	rime and viol	ence in Q	ing China, 1	722-1911:	A topic mod	leling appro	oach - Mille	er, IM , 201	3 POETICS				
weight: 0.1	16 title: Ins	stitutional	izing Big Dat	a methods	in social an	d political	research - A	honen, P,	2015 BIG I	OATA & SO	DCIETY				
weight: 0.0	09 title: Te	xt Mining	in Organizat	tional Rese	earch - Koba	yashi V.B.	, Mol S.T., I	Berkers H.A	A., Kismihó	k G., Den H	lartog D.N.	2018 Org	anizational	Research M	lethod
weight: 0.0	07 title: Be	yond Key	words: Track	ting the Ev	volution of C	Conversatio	nal Clusters	in Social N	I edia						
-	Houghton	J.P., Sieg	el M., Madni	ck S., Tou	naka N., Na	kamura K.	, Sugiyama '	T., Nakagav	va D., Shiri	nen B., 201	7 Sociologie	al Method	s and Resea		
weight: 0.0	-weight: 0.07 title: Introduction-Topic models: What they are and why they matter - Mohr, JW; Bogdanov, P, 2013 POETICS														



Visualization: A key step in the rendering process





The Importance of Visuals

- Theories of institutions, culture, relationality and neo-structuralism have all underscored the importance of visuals:
 - As artifacts (especially symbols) in cultures
 - As boundary objects in field relations
 - As representations of deeper structure
 - As rhetorical devices
 - As improved measures of extant concepts.



Two illustrations of visualization in advanced topic modeling techniques

- 1. Structural topic modeling (STM)
 - (Richard Haans and Rodrigo Valadao)
- 2. Hierarchical stochastic block modeling (hSBM)
 - (Tim Hannigan and Hovig Tchalian)



Moving Beyond LDA & Standard Topic Modeling – STM

Example / Exercise Part I (Richard Haans & Rodrigo Valadao)





Hannigan, Haans, Glaser, Tchalian, Valadao, Jennings IDeaS August 7, 2020

STM and rendering





Richard Haans, Erasmus University Rotterdam, August 7th 2020

Basic LDA



Figure 1: Graphical model representation of LDA. The boxes are "plates" representing replicates. The outer plate represents documents, while the inner plate represents the repeated choice of topics and words within a document.

(darker circle is what is observed; white circles what is learned)

The topic model learns **only** from the observed words co-occurrences in documents.

Assumption: identical generative processes behind texts in a corpora: documents are created based on drawing from a fixed set of topics—unchanging over time, independent of who generated the topics, etc.



Structural TM



A recent innovation is the ability to incorporate information from metadata into the estimation of the topic-word distribution or the document-topic proportions. Most common is the latter.

This enables understanding how e.g. characteristics of the document producer or contextual factors shape the extent to which topics are used in documents.



Canonical references

- Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural Topic Models for Open-Ended Survey Responses. *American Journal of Political Science*, 58(4), 1064–1082. <u>https://doi.org/10.1111/ajps.12103</u>
- Roberts, M. E., Stewart, B. M., & Airoldi, E. M. (2016). A Model of Text for Experimentation in the Social Sciences. *Journal of the American Statistical Association*, 11(515), 988–1003. <u>https://doi.org/10.1080/01621459.2016.1141684</u>
- Schmiedel, T., Müller, D., & vom Brocke, J. (2018). Topic Modeling as a Strategy of Inquiry in Organizational Research: A Tutorial With an Application Example on Organizational Culture. *Organizational Research Methods*, 109442811877385. <u>https://doi.org/10.1177/1094428118773858</u>

See: https://www.structuraltopicmodel.com/ for info on the method and applications. In particular: the **'STM'** package in R opens many uses.



'STM' package

The STM package in R is attractive because essentially works from the basic topic modeling approach using packages like 'topicmodels'.

See e.g. the materials from https://ideas-repo.github.io/workshops/

The metadata that was used *ex post* in those sessions can now be incorporated directly into the topic model.



Usual workflow (the practice)

- 1. Read the corpus; clean as usual using packages like '*tm*' (see 2017 session).
- 2. Turn corpus into document-term matrix.
- 3. Read the metadata; make sure sequence of documents is identical to the sequence in the corpus / dtm (sorting can be different).
- 4. Use the *readCorpus* function with "*type = c("slam")*" to convert the dtm to the STM format. Add the metadata (again; sorting has to be identical).
- Use functions like *searchK* to identify best-fitting number of topics; *stm* to estimate the selected model; *labe/Topics* to render topics; and *estimateEffect* and *plat* to interpret effects of covariates.



A Research Application & Exercise

EARLY MOMENTS OF INSTITUTIONAL CHANGE

Enable and constrain **possibilities** for institutional change.

(Hannigan & Casasnovas, 2020; Obstfeld et al., 2020; Thompson et al., 2018; Lounsbury and Glynn, 2019)

POSSIBILITIES

- Discursively constituted.
- Precursor to action.
- Interstices of identity positions → shaped by category schemas.
 - (Lounsbury and Glynn, 2019)

CATEGORY SCHEMAS

Analytically, by the time product categories coalesce in a market or industry, we have already lost sight of the early moments of institutional change.

MEANING INFRASTRUCTURE

- Product categories → cognitive infrastructure of markets (Lounsbury and Rao, 2004).
- Meaning infrastructure → building blocks of an underlying institutional meaning system.

How to capture the *meaning infrastructure* that shapes the space of possibilities at the early moments of institutional change?



Rodrigo Valadao, University of Alberta, August 7th 2020

Methods

EMPIRICAL SETTING

DATA COLLECTION

The Emerging Field of Data Science: a case of an emergent *(Maguire et al., 2004)*, **interstitial issue field** *(Zietsma et al., 2017)*

- Abductive approach: 30 semi-structured interviews and 185 archival interviews with well-positioned actors (e.g., chief-data scientists, VPs of data science), conducted between 2017 and 2019.
- Computational Approach: Search on EBSCOhost Web for publications by Harvard Business Review articles that contained the keywords "data" or "analy*" and issued between 1978 and 2018 (N = 3,005).



- Abductive approach: close examination of the interviews to develop a rich understanding of the empirical context (Kaplan, 2015; see Hirsch & Lounsbury, 1997 and Lounsbury, 1998, 2001 for a similar methodological approach).
- Computational approach: Structural Topic Modeling (STM) of the HBR articles following a three-stages rendering process (see Hannigan et al., 2019).



Rendering with STM (our demo)



These 3 artifacts and additional instructions are going to be provided for discussion in the Break-Out session



Axial Coding

- Topics interpreted as constitute the meaning of data science.
- STM x "Standard" Topic

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elementary categories of meaning that	19	oper, job, find FREX: island, team, profi, done, stori, baghai, invad, employe, head, knew	misperce manager
g infrastructure of the emerging field	3	Highest Prob: analyt, work, research, experi, insight, idea, project, program, knowledg, expert FREX: knowledg, scientif, human, social, insight, embrac, analyt, idea, collabor, expert	Explainir experime new tech
	5	Highest Prob: manag, busi, invest, may, review, strateg, capit, portfolio, asset, take FREX: review, busi, portfolio, invest, asset, ventur, loneli, extern, manag, owner	Using an and in Ia Ieadersh
c Modeling	11	Highest Prob: compani, will, make, decis, strategi, focus, chang, opportun, import, way FREX: decis, internet, structur, make, opportun, focus, will, strategi, shift, perspect	Assessin of the or
	15	Highest Prob: develop, new, problem, model, need, can, improv, help, tool, complex FREX: problem, softwar, solut, complex, engin, involv, innov, develop, capabl, model	Analyzing navigate
	7	Highest Prob: get, just, know, want, say, look, one, day, person, keep FREX: hous, tell, get, facebook, feel, doesnt, want, someth, keep, say	Monitori strategie
	18	Highest Prob: custom, product, servic, consum, retail, brand, offer, store, segment, buy FREX: assort, loyalti, journey, flourish, merchandis, platform, buy, custom, seller, store	Understa brand rel organiza
	6	Highest Prob: cost, rate, growth, increas, valu, demand, per, exhibit, averag, expect FREX: per, margin, par, cost, increment, dollar, fix, variabl, exhibit, percentag	Using da regional
	9	Highest Prob: product, price, qualiti, advertis, manufactur, sale, chang, relat, line, produc FREX: telemarket, qualiti, price, manufactur, defect, japanes, advertis, inventori, distributor, volum	Using da investme determin
	12	Highest Prob: system, manag, plan, base, oper, order, process, resourc, control, use FREX: apex, oil, system, abc, iri, order, termin, hase, suppli, personnel	Using cor related a the proje
		Topics (i.e., clusters of words	
		from STM)	
ent			

Topic

1

14

Raw Words	First Order Codes	Second Order Codes	Aggregate Level	Ref.
Highest Prob: leader, execut, women, leadership, hire, talent,	Using applytics to compare leadership and to promote			
divers, cant, men, analyst	Using analytics to compare leadership and to promote	Promoting workplace	Managina Davala	
FREX: women, men, femal, male, mentor, ect, divers,	diversity (i.e. women, arro-americans, hispanics) in	diversity	Managing People	A
leadership, star, hire	organizations			
Highest Prob: perform, sale, firm, pay, forc, effect, number, rep,				
compens, among	Using data related to traing, incentives and performance to	Managing people based on	Managing Recold	^
FREX: rep, salesperson, pay, incent, quota, micromarket, metric,	determine how to manage the sales force of an organization	analytics	Managing reopie	A
perform, reward, fleet				
Highest Prob: employe, peopl, team, need, work, better, learn,	Discussing how the performance of a team can be			
oper, job, find	misnerceived and how other factors (i.e. external politics	Evaluating team	Managing People	۵
FREX: island, team, profi, done, stori, baghai, invad, employe,	management neglect) can have influence on the outcomes	performance	Managing reopie	<u>^</u>
head, knew				
Highest Prob: analyt, work, research, experi, insight, idea,	Explaining the concepts of scientific theory and			
project, program, knowledg, expert	experimentation and how it influences the development of	Forstering research and	Strategizing	в
FREX: knowledg, scientif, human, social, insight, embrac,	new technologies and products	innovation	ou or construction of the	
analyt, idea, collabor, expert				
Highest Prob: manag, busi, invest, may, review, strateg, capit,	Using analytics to recommend investments in the long term			
portfolio, asset, take	and in large scale to investors, members of boards and	Allocating resources	Strategizing	в
FREX: review, busi, portfolio, invest, asset, ventur, loneli,	leadership of asset owners	Anocating resources	ouoceanie	
extern, manag, owner				
Highest Prob: compani, will, make, decis, strategi, focus, chang,				
opportun, import, way	Assessing the impact of digitalization in strategic decisions	Innovation shaping	Strategizing	в
FREX: decis, internet, structur, make, opportun, focus, will,	of the organization and in the way they do business	decisions	011010512115	-
strategi, shift, perspect				
Highest Prob: develop, new, problem, model, need, can,				
improv, help, tool, complex	Analyzing how managers use intution and analytical tools to	Making decisions based on	Strategizing	в
FREX: problem, softwar, solut, complex, engin, involv, innov,	navigate complex problems and uncertainty	analytics		-
develop, capabl, model				
Highest Prob: get, just, know, want, say, look, one, day, person,				
keep	Monitoring personal behaviors to define digital marketing	Monitoring customers'	Understanding	с
FREX: hous, tell, get, facebook, feel, doesnt, want, someth,	strategies customized to consumers	preferences	Customers	-
keep, say				
Highest Prob: custom, product, servic, consum, retail, brand,				
offer, store, segment, buy	Understanding how customers' emotional connection with a	Monitoring customers'	Understanding	с
FREX: assort, loyalti, journey, flourish, merchandis, platform,	brand relates to their behavior and how it impacts the	emotions	Customers	
buy, custom, seller, store	organization			
Highest Prob: cost, rate, growth, increas, valu, demand, per,				
exhibit, averag, expect	Using data analysis and statistics to predict the behavior of	Predicting global trends in	Market Forecasting	D
FREX: per, margin, par, cost, increment, dollar, fix, variabl,	regional economies in the global scenario	economy	-	
exhibit, percentag				
Highest Prob: product, price, qualiti, advertis, manufactur, sale,	Using data to evaluate the relationship between			
chang, relat, line, produc	investments in advertisement and the sensitivity of price in	Indentifying the optimum	Market Forecasting	D
FREX: telemarket, qualiti, price, manufactur, defect, japanes,	determined markets	price	Ŭ	
advertis, inventori, distributor, volum				
Highest Prob: system, manag, plan, base, oper, order, process,	Using computational tools to perform project management			
resourc, control, use	related activities (i.e. budgeting, monitoring costs, stages of	Managing processes with	Managing Processes	E
FREX: apex, oil, system, abc, iri, order, termin, hase, suppli,	the project)	technology		-
personnel				
Ţ				

Rodrigo Valadao, University of Alberta, August 7th 2020

Axial Coding

Map of Correlations

в

С

с

А

Topics (from previous slide) B A B B Strategizing Managing Managing Strategizing Strategizing Topic 11 Topic 19 Topic 14 Topic 5 Topic 15

	Aggregate	Managing		Courses alalana		Understanding		Understanding		Church I-line		Managing Managing Strategizing St		Strategising		Market		Market		Managing					
	Level	People		Strategizing		Customers		Customers		Strategizing		People		People		Strategizing	jizing stra			Forecasting		Forecasting		Processes	
		Topic 1		Topic 3		Topic 18		Topic 7		Topic 11		Topic 19		Topic 14		Topic 5		Topic 15		Topic 6		Topic 9		Topic 12	
	2nd	Promoting		Forstering		Monitoring		Monitoring		Innovation		Evolution toon	_	Managing		Allocating		Making		Predicting		Indontifying the		Managing	
	Order	workplace		research and		customers'		customers'		shaping people based on Allocat		Allocating		decisions based		global trends in		Indentitying the		processes with					
	Year	diversity		innovation		emotions		preferences		decisions		performance		analytics		resources	resources on analytics			economy		optimum price		technology	
	2018	0.06936	••••	0.07944	••••	0.07337	••••	0.07918	••••	0.03551	••••	0.04498	••••	0.01942	•	0.00282		0.01670	•	-0.05112	•••	-0.14532	•••	-0.22783	•••
	2017	0.07653	••••	0.06398	••••	0.02706	•	0.04210	••••	0.04642	••••	0.01841	•	0.03575	••••	0.02398	•••	0.01223		-0.04062	•••	-0.14568	•••	-0.22653	•••
	2016	0.16777	••••	0.11799	••••	0.03071	••	0.04789	••••	0.02542	••	0.03873	••••	0.03283	••••	0.00605		0.00743		-0.05068	•••	-0.14694	•••	-0.23379	•••
	2015	0.04016	••••	0.04344	••••	0.07583	••••	0.04321	••••	0.01987	••	0.01431	•	0.06237	••••	0.00235		-0.00442		-0.04328	•••	-0.14436	•••	-0.23069	•••
	2014	0.03228	••••	0.06270	••••	0.08315	••••	0.04428	••••	0.04063	••••	0.01759	••	0.01340		0.02713	••••	0.03895	••••	-0.03964	•••	-0.13253	•••	-0.22168	•••
	2013	0.04423	••••	0.07603	••••	0.04442	••••	0.05338	••••	0.03763	••••	0.04798	••••	0.02350	••	0.01463	•	0.02333	••••	-0.04544	•••	-0.13916	••••	-0.22099	•••
	2012	0.04096	••••	0.04521	••••	0.06790	••••	0.04004	••••	0.02960	••••	0.01719	••	0.04711	••••	0.00844		0.00724		-0.01605		-0.13038	•••	-0.22630	•••
	2011	0.04143	••••	0.02370	••	0.09366	••••	0.02787	••	0.02692	••••	0.00077		0.01401		0.02572	•••	0.00054		0.00311		-0.13775	•••	-0.22686	•••
	2010	0.09982	••••	0.06019	••••	0.03074	••	0.03094	••••	0.03474	••••	0.02366	••	0.02620	••]	0.01304		0.02248	••	-0.03010	••	-0.13874	••••	-0.21963	•••
	2009	0.10652	••••	0.03740	••••	0.03324	••••	0.03278	••••	0.04294	••••	0.02638	••••	0.01728	•	0.03627	••••	0.01107		-0.02480	•	-0.13738	••••	-0.22650	•••
	2008	0.08586	••••	0.03216	••••	0.05257	••••	0.03107	••••	0.04196	••••	0.03404	••••	0.01353		0.02690	••••	0.01738	<u>۱</u>	-0.02528	•	-0.13254	••••	-0.20958	•••
. <u></u>	2007	0.05371	••••	0.03835	••••	0.05589	•••	0.07460	••••	0.04261	••••	0.04133	••••	0.02048	• 1	0.02547	••••	0.01008		-0.04576	•••	-0.13624	••••	-0.22061	•••
in	2005	0.01667		0.03897	••••	0.07641		0.04222	••••	0.03844	••••	0.03384	•••	0.01891		0.00119		0.00582		-0.04542	••	-0.13270	••••	-0.20283	•••
÷	2004	0.03816	•••	0.02406		0.03808	••	0.01941	•	0.01372		0.04408	••••	0.07565	••••	0.00532		-0.00757		-0.00116		-0.12612	••••	-0.22019	•••
	2003	0.03770		0.04646	••••	0.02260	•	0.04004	••••	0.02565	••	0.03315	••••	0.01234		0.01009		0.03211		-0.03971	••••	-0.12626	••••	-0.21879	•••
Ц	2002	0.01335		0.13877	••••	0.01145		0.01460		-0.00239		0.09866	••••	0.01109		-0.00460		0.03286		-0.03726	•	-0.06205	••	-0.20528	•••
Ξ.	2001	0.02889	•	0.02648		0.04867		0.02391		0.07691	••••	0.04166		0.01270		0.03258		0.01553		-0.03601	••	-0.12688	••••	-0.20541	••••
H	1998	0.01331		0.01354		0.03838		0.01814	•	0.02006	••	0.01710	•	0.01728	•	0.00245		-0.00343		0.01110		-0.11339		-0.12848	***
ü	1997	0.00796		0.01772		0.04673		0.03812		0.01195		0.00412		0.01092		0.00534		0.00610		-0.02178		-0.05101		-0.20490	***
>	1996	0.01823		0.02304		0.05718		0.02502		0.03414		0.01350		0.00628		0.02197		0.00340		-0.01779		-0.09205		-0.18910	••••
	1995	0.01225		0.01674		0.01499		0.01273		0.02092	· .	0.00788		0.02431	· .	0.02339	Ľ.,	0.01154		0.02467		-0.09431		-0.18782	
	1994	-0.00273		0.00681		0.01185		-0.00579		-0.01088		-0.01025		0.00320		-0.01019		0.00416		0.19148		-0.06439		-0.15487	
	1991	0.00961		0.01676		0.01088		0.01924		0.00343		0.01955	1.1	0.00192		0.00371		-0.00047		-0.02958		-0.08543		-0.18612	
	1990	0.011/1		0.01112		0.01581		0.00488		0.00928		0.00189		0.03754		0.00789		0.00197		-0.004/1		-0.08961		-0.15432	
	1989	0.00247		0.00728		0.02605		0.00190		0.00036		-0.00390		0.02364		0.00714		-0.00206		0.00268		-0.03446	·	-0.12227	
	1988	0.00737		0.03273		0.00077		0.00199		-0.00085		0.00246		0.01437		0.00714		0.01452		0.01591		-0.07693		-0.15522	
	1980	0.00171		0.01637		0.02930		0.00990		0.01279		-0.00231		0.00590		-0.00504		0.01560		-0.00380		-0.02580	I	-0.14004	
	1985	0.01218		0.00374		-0.00286		0.00808		-0.00928		0.00585		-0.00547		-0.00674		-0.01365		-0.04133		-0.00833		-0.20902	
	1983	0.01090		0.00303		-0.00338		0.03000		-0.01128		-0.00296		0.00307	• 1	0.00167		-0.01223		0.04820		0.02425		-0.1/53/	
	1983	0.00334		0.00133		-0.00241		0.00343		-0.01128		-0.00296	•	-0.00180		0.00107		-0.01133		-0.02838		-0.09108		-0.10385	
	1081	0.00012		0.01345		-0.00201		-0.00144		0.00003		-0.002255		-0.00180		0.00004		0.01234		-0.02838		-0.05108		-0.05772	
	1980	0.00581		0.00139		-0.00813		-0.00144		-0.00184		0.00327		0.00148		0.05195		-0.00949		0.14386		-0.02796		-0.16891	
	1979	-0.00170		-0.00043		-0.00815		-0.00530		-0.00164		-0.01067		-0.00406		0.00285		-0.00934		0.04460		0.03090	.	-0.04393	
	(intercent)	0.00170		0.01012		0.01737		0.01862		0.03736		0.02624		0.02312		0.03644		0.04202		0.06896		0.15401		0.24282	
_	Intercepti	0.0004		0.01013		0.01/5/		0.01002		0.03130		0.02024		0.02312		0.05044		0.04203		0.00050		0.15401	<u>a - 1</u>	0.24202	i





*p < .05; **p < .01; ***p < .001

Greater than the mean for the topic

Smaller than the mean for the topic

Rodrigo Valadao, University of Alberta, August 7th 2020

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Break-Out Session 1





Instructions

A. Each group will receive a handout with instructions and a copy of the three theoretical artifacts presented here.

B. Key Task: Discuss with your colleagues some potential interpretations of the theoretical artifacts and unfolding theorizations related to the research question: *How to capture the meaning infrastructure that shapes the space of possibilities at the early moments of institutional change?*

C. Pay special attention to patterns that might be identifiable into the artifacts , and take into consideration the following additional information:



In the interviews, most informants described 2010 as the year of emergence of Data Science as a field

D. After the break-out session, we will briefly present a potential theorization and hear back from the groups.

Discussion

- Positive and negative associations of elementary category schemas of meaning over time.
- 2000 x 2010: Divergence in the year detected by different approaches as the beginning of the emergence of the field (computational vs interviews).



		А		В		С		С		В		А		А		В		В		D		D		E	
	Aggregate	Managing		Strategizing		Understanding		Understanding		Stratogizing		Managing		Managing		Strategizing		Stratogizing		Market		Market		Managing	
	Level	People		Strategizing		Customers		Customers		Suarcgizing		People		People		Strategizing		Suategizing		Forecasting		Forecasting		Processes	
		Topic 1		Topic 3		Topic 18		Topic 7		Topic 11		Topic 19		Topic 14		Topic 5		Topic 15		Topic 6		Topic 9		Topic 12	
	2nd	Promoting		Forstering		Monitoring		Monitoring		Innovation		Evaluation		Managing				Making		Predicting		Indentifying		Managing	
	Order	workplace		research		customers'		customers'		shaping		team		people		Allocating		decisions		global		the		processes	
		diversity		and		emotions		nreferences 4		decisions		nerformance		based on		resources		based on		trends in		optimum		with	
	Year	unversity		innovation		emotions		preferences	4	uccisions		periormance	•	analytics				analytics		economy		price		technology	1
	2018	0.06936	••••	0.07944	••••	0.07337	•••	0.07918		0.03551	•••	0.04498	••••	0.01942	•	0.00282		0.01670	٠	-0.05112	•••	-0.14532		-0.22783	••••
	2017	0.07653	••••	0.06398	••••	0.02706	•	0.04210		0.04642	•••	0.01841	•	0.03575	••••	0.02398	•••	0.01223		-0.04062	•••	-0.14568		-0.22653	•••
	2016	0.16777	••••	0.11799	••••	0.03071	••	0.04789	•••	0.02542	••	0.03873	••••	0.03283	••••	0.00605		0.00743		-0.05068	•••	-0.14694	•••	-0.23379	•••
	2015	0.04016	••••	0.04344	••••	0.07583	••••	0.04321	••••	0.01987	••	0.01431	•	0.06237	••••	0.00235		-0.00442		-0.04328	•••	-0.14436	•••	-0.23069	••••
e e	2014	0.03228	••••	0.06270	•••	0.08315	••••	0.04428	••••	0.04063	•••	0.01759	••	0.01340		0.02713	••••	0.03895	•••	-0.03964	•••	-0.13253	•••	-0.22168	••••
2	2013	0.04423	••••	0.07603	•••	0.04442	••••	0.05338	•••	0.03763	•••	0.04798	••••	0.02350	••	0.01463	•	0.02333	•••	-0.04544	•••	-0.13916	•••	-0.22099	••••
6	2012	0.04096	••••	0.04521	•••	0.06790	••••	0.04004	•••	0.02960	•••	0.01719	••	0.04711	••••	0.00844		0.00724		-0.01605		-0.13038	•••	-0.22630	••••
50	2011	0.04143	••••	0.02370	••	0.09366	••••	0.02787	••	0.02692	••••	0.00077		0.01401		0.02572	••	0.00054		0.00311		-0.13775	•••	-0.22686	••••
Ĕ	2010	0.09982	••••	0.06019	••••	0.03074	••	0.03094	••••	0.03474	••••	0.02366	••	0.02620	••	0.01304		0.02248	••	-0.03010	••	-0.13874	•••	-0.21963	••••
<u>ل</u> ت	2009	0.10652	••••	0.03740	••••	0.03324	••••	0.03278	••••	0.04294	•••	0.02638	••••	0.01728	•	0.03627	••••	0.01107		-0.02480	•	-0.13738	•••	-0.22650	••••
P	2008	0.08586	••••	0.03216	••••	0.05257	••••	0.03107	••••	0.04196	••••	0.03404	••••	0.01353		0.02690	••••	0.01738	•	-0.02528	•	-0.13254	••••	-0.20958	••••
e.	2007	0.05371	••••	0.03835	••••	0.05589	••••	0.07460	••••	0.04261	••••	0.04133	••••	0.02048	•	0.02547	••••	0.01008		-0.04576	••••	-0.13624	••••	-0.22061	••••
ш	2005	0.01667		0.03897	••••	0.07641	••••	0.04222	••••	0.03844	••••	0.03384	••	0.01891		0.00119		0.00582		-0.04542	••	-0.13270	••••	-0.20283	••••
	2004	0.03816	••	0.02406	••	0.03808	•••	0.01941	•	0.01372		0.04408	••••	0.07565	••••	0.00532		-0.00757	_	-0.00116		-0.12612	••••	-0.22019	••••
	2003	0.03770	••••	0.04646	••••	0.02260	•	0.04004	••••	0.02565	••	0.03315	••••	0.01234		0.01009		0.03211	•••	-0.03971	••••	-0.12626	••••	-0.21879	••••
	2002	0.01335		0.13877	••••	0.01145		0.01460		-0.00239		0.09866	••••	0.01109		-0.00460		0.03286	••	-0.03726	•	-0.06205	••	-0.20528	••••
	2001	0.02889	•	0.02648	••	0.04867	••••	0.02391	••	0.07691	••••	0.04166	••••	0.01270		0.03258	••••	0.01553		-0.03601	••	-0.12688	••••	-0.20541	••••
	1998	0.01331		0.01354		0.03838	••••	0.01814	•	0.02006	••	0.01710	•	0.01728	•	0.00245		-0.00343		0.01110		-0.11339	••••	-0.12848	••••
	1997	0.00796		0.01772		0.04673		0.03812		0.01195		0.00412		0.01092		0.00534		0.00610		-0.02178		-0.05101		-0.20490	••••
	1996	0.01823		0.02304	••	0.05718	••••	0.02502	••	0.03414	••••	0.01350		0.00628		0.02197	•••	0.00340		-0.01779		-0.09205	••••	-0.18910	••••
	1995	0.01225		0.01674		0.01499		0.01273		0.02092	•	0.00788		0.02431	•	0.02339	•	0.01154		0.02467		-0.09431	••••	-0.18782	
	1994	-0.00273		0.00681		0.01185		-0.00579		-0.01088		-0.01025		0.00320		-0.01019		0.00416		0.19148	••••	-0.06439		-0.15487	••••
	1991	0.00961		0.01676		0.01088		0.01924		0.00343		0.01955	•	0.00192		0.00371		-0.00047		-0.02958	•	-0.08543	••••	-0.18612	
	1990	0.01171		0.01112		0.01581		0.00488		0.00928		0.00189		0.03754	••••	0.00789		0.00197		-0.00471		-0.08961	••••	-0.15432	
	1989	0.00247		0.00728		0.02605	•	0.00190		0.00636		-0.00390		0.02364	•	0.01681	•	-0.00206		0.00268		-0.03446	•	-0.12227	••••
	1988	0.00737		0.03273		0.00077		0.00199		-0.00085		0.00246		0.01437		0.00714		0.01452		0.01591		-0.07693		-0.15322	
	1986	0.00171		0.01657		0.02930	•	0.00996		0.01279		-0.00231		0.00396		-0.00504		0.01980		-0.00386		-0.02580		-0.14064	
	1985	0.01218		0.00574		-0.00286		0.00808		-0.00928		0.00583		-0.00547		-0.00674		-0.01565		-0.04133		-0.06833		-0.20902	
	1984	0.01690		0.00905		-0.00338		0.03000		0.00076		0.01567	Ľ.,	0.00967		0.03621		-0.01223		0.04826		-0.02429		-0.17937	
	1983	0.00394		0.00139		-0.00241		0.00343		-0.01128		-0.00296	1. I	0.02256		0.00167		-0.01133		0.04130		0.09147		-0.16589	
	1982	0.00812		0.01543		-0.00261		0.03313		0.00808		0.02155		-0.00180		0.00604		0.01234		-0.02838		-0.09108		-0.09772	
	1981	0.00055		0.00484		-0.00505		-0.00144		0.00092		-0.00327		-0.00148		0.01013		0.01475		0.06577		-0.05919		-0.06594	
	1980	0.00581		0.00139		-0.00813		-0.00536		-0.00184		0.00080		0.00135		0.05195		-0.00948		0.14386		-0.02796		-0.16891	
	1979	-0.00170		-0.00042		-0.00206		-0.00698		-0.00364		-0.01067		-0.00406		0.00285		-0.00934		0.04460		0.03090		-0.04393	
	(intercept)	0.00684		0.01013		0.01/3/	•	0.01862		0.03736		0.02624		0.02312		0.03644		0.04203		0.06896		0.15401		0.24282	
		*p < .05: **p	< .01:	***p < 001																					

Greater than the mean for the topic

Smaller than the mean for the topic

Rodrigo Valadao, University of Alberta, August 7th 2020

Discussion



A meaning infrastructure is formed **through the amalgamation of novel category schemas of meaning in combination with the exclusion of others**

Distinct periods during the early moments of institutional change:



- First period (i.e., 2000-2010) \rightarrow tacit and not evident.
- Second Stage (i.e., 2010-ongoing): might assign a more agentic phase, in which new practices start to become more closely connected to the meaning infrastructure.







Rodrigo Valadao, University of Alberta, August 7th 2020

The Big Picture about STM

Meaning is a key component to understand change but has been difficult to operationalize it empirically (Mohr et al., 2020).

STM enables to develop new types of visualizations and opens an array of possibilities for novel theorizations.

Future Directions:



Studies can **increase the variety of metadata** used as covariates in the STM technique. **Authorship**, for example, shall enable to populate studies of meaning with a more agentic and multidimensional perspective.

Future studies might want to **take into account the pace of change.** The angular coefficient of the correlations produced by the STM technique might afford this sort of analysis, which requires further development of the technique.

Moving Beyond LDA & Standard Topic Modeling – hSBM

Example / Exercise Part 2 (Hovig Tchalian & Tim Hannigan)





80th Annual Meeting of the Academy of Management

Hannigan, Haans, Glaser, Tchalian, Valadao, Jennings IDeaS August 7, 2020

Building Up Visuals for Theorization Case Application & Exercise

Figure 3 Topic Modeling Rendering in Theory-Building Spaces



Hannigan et al. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals*, 13(2), 586-632,





hLDA As Visual Artifact: *Malaysia Flight 370*



Figure 3: Our simple breadcrumb trail and contextual anchor offer constant context as the user explores the visualization. Highlighted slices within the contextual anchor are those currently displayed in the sunburst visualization.

plane, crash, crashed
plane, landed, land
plane, think, people
pilot, plane, hijacking
terrorist, terrorism, passports
suicide, pilot, ocean
Shah, Anwar, political
plane, China, world
phone, phones, cell
evidence, think, make

Table 1: The 10 high-level topics of the model generated from running HLDA on the Malaysia Flight MH-370 corpus. The bolded topics suggest specific theories regarding the status of the plane.

crash, water, crashed
failure, catastrophic, mayday
mechanical, failure, days
plane, ocean, did
plane, error, lost





Two Alternative (and Distinct) Hierarchical Models

hLDA

Supervised / top-down model

- Researcher chooses # of levels (but not # of topics)
- Topics can be difficult to label / interpret
- Visualizations can be crude (excel + sunburst diagram)

hSBM

Unsupervised, network-based model

- Model chooses number of topics and number of levels (optimizes both parameters)
- Topics more interpretable + traceable (docs < > terms)
- Visualization more dynamic (esp. with code-level access)
- Overcomes limitations of LDA models with natural language; ie, burstiness, correlations between topics



Blei, Griffiths & Jordan, The nested Chinese restaurant process and Bayesian nonparametric inference of topic hierarchies (Journal of the ACM, Vol. 57, No. 2, Article 7 2010)

HSBM Offers Powerful Visualization + Theorization

A network approach to topic models -> hierarchical stochastic block modeling (hSBM)

- Canonical papers:
 - Gerlach, M., Peixoto, T. P., & Altmann, E. G. (2018). A network approach to topic models. *Science Advances*, 4(7), eaaq1360.
 - Peixoto, T. P. (2014). Hierarchical Block Structures and High-Resolution Model Selection in Large Networks. *Physical Review X*, 4(1), 011047.
- hSBM software (code): https://github.com/martingerlach/hSBM_Topicmodel/blob/master/TopSBM-tutorial.ipynb





Case: Emergence of the Electric Vehicle Market

- Exploratory Research Question: *Is there an inflection point in the EV market emergence where the discourse changes?*
- Following the Rosa et al. (1999) study on the minivan market, we track discourse from expert publications in the Electric Vehicle market
- First exploration: whether the announcement of the Tesla Model S (June 30, 2008) corresponded with a discourse change





• Simple frequency analysis of article counts is promising, showing increase over time; but content analysis is inconclusive







Case: Emergence of the Electric Vehicle Market

- We used two years of Documents textual data (articles from expert publications) before and after the Model S announcement (2006-06-30 -> 2010-06-30)
- The figure on the right shows the hSBM visual output
- There are 4 levels of topics in this hierarchy
- We manually read the topics at the top level of abstraction, then went down to level 3 which were meaningful
- We then tracked topic salience over time (next slide)

Level 4 Level 3 Level 2 Level 1 Words \downarrow



Break-Out Session 2

- Excel includes three artifacts:
 - 1. hSBM visualization
 - 2. hSBM topics outputs
 - Top 2 levels: 4 + 3
 - Topic-specific terms
 - Ranked by weight (high >> low)
 - 3. Sheets for your additions



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- Follow Excel instructions:
 - I. Use hSBM visual to inspect topics
 - 2. Label L4 topics + L3 sub-topics, iterating back to L4
 - 3. Identify preliminary theoretical insights







Discussion: Emergence of the EV Market



- Because overall article counts increased in the latter part of the period, we would expect to see some overall increase in topic salience over time
- From this figure, we see that Customer Design, EV Technology and Consumer Development topics increased after the Model S announcement
- Topics around Utilities, Smart Grid and the Nissan Leaf (EV) increased far slower •



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Theorization Is a Dynamic, Iterative Process

Figure 3 Topic Modeling Rendering in Theory-Building Spaces



Hannigan et al. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy* of Management Annals, 13(2), 586-632,





Rendering with STM & hSBM Enhances Visuals

- Theories of institutions, culture, relationality and neo-structuralism rely on visuals and can be enhanced by rendering of visuals with topic modeling.
 - As artifacts (especially symbols) in cultures (likely enhanced in terms of capturing centrality of key cultural artifacts)
 - As boundary objects in field relations (likely, because discourse strands become more evident)
 - As representations of deeper structure (in combo with LDAviz, become more powerful)
 - As rhetorical devices (very likely, adding to particular storylines or types of rhetoric...)
- As improved measures of extant concepts (already true, based on examples)

Topic Modeling Is An Interpretive Data Science (IDS)

- LDA and other implementations of topic modeling identify *latent structure*, based on a (dirichlet) probability distribution
- But generating insights requires a healthy dose of interpretation
- IDS combines quantitative *and* qualitative insights
- Methods more advanced than LDA allow for a more dynamic, iterative process of theorization
- Visualization can act as a critical aid to the theorization process





What's Next?

- IDeaS Workshop late 2020 or early 2021 = our "big tent" community
- New, and update: IDeaS general page: <u>http://www.interpretivedatascience.com/</u>
- Updated GitHub: <u>https://ideas-repo.github.io</u>
- Special Issue, we hope. 😳
- We hope that you folks don't mind **being signed up to our community**. If you don't want any info on the IDeaS event, please let me know.





Topic Modeling Advances

Thank You!





80th Annual Meeting of the Academy of Management

Hannigan, Haans, Glaser, Tchalian, Valadao, Jennings IDeaS August 7, 2020