



Data-Driven Behavioral Analytics: Observations, Representations and Models

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<http://www.meng-jiang.com/tutorial-cikm16.html>

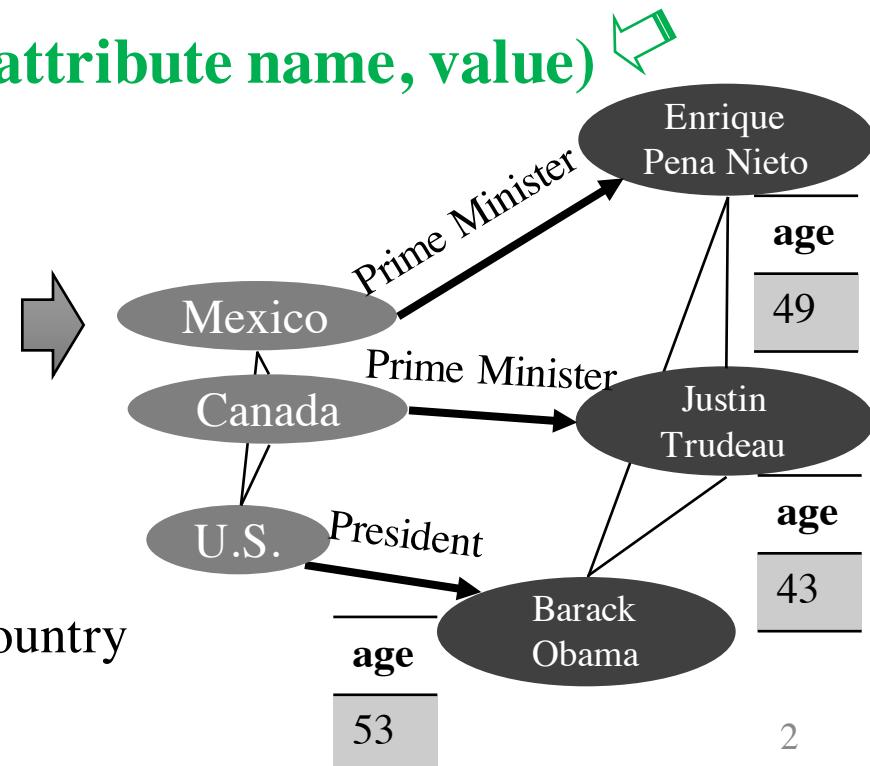
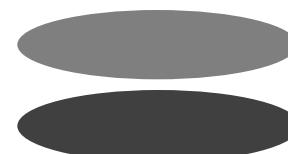
Construction of Heterogeneous Information Networks from Text

Philosophy: Not extensive “labeling” but exploring the power of massive text corpora!

- ❑ Mining phrases (the minimal semantic units)
- ❑ Entity recognition and typing

- ❑ **Attribute discovery (entity, attribute name, value)**

...here by **Canada Prime Minister Justin Trudeau, 43**, the so-called #APEChottie...of Mexico's **Enrique Pena Nieto, 49**, ... United States President **Barack Obama, 53**, who...



Attribute Discovery

- ❑ Given text corpus (news, tweets, web documents)
 - ❑ U.S. President Barack Obama told reporters ...
 - ❑ President Blaise Compaore of Burkina Faso said ...
 - ❑ Canada 's Prime Minister Justin Trudeau and his wife Sophie arrived ... Justin Trudeau, 43, ...
- ❑ Find
 - ❑ \$COUNTRY: president, prime minister ...
 - ❑ \$PERSON: wife, age ...
 - ❑ (U.S., president, Barack Obama)
 - ❑ (Burkina Faso, president, Blaise Compaore)
 - ❑ (Canada, prime minister, Justin Trudeau)
 - ❑ (Justin Trudeau, wife, Sophie), (Justin Trudeau, age, 43)

Google's Systems (Alon Halevy et al.)

- ❑ Biperpedia (VLDB'14): attribute name extraction
 - ❑ With query log (“canada prime minister”), replace entity mentions (“canada”) with E and noun phrases (“prime minister”) with A, and then find E-A patterns:
 - ❑ “E ’s A”, “E A”, “A E”, “A of the E”, etc.
 - ❑ Take E-A patterns to web documents for attributes:
 - ❑ E: U.S., A: president (“E A”)
 - ❑ E: Canada, A: prime minister (“E ’s A”)
 - ❑ Place the attributes on the hierarchy (Location.Country)
- ❑ ReNoun (EMNLP'14): slot filling
 - ❑ Pre-defined set of attributes, human annotations, learning

Google's Approaches on Attribute Extraction

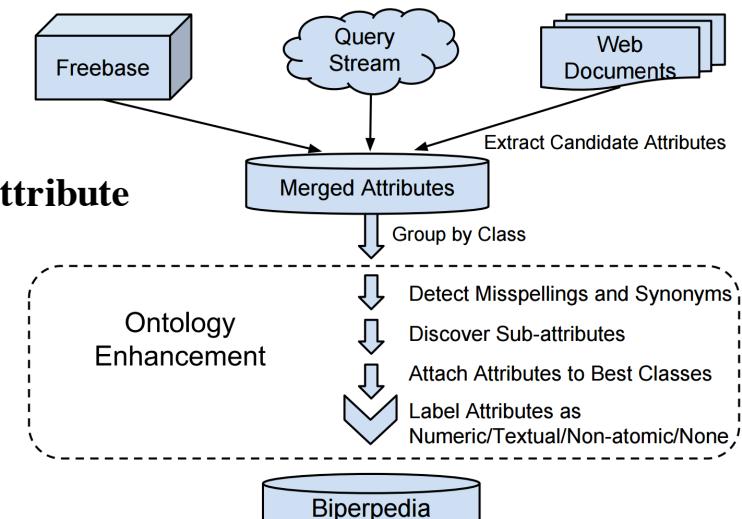
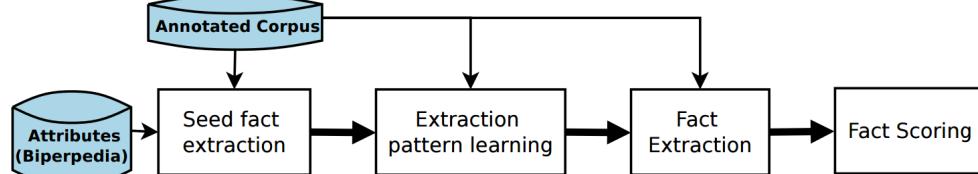
- Given Google's **query log**, web text and knowledge bases
 - "Obama wife name" ... "Japan asian population", "Brazil female latino population", "Princeton economist" ...
 - "Obama's wife, Michelle Obama, is a lawyer...", "Princeton economist Paul Krugman was awarded..." ...
 - Obama: \$Person, \$President; Japan, Brazil: \$Location, \$Country; Princeton: \$Organization, \$University...

- Biperpedia (VLDB'14): **Attribute Name Extraction** from query log

- \$Person: wife name, daughter name
- \$Country: asian population, female latino population
- \$University: economist

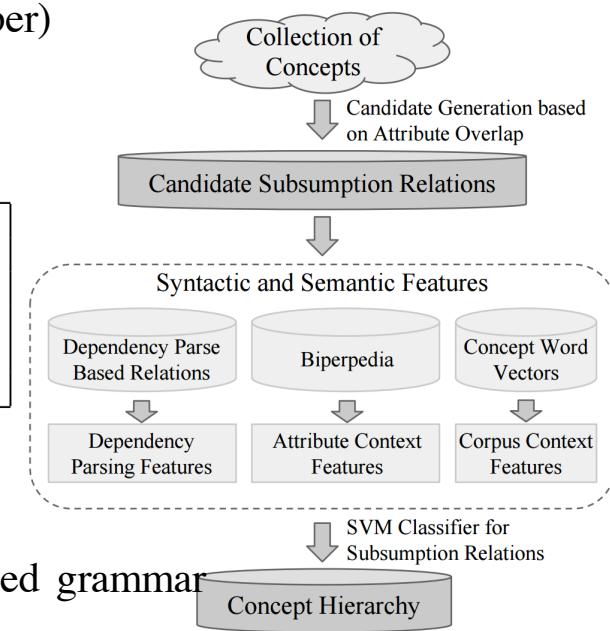
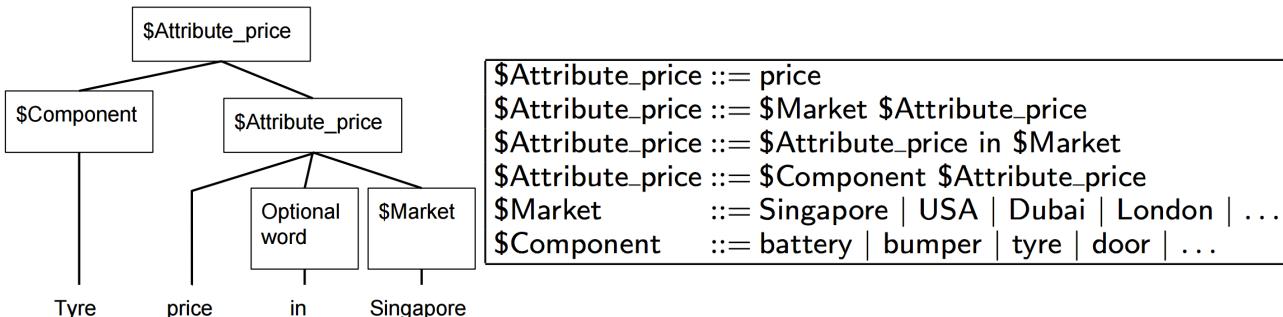
- ReNoun (EMNLP'14): **Fact Extraction for Noun Phrase Attribute**

- (Obama, wife, Michelle Obama)
- (Princeton, economist, Paul Krugman)



Google's Approaches on Attribute Extraction

- Latte (WebDB'15 Best Paper): **Concept (Type) Hierarchy Extraction** with attribute features
 - {country, address, zip code}: \$University (sub) - \$Location (super)
 - {online payment, non profit, tax return}: \$University (sub) - \$Organization (super)
 - {daughter name, wife name, age}: \$President (sub) - \$Person (super)



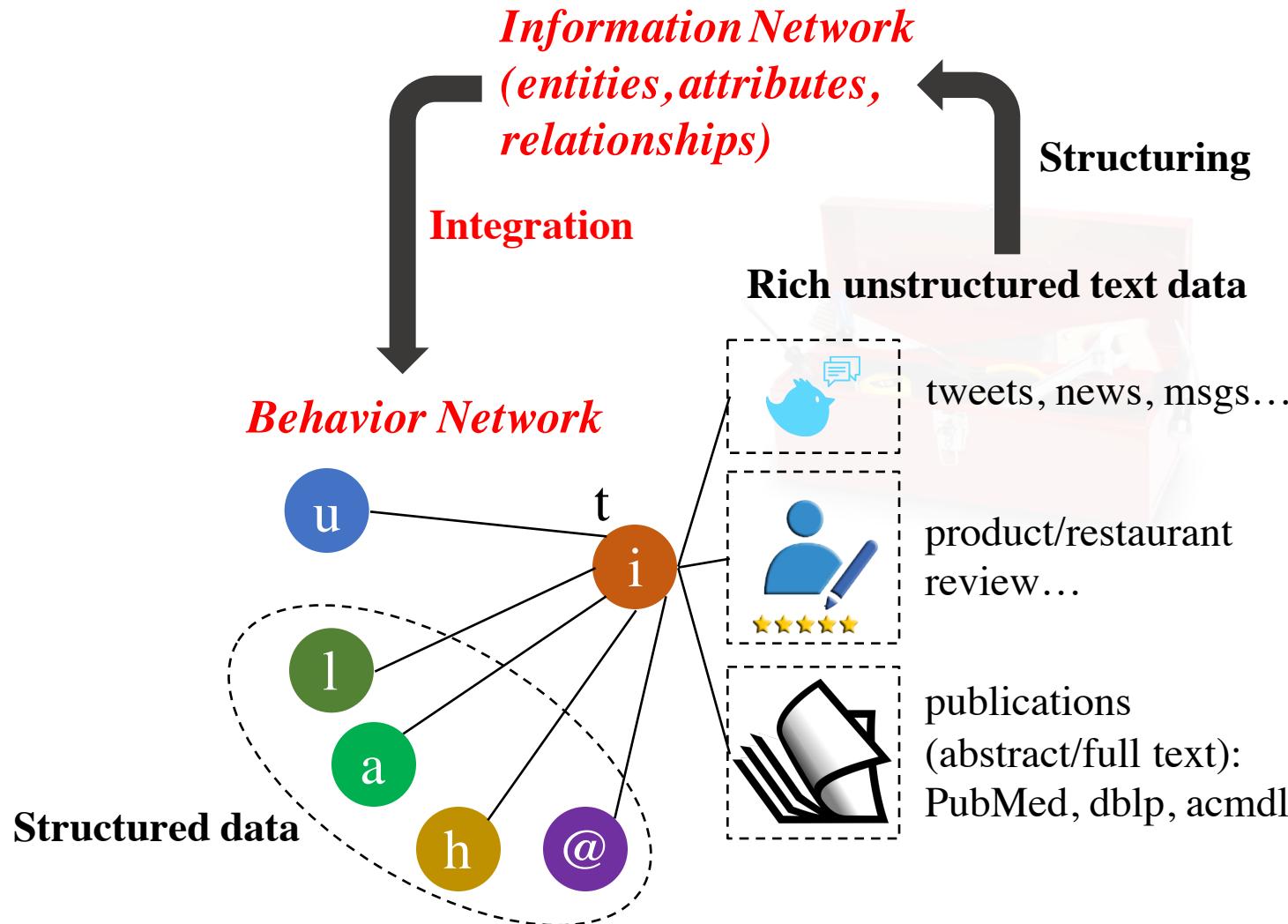
- ARI (WWW'16): **Attribute Name Structure Extraction** with rule-based grammar
 - Long-tail distribution of attribute names
 - \$Person: \$FamilyMember (name) - daughter, wife, mother, daughter name, wife name
 - \$Country: (\$Gender) (\$Ethnicity) population - asian population, female latino population



Limitations

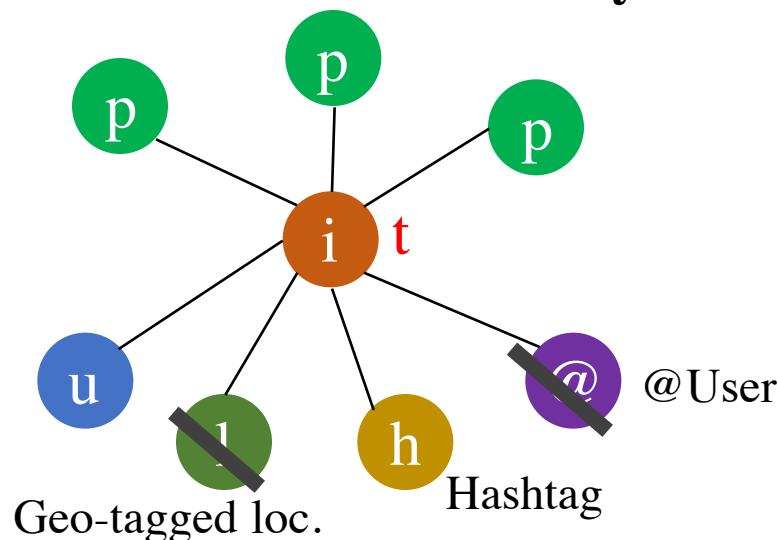
- ❑ Problem setting
 - ❑ Simultaneously extract attribute names and values?
 - ❑ Values for an open set of attribute names?
- ❑ Data sources
 - ❑ Query streams are unavailable.
 - ❑ Annotations are expensive: only for general-domain
 - ❑ Massive text corpora are unlimited!
- ❑ Poor precision and recall using E-A patterns
 - ❑ “A, E” pattern: “... yesterday, Obama ...”
 - ❑ Missing long structure: “President Obama ’s government of U.S.” (“A1 E1 ’s A2 E2”????)

Data to Network to Knowledge



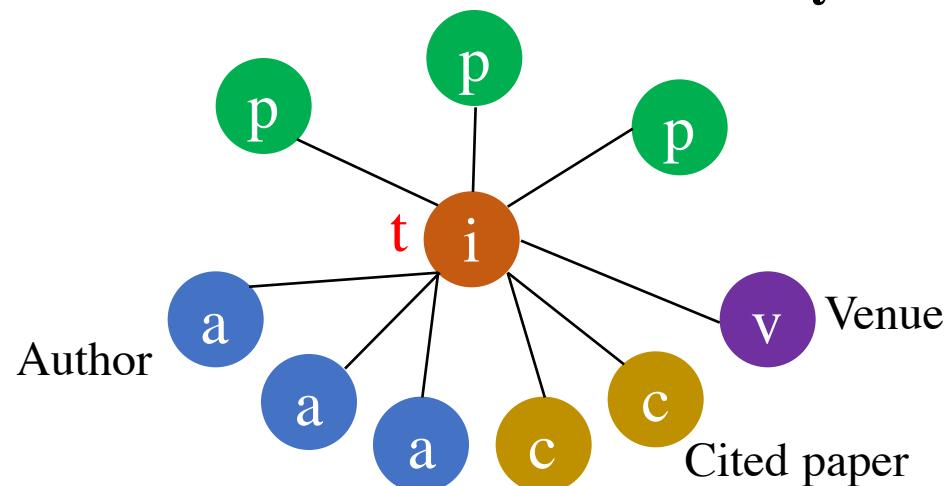
Bring Phrases to Behavior Modeling

- ❑ Tweeting behavior
 - ❑ Event **summary**



20:03:09 @ebekahws
this better be the best halftime show ever
in the history of halftimes shows. ever.
#SuperBowl

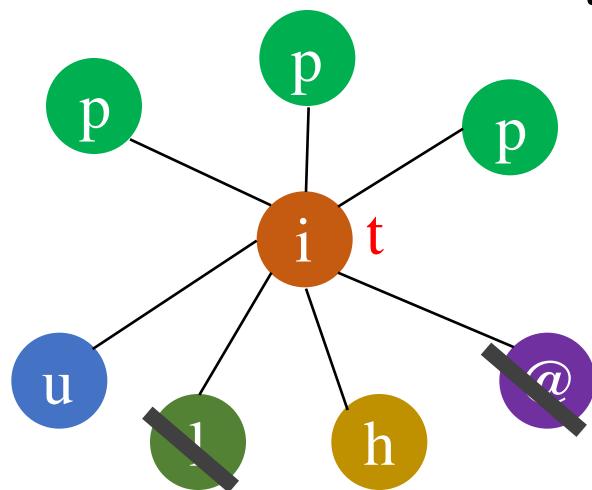
- ❑ Paper-publishing behavior
 - ❑ Research trend **summary**



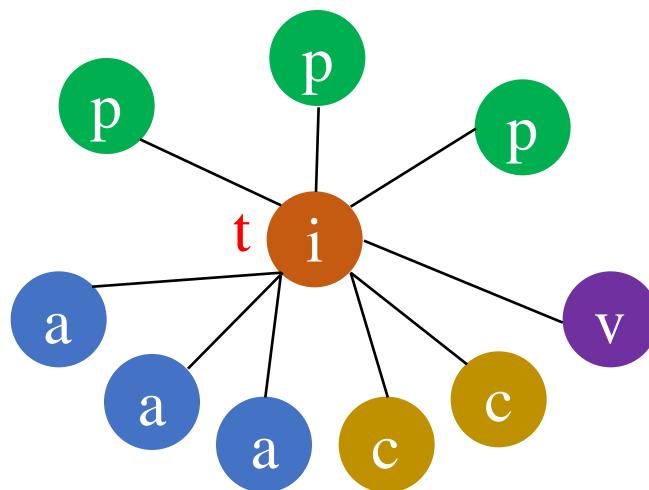
2009 P. Melville, W. Gryc, R. Lawrence,
“Sentiment analysis of blogs by combining
lexical knowledge with text classification”,
KDD’09. Refs: p81623, p84395...

Tensor Fails

- ❑ Tweeting behavior
 - ❑ Event **summary**

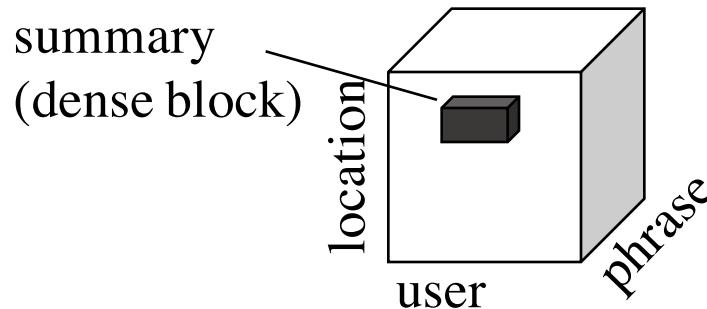


- ❑ Paper-publishing behavior
 - ❑ Research trend **summary**



Q: How to represent and summarize **dynamic multi-contextual** behaviors?

A set of values in dimensions (*one-guaranteed value, empty value, multi-values*)



Two-Level Matrix and “Tartan”

	User	Phrase		URL	Loc.	Hashtag	
Time slice t	1 1 1 2
Behavior (tweeting)	...	1 1	... 2 0 1 1	...	1 1
t+1	1 ... 1 1 ... 1	...	1 1
t+2	...	1 1	... 2 2 1 1	...	1 1

“User-Phrase-URL” Tartan (Advertising campaign)

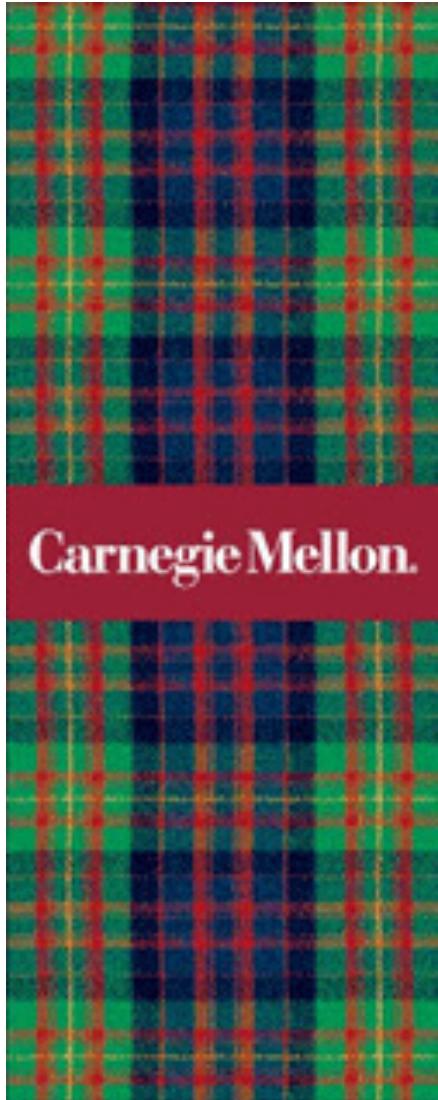
Multicontextual (dimensions, dimensional values)

Dynamic (consecutive time slices)

“Phrase-Location-Hashtag” Tartan (Local event)

The diagram illustrates a two-level matrix structure. The columns represent dimensions: User, Phrase, URL, Loc., and Hashtag. The rows represent time slices: t, t+1, and t+2. The matrix is divided into two main regions by a diagonal line from the top-left to the bottom-right. The upper region, labeled "User-Phrase-URL" Tartan (Advertising campaign), spans from t to t+1. The lower region, labeled "Phrase-Location-Hashtag" Tartan (Local event), spans from t+1 to t+2. The matrix cells contain binary values (0 or 1). The "Phrase" dimension is shown in two levels: a primary level across the first three time slices and a secondary level within each slice. The "Loc." and "Hashtag" dimensions are also shown in two levels. The "User" dimension is constant across all time slices. The "URL" dimension is present in the first two time slices. The "Behavior (tweeting)" dimension is represented by the values in the "Phrase" cells.

CMU Tartans



Optimize with MDL Principle

- Maximize the number of bits by encoding the Tartan

$$f(\mathcal{A}, \mathcal{X}) = L(\mathcal{X}^{\mathcal{A}}) - L(\mathcal{A}) - L(\mathcal{X}^{\mathcal{A}} \setminus \mathcal{A}).$$

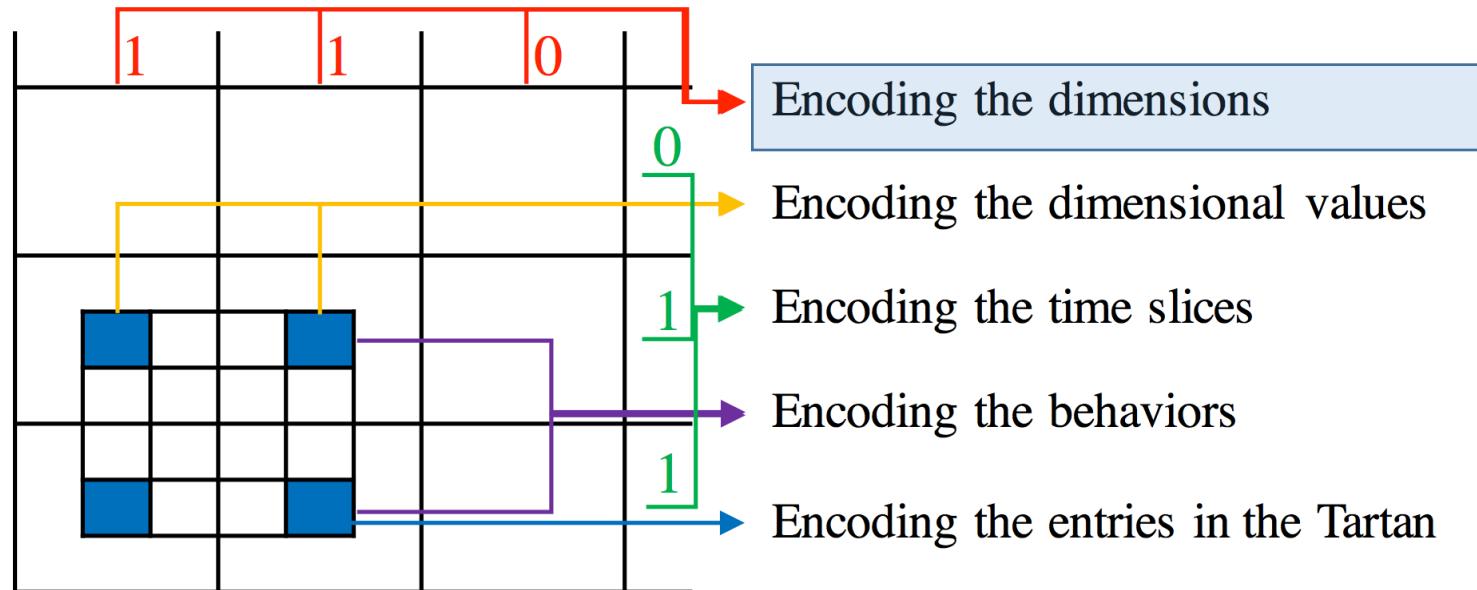
User	Phrase	URL	Loc.	Hashtag	
...	
1 1	1 1 1 2	1 1	1 1	1 1	
...	
Time slice t	“User-Phrase-URL” Tartan (Advert)				
...	1 ... 1 1 ... 1	1 1	1 1	1 1	
...	
Behavior (tweeting)	2 0 1 1	1 1	1 1	1 1	
...	
t+1	1 ... 1 1 ... 1	1 1	1 1	1 1	
t+2	2 2 1 1	1 1	1 1	1 1	‘Phrase-Location-Hashtag’ Tartan (Local event)

$L(\mathcal{X}^{\mathcal{A}}) = g(V + C, C) + L_{\mathcal{D}}(\mathcal{A}) + L_{\mathcal{T}}(\mathcal{A}) + \sum_{d \in \mathcal{D}} \log^* N_d + \sum_{t \in \mathcal{T}} \log^* E^{(t)}.$

$L(\mathcal{A}) = L_{\mathcal{D}}(\mathcal{A}) + L_{\mathcal{V}}(\mathcal{A}) + L_{\mathcal{T}}(\mathcal{A}) + L_{\mathcal{B}}(\mathcal{A}) + L_{\mathcal{A}}(\mathcal{A}).$

$L(\mathcal{X}^{\mathcal{A}} \setminus \mathcal{A}) = g(V + C - v - c, C - c);$

Encoding Tartan: Dimensions



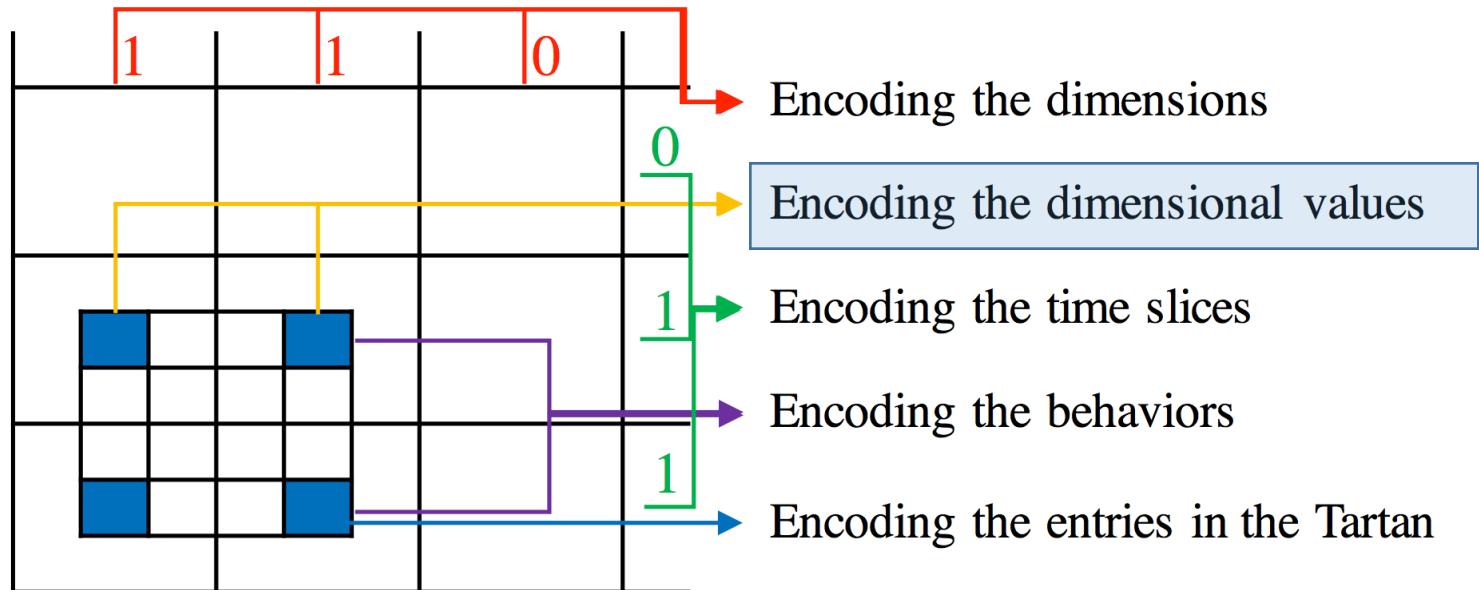
$$H_{\mathcal{D}}(X) = - \sum_{x \in \{0,1\}} P(X = x) \log P(X = x)$$

$$= - \left(\frac{D^{\mathcal{A}}}{D} \log \frac{D^{\mathcal{A}}}{D} + \frac{D-D^{\mathcal{A}}}{D} \log \frac{D-D^{\mathcal{A}}}{D} \right).$$

$$L_{\mathcal{D}}(\mathcal{A}) = \log^* D + \log^* D^{\mathcal{A}} + D \cdot H_{\mathcal{D}}(X)$$

$$= \log^* D + \log^* D^{\mathcal{A}} + g(D, D^{\mathcal{A}}),$$

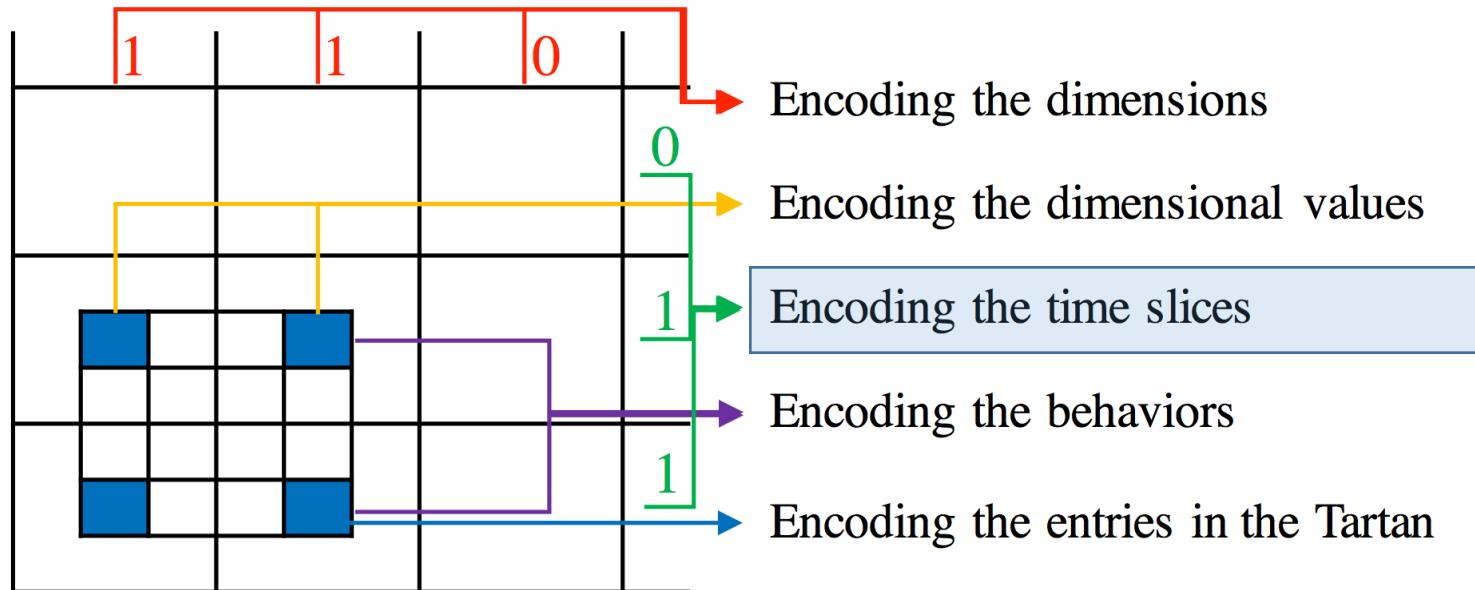
Encoding Tartan: Dimensional Values



$$H_{\mathcal{V}_d}(X) = - \left(\frac{n_d}{N_d} \log \frac{n_d}{N_d} + \frac{N_d - n_d}{N_d} \log \frac{N_d - n_d}{N_d} \right).$$

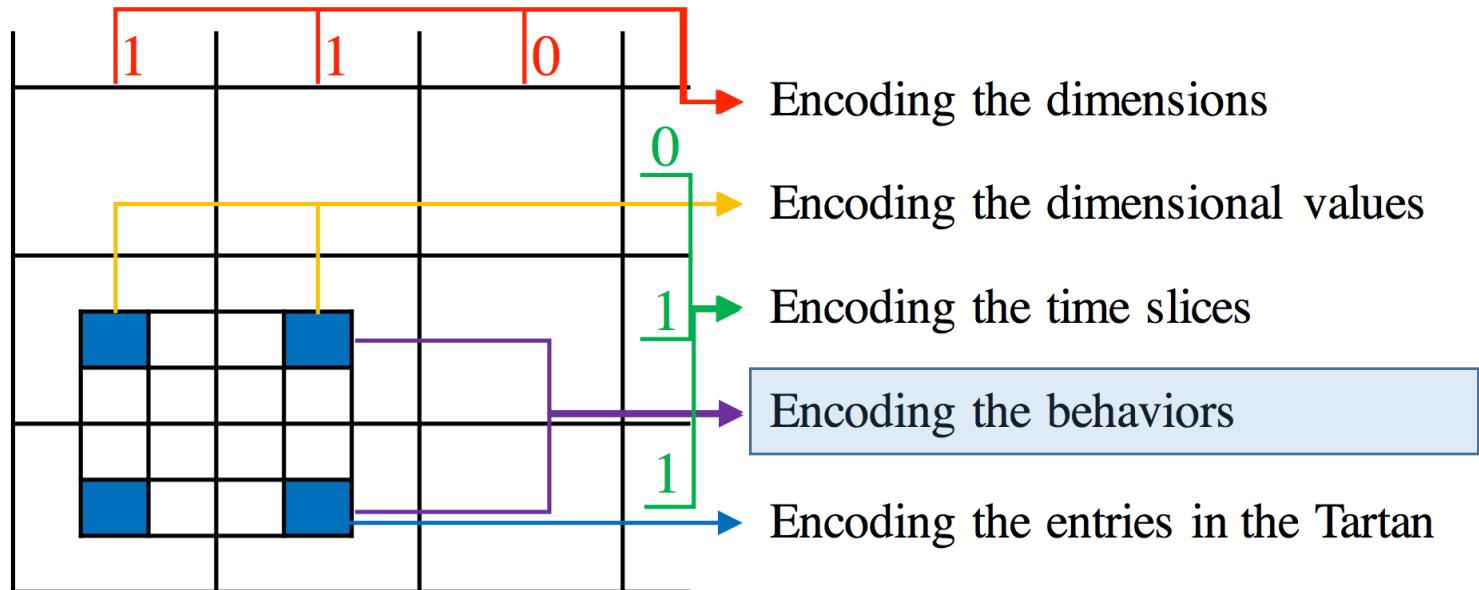
$$L_{\mathcal{V}}(\mathcal{A}) = \sum_{d \in \mathcal{D}} \left(\log^* N_d + \log^* n_d + g(N_d, n_d) \right).$$

Encoding Tartan: Time Slices



$$L_{\mathcal{T}}(\mathcal{A}) = \log^* T + \log^* T^{\mathcal{A}} + \log^* t_{start}$$

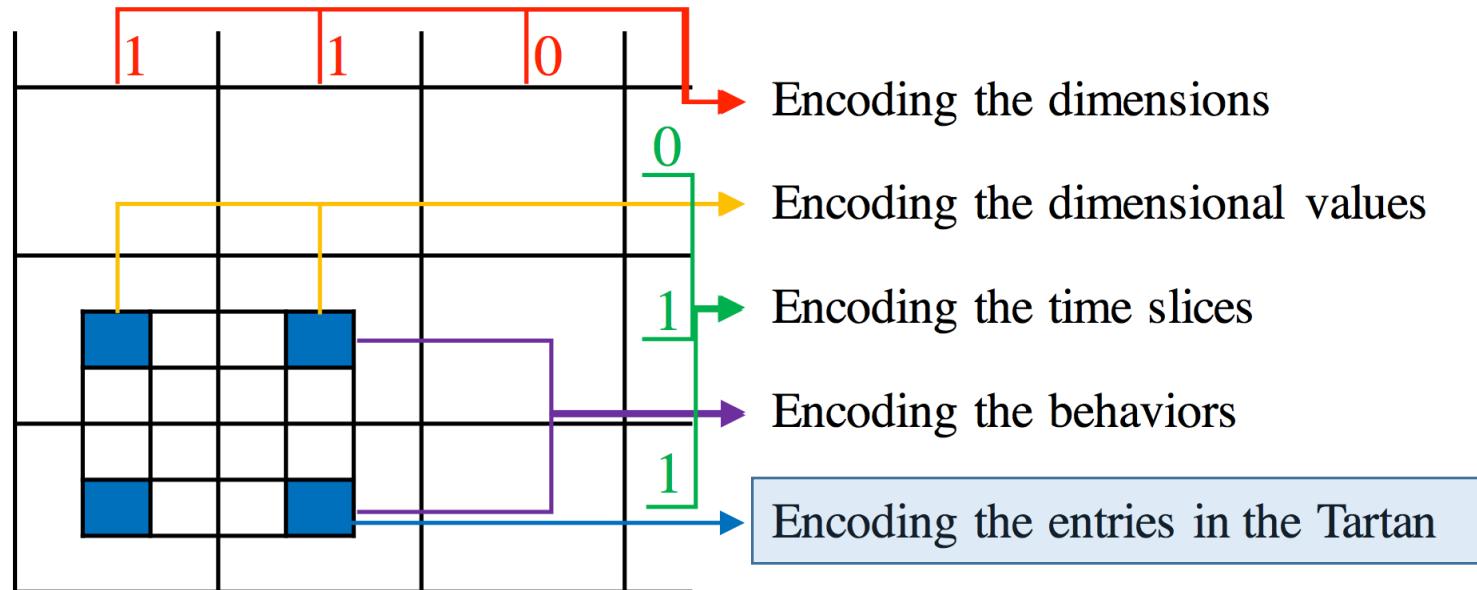
Encoding Tartan: Behaviors



$$H_{\mathcal{B}^{(t)}}(X) = - \left(\frac{e^{(t)}}{E^{(t)}} \log \frac{e^{(t)}}{E^{(t)}} + \frac{E^{(t)} - e^{(t)}}{E^{(t)}} \log \frac{E^{(t)} - e^{(t)}}{E^{(t)}} \right).$$

$$L_{\mathcal{B}}(\mathcal{A}) = \sum_{t \in \mathcal{T}} \left(\log^* E^{(t)} + \log^* e^{(t)} + g(E^{(t)}, e^{(t)}) \right).$$

Encoding Tartan: Entries



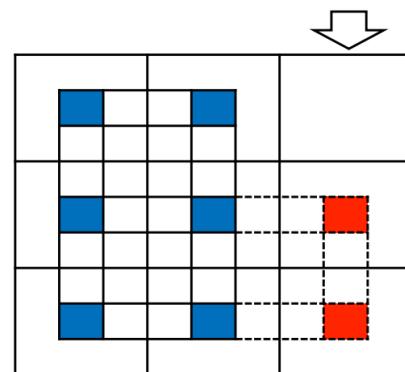
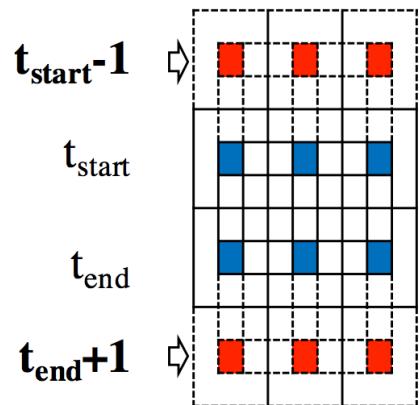
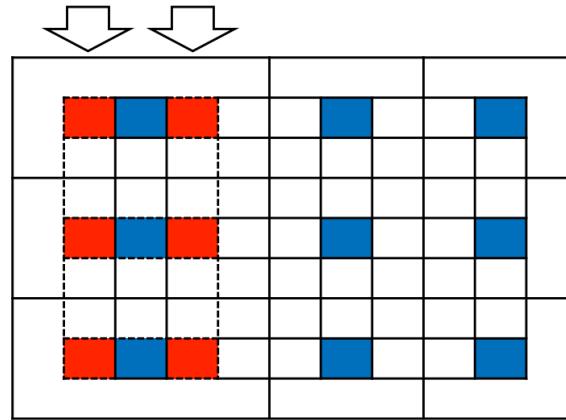
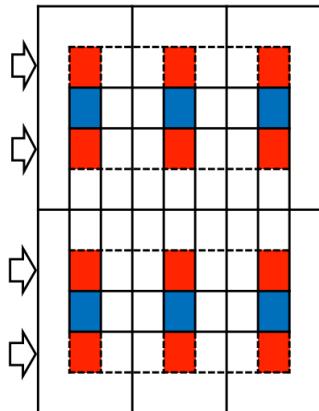
$$v = \left(\sum_{d \in \mathcal{D}} n_d \right) \left(\sum_{t \in \mathcal{T}} e^{(t)} \right).$$

$$c = \sum_{d \in \mathcal{D}, t \in \mathcal{T}} \sum_{b \in \mathcal{B}^{(t)}, i \in \mathcal{V}_d} \chi_d^{(t)}(b, i).$$

$$H_{\mathcal{A}}(X) = - \left(\frac{c}{v+c} \log \frac{c}{v+c} + \frac{v}{v+c} \log \frac{v}{v+c} \right).$$

$$L_{\mathcal{A}}(\mathcal{A}) = (v + c) H_{\mathcal{A}}(X) = g(v + c, c).$$

Greedy Search for the Local Optimum



Time complexity:

$$\mathcal{O}(\sum_d N_d \log N_d + \sum_t E^{(t)} \log E^{(t)})$$



Experimental Results

□ DM/ML research trend summaries with DBLP data

Author	Venue	Keyword	Cited	#Paper	Venue	Keyword	#Paper
76 Cheng-xiang Zhai Hui Fang S. Kambhampati	7 SIGIR VLDB TKDE	7 “information retrieval” “data integration” “text classification”	68 p56743 ¹ p62995 p76869	32 2003- 2007	5 ICML NIPS ...	6 “reinforcement learning” “machine learning”	40 1997- 2002

¹ “A language modeling approach to information retrieval”

Author	Venue	Cited	#Paper	Venue	Keyword	#Paper	Author	Venue	Keyword	#Paper
6 Jiawei Han Xifeng Yan	1 SIG- MOD	1 p76095 ²	22 2004- 2010	3 ICDM AAAI TKDE	1 “anomaly detection”	25 2005- 2013	27 C. Faloutsos J. Pei P. S. Yu X. Lin C. Aggarwal...	6 KDD ICDM ICDE TKDE ...	12 “large graphs” “data streams” “evolving data” “evolving graphs” ...	70 2006- 2013

² “Frequent subgraph discovery”

Author	Venue	Keyword	Cited	#Paper	Author	Venue	Keyword	#Paper
12 Ryen White Hang Li Tie-Yan Liu Zhaohui Zheng...	5 SIGIR WWW WSDM CIKM...	3 “web search” “click-through data” “sponsored search”	12 p82630 ³ p116290 p103899 p106191...	32 2006- 2013	8 Qiang Yang Dou Shen Sinno Pan...	3 KDD PAKDD AAAI	6 “transfer learning” “data mining” “localization models”	17 2007- 2010

³ “Optimizing search engines using clickthrough data”



Experimental Results

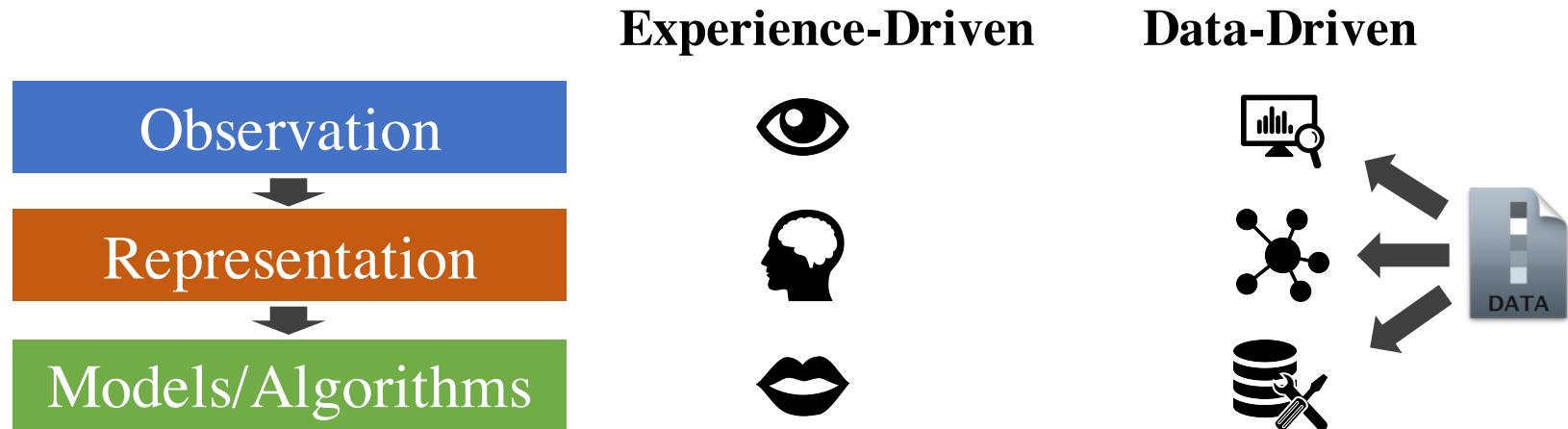
Event summaries with Super Bowl 2013 tweets

							user	phrase	hashtag	URL	3,397 tweets
16:30		16:30:31 <u>My prediction</u> Ravens 34 Niners 31 16:30:57 Ready for the big game :D, <u>my prediction</u> 24-20 SF #SuperBowl	“my prediction”	(3,325)	226	(0)	(0)				Tartan #1: (1 dim) 16:30-17:30
17:00		16:31:14 <u>My prediction</u> for superbowl.. 48.. Jets over Bears 17-13 Mark Sanchez MVP 16:32:24 <u>I predict</u> Baltimore Ravens will win 27 to 24 or 25 or 26. Basically it will be a <u>close game</u> .									Tartan #2: (3 dims) 17:00-18:00
17:30		17:30:51 RT @LMAOTWITPICTS: <u>Make Your Prediction</u> . Retweet For 49ers http://t.co/KKksEist 17:31:01 RT @LMAOTWITPICTS: <u>Make Your Prediction</u> . Retweet For 49ers http://t.co/KKksEist 17:31:16 RT @LMAOTWITPICTS: <u>Make Your Prediction</u> . Retweet For 49ers http://t.co/KKksEist 17:31:19 RT @LMAOTWITPICTS: <u>Make Your Prediction</u> . Retweet For 49ers http://t.co/KKksEist	“make your prediction”	(196)	4	1	1				
18:00		18:55:03 RT @49ers: Kaepernick is sacked on 3rd and goal. #49ers K David Akers makes 36-yard FG. Baltimore leads 7-3 with 3:58 left in 1st Qtr. #SB47 18:55:04 RT @49ers: Kaepernick is sacked on 3rd and goal. #49ers K David Akers makes 36-yard FG. Baltimore leads 7-3 with 3:58 left in 1st Qtr. #SB47 18:55:44 RT @Ravens: David Akers is good from 36 yards to make the score 7-3 Ravens. Nice job by the defense to tighten up in the red zone.	“7-3”, “1 st Qtr”	(213)	21	3	(0)				Tartan #3: (2 dims) 18:30-19:30
19:00		20:20:01 RT @ExtraGrumpyCat: No Superbowl halftime show will ever surpass this. http://t.co/0VSy7Cv6 20:20:02 RT @WolfpackAlan: No Superbowl halftime show will ever surpass this. http://t.co/6Bll0PXs 20:20:04 RT @ExtraGrumpyCat: No Superbowl halftime show will ever surpass this. http://t.co/0VSy7Cv6 20:20:05 RT @WolfpackAlan: No Superbowl halftime show will ever surpass this. http://t.co/6Bll0PXs	halftime show”	(617)	11	4	4				Tartan #4: (3 dims) 20:00-21:00
19:30											
20:00		20:20:47 (Manhattan, NY)...and every one of those girls took #ballet #Beyonce #superbowl 20:22:01 (New York, NY) I have <u>the biggest lady boner</u> for Beyonce #BeyonceBowl #DestinyBowl #DestinysChild #SuperBowl									Tartan #5: (3 dims) 20:00-21:00
20:30		20:24:32 (Manhattan, NY) No one can ever <u>top</u> that performance by Beyonce EVER. #Beyonce #superbowl #halftimeshow	“beyonce”, #beyonce, #superbowl, #DestinysChild	2	55	17	(0)				
21:00		21:44:42 Ahora si pff #49ers 23-28 #Ravens 21:44:44 Baltimore #Ravens 28-23 San Francisco #49ers 21:44:50 FG Akers #49ers 23-28 #Ravens 3Q 3:10 #SuperBowlXLVII #SuperBowl #NFL	“28-23”, #49ers, #Ravens	(650)	69	11	(0)				Tartan #6: (2 dims) 21:00-22:00
21:30											
22:00		22:42:27 Congratulations Ravens!!!! 22:42:43 Congratulations Ray Lewis and the Ravens. 22:42:43 Game over! Ravens won ray got his retirement ring now all y'all boys and girls go to sleep! 22:42:52 @LetThatBoyTweet: Game over. Ravens win the Super Bowl.”	“congratulations”, “game over”	(1942)	248	(0)	(0)				Tartan #7: (1 dim) 22:00-23:30



Summary

- ❑ Structuring text into heterogeneous information networks
- ❑ **Observations, Representations, Models**
 - ❑ **ToPMine/SegPhrase:** Quality phrase mining
 - ❑ **ClusType:** Entity recognition and typing
 - ❑ **MetaPAD:** Data-driven automatic attribute discovery for attributed network construction
 - ❑ Integrating text mining techniques
 - ❑ **Meta Pattern Mining**
- ❑ Integrating phrases into behavioral analysis
- ❑ **Observations, Representations, Models**
 - ❑ **CatchTartan:** Dynamic multicontextual. Tensor fails.

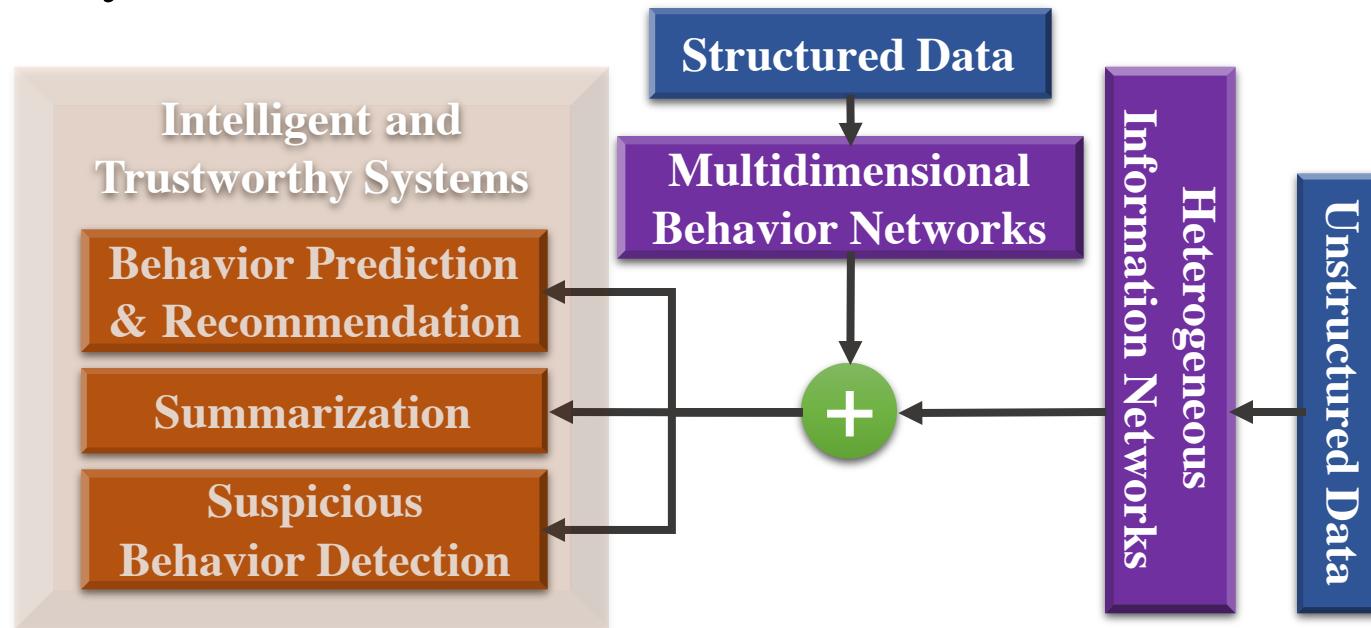


Conclusion

Data-Driven Behavioral Analytics

Data-Driven Behavioral Analytics

- ❑ Mining behavior networks with social and spatiotemporal contexts to support intelligent and trustworthy systems
 - ❑ Mining for behavior prediction and recommendation
 - ❑ Mining for suspicious behavior detection
- ❑ Structuring behavioral content and integrating behavioral analysis with information networks





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Research
微软亚洲研究院



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Thank you!

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