

# Visualización de Información

## IIC2026

*Visualización de Texto II*

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(algunas slides de Lucas Valenzuela)

En esta clase, ejemplos y casos de estudio de visualización de texto, documents, corpora  
(document corpus)

# Word Clouds

performance

peoples

document

visuals

call

aimed

sets

given

collection

use

word

derive

work

people

generate

intuition

frequency

present

present

clouds

lists

design

often

associated

data

lists

summaries

used

studies

value

quantitative

information

four

values

exploring

use

extracting

user

call

given

collection

document

aimed

sets

use

call

## Ejemplos

- [http://www.science.smith.edu/dftwiki/index.php/Visualizations:\\_Lexical/Text](http://www.science.smith.edu/dftwiki/index.php/Visualizations:_Lexical/Text)
  - Wordle.net



# Ejemplos

- [http://www.science.smith.edu/dftwiki/index.php/Visualizations:\\_Lexical/Text](http://www.science.smith.edu/dftwiki/index.php/Visualizations:_Lexical/Text)

**Category:** Lexical/Text

**Author/Source:** Money.cnn.com ↗

**Implementation:** NA

**Date:** Feb. 2011

*The best companies to work at, in the States. The left diagram shows the companies, the bubble size indicating the measure of goodness: large = good. The chart on the right indicates the most frequent words used when describing these companies. When one clicks on a word, sample phrases containing the word fly by...*



# Ejemplos

- <http://www.science.smith.edu/dftwiki/index.php/Visualizations>: Lexical/Text

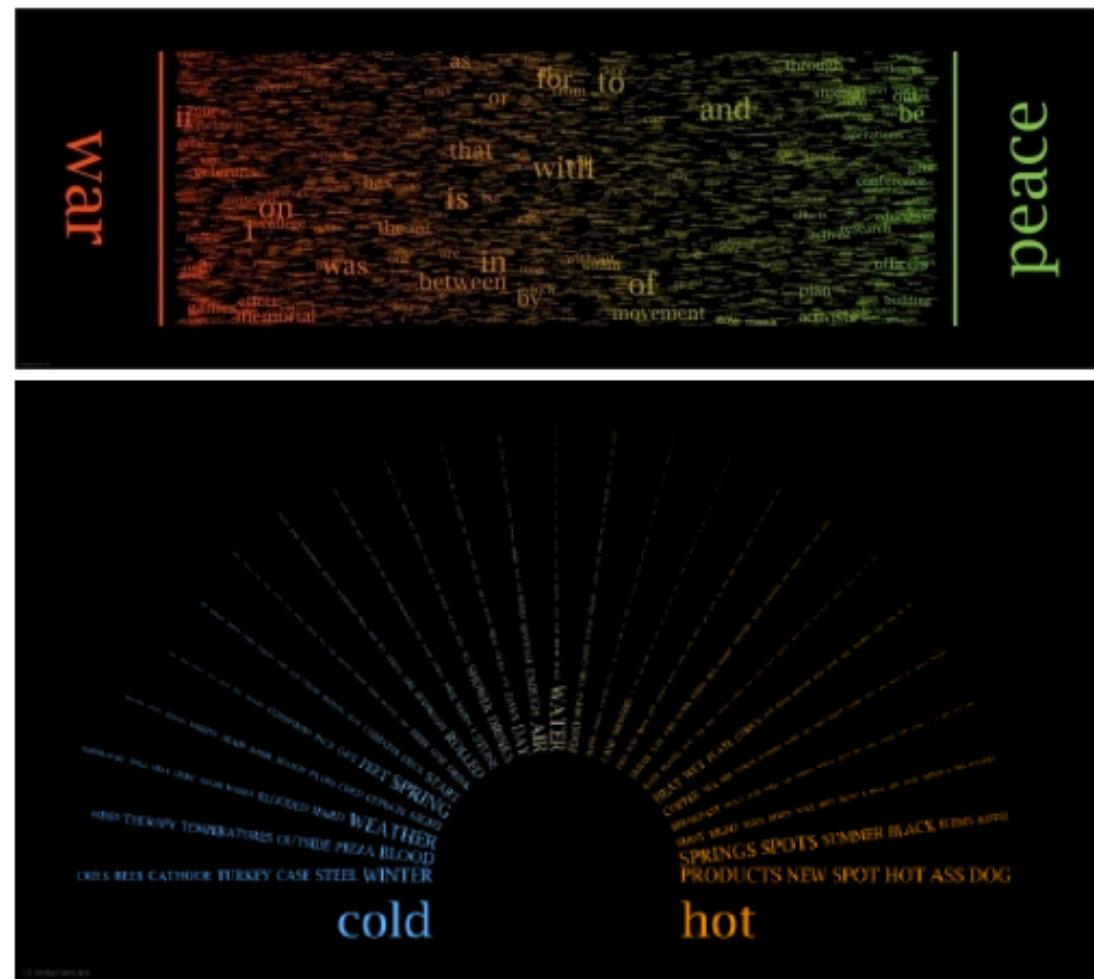
## **Category:** Lexical/Text

**Author/Source:** chrisharrison.net ↗

**Implementation:** NA

Date: 2010

From Chris Harrison's page [Using Google's enormous bigram dataset](#), I produced a series of visualizations that explore word associations. Each visualization pits two primary terms against each other. Then, the use frequency of words that follow these two terms are analyzed. For example, "war memorial" occurs 531,205 times, while "peace memorial" occurs only 25,699. A position for each word is generated by looking at the ratio of the two frequencies. If they are equal, the word is placed in the middle of the scale. However, if there is an imbalance in the uses, the word is drawn towards the more frequently related term. This process is repeated for thousands of other word combinations, creating a spectrum of word associations. Font size is based on a inverse power function (uniquely set for each visualization, so you can't compare across pieces). Vertical positioning is random.





Felix, C., Franconeri, S., & Bertini, E. (2017).  
Taking Word Clouds Apart: An Empirical Investigation of the Design  
Space for Keyword Summaries.  
*IEEE Transactions on Visualization and Computer Graphics.*

# Espacio de Diseño

- Layout: Estrategia usada para posicionar las palabras
- Codificación visual: Canal visual usada para codificar magnitud

# Layouts

- Spatial: Palabras ubicadas sin alineación particular
- Row: Palabras alineadas respecto a múltiples filas
- Column: Palabras alineadas respecto a múltiples columnas

	mistake	ridiculous		beware
pay		finally	appointment	awful
waiting	phone		customer	charged
	billing	waste		charge
bill				
	worse	supposed		
		incompetent		

terrible	poor	call	bad	asked	charge	phone
refund	people	pay	incompetent	telling	awful	
worst	worse	rude	refused	paid	supposed	

worse	awful	bill
people	waited	unprofessional
mistake	refund	told
doctor	avoid	supposed
rude	refused	money
asked	terrible	appointment
insurance	business	charge



Spatial



Row



Column

# Estrategias de codificación

- Tamaño de Fuente
- Intensidad de Color
- Largo de Barra
- Tamaño de Círculo
- No Encoding

told  
mistake

told  
paid

told  
poor

insurance  
told

told  
supposed

Font  
Size

Color  
Intensity

Bars  
Length

Circle  
Area

Control

# Espacio de Diseño Combinado

told  
supposed

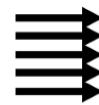
told  
paid

**told**  
mistake

told  
poor

insurance  
told

Value Encoding												
	No Encoding		Font Channels				Additional Mark Channels					
	Control		Color Intensity		Font Size		Bar Length		Circle Area			
Keyword Position	Column	unprofessional	arrogant	unprofessional	arrogant	unprofessional	<b>arrogant</b>	unprofessional	arrogant	unprofessional	arrogant	
	Row	price	long	price	long	price	long	price	long	price	long	
	Spatial	overpriced	rude	overpriced	rude	overpriced	rude	overpriced	rude	overpriced	rude	
		time	wrong	time	wrong	time	wrong	time	wrong	time	wrong	
		unprofessional	price	overpriced	unprofessional	price	overpriced	unprofessional	price	unprofessional	price	
		time	arrogant	long	rude	time	arrogant	long	rude	overpriced	time	
		wrong			wrong		long	rude	wrong	arrogant	long	
		rude			rude			rude		rude		
		time	arrogant	price	time	arrogant	price	time	arrogant	time	arrogant	
		unprofessional			unprofessional		unprofessional		unprofessional	unprofessional	price	
		wrong	long	overpriced	wrong	long	overpriced	wrong	long	wrong	long	



¿Cuál Funciona mejor?

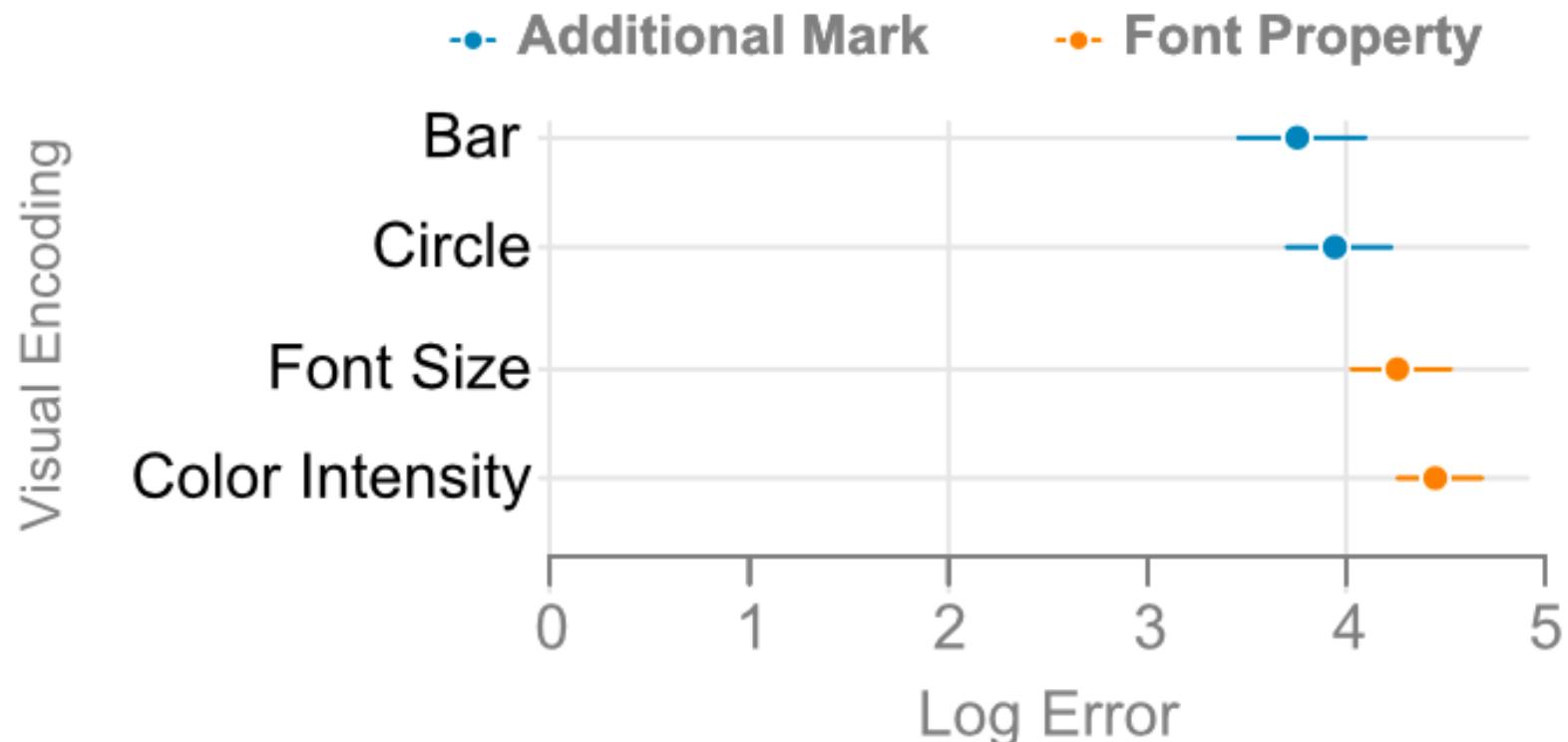
¿mejor para qué?

# Tareas

- **Comparar Valores:** Comparar magnitudes de dos palabras seleccionadas
- **Buscar Palabras:** Buscar por una palabra específica en el cloud
- **Identificar Tópicos:** Elegir a qué tema corresponde una palabra (de una lista)
- **Construir Tópicos:** Describir qué temas hay incluidos en una word cloud.

# Resultados

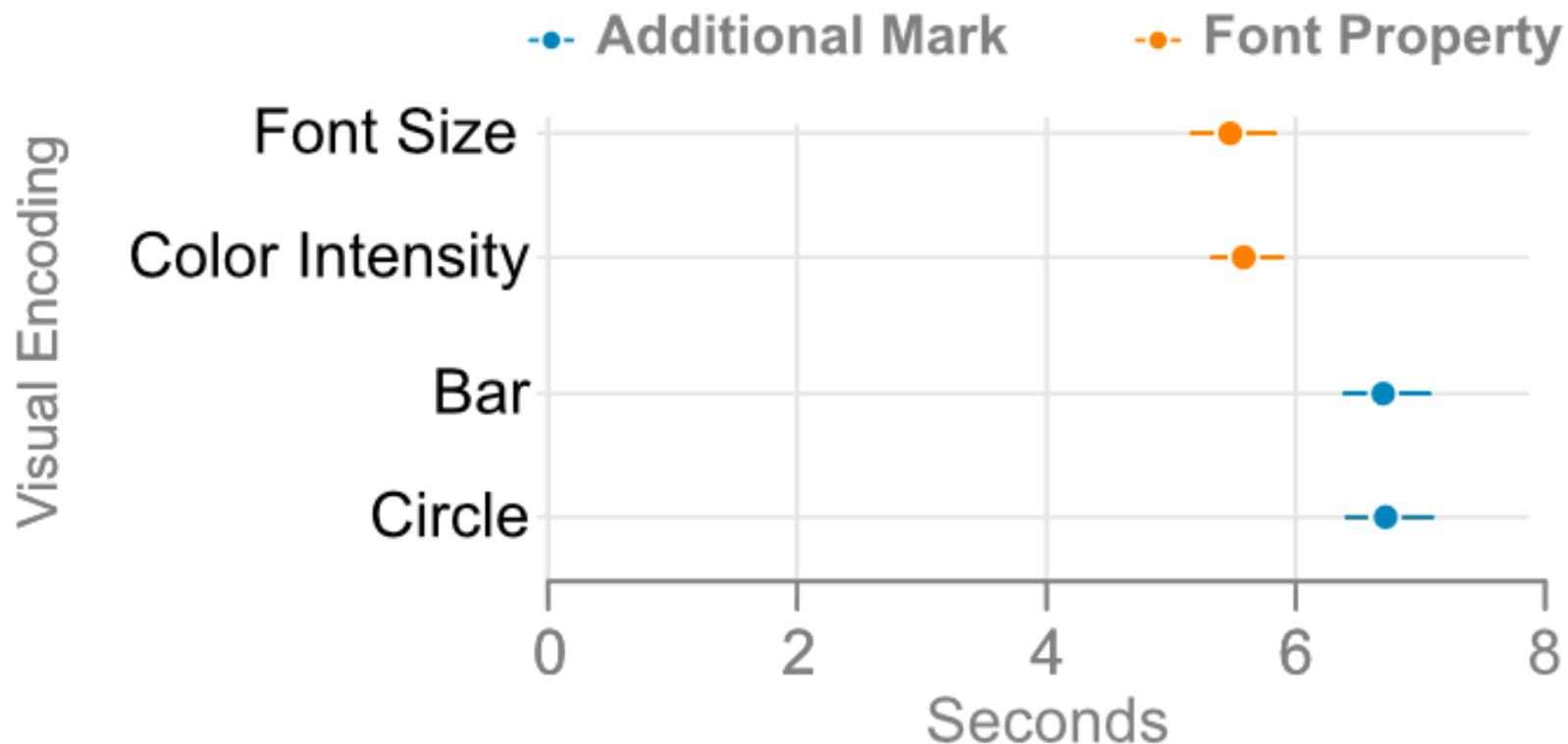
- **Barras alineadas son mejores para leer valores con precisión (al comparar palabras)**



The amount of error we found in different designs, when participants are asked to compare magnitudes associated to two words. Bar and circle score better than font size and color intensity.

# Resultados

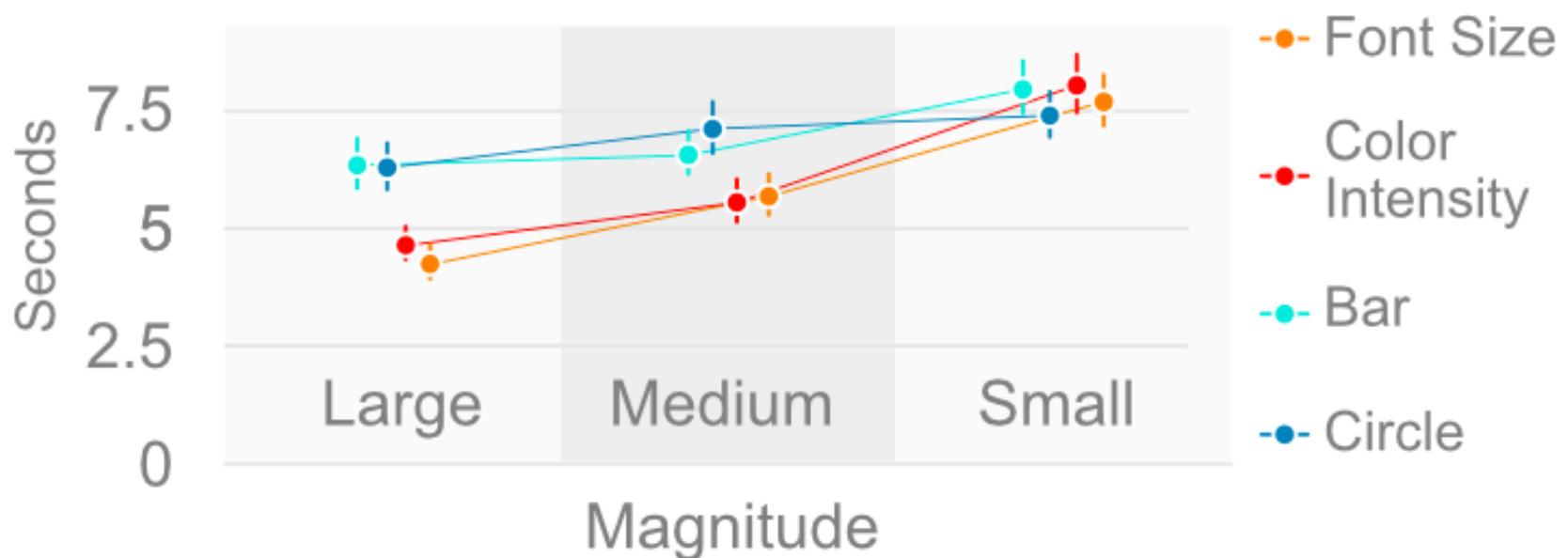
- Tamaño de la fuente e intensidad de color funcionan mejor para búsqueda de palabras



The amount of time it took participants to find specific words with different designs. Font size and color intensity score better than bar and circle.

# Resultados

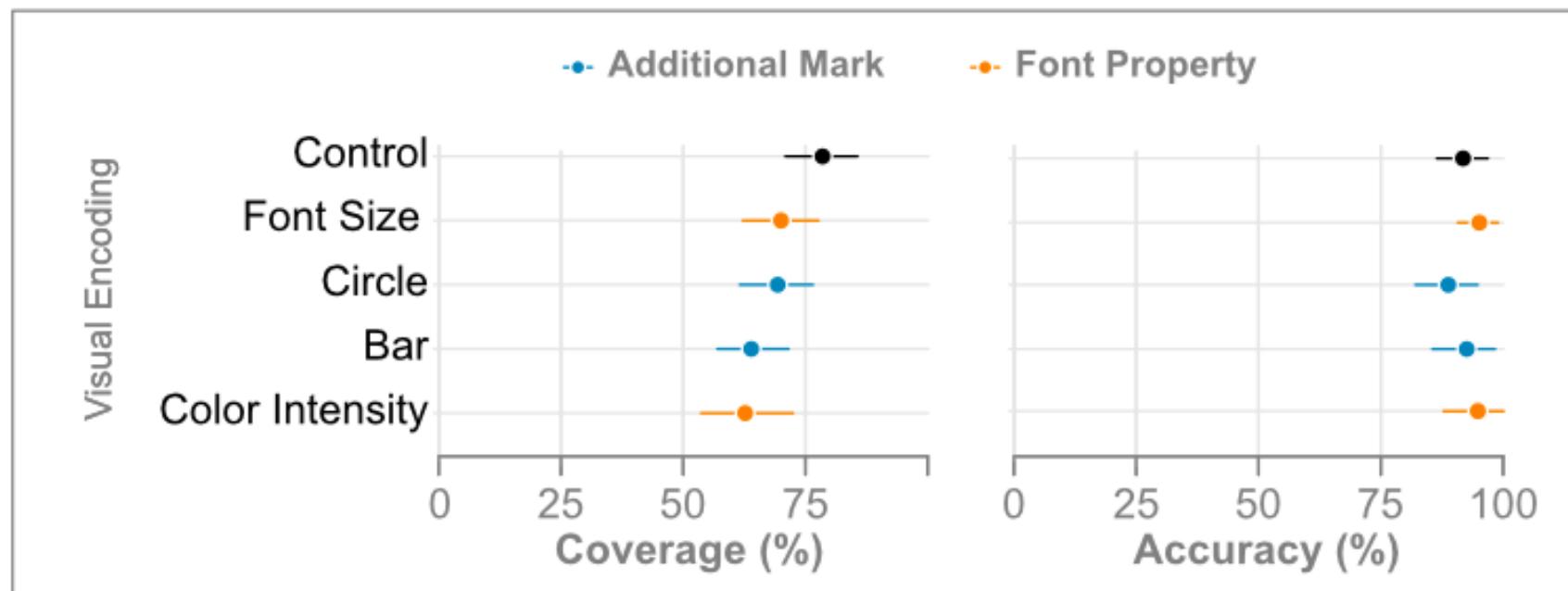
- Ventaja de la “propiedades de fuente” se desvanecen cuando la pabra objetivo e pequeña



Time it takes to find a word when associated to different magnitudes. The advantage of font properties vanished when the target gets smaller.

# Resultados

- En Tareas más complejas, los resultados no se ven igualmente reflejados (tópicos)
- Listas simples de palabras pueden funcionar bastante bien



Coverage and accuracy of topics detected when asked to identify topics in the word cloud. Performance is similar across all conditions. Simple lists (control) work pretty well.

# Recomendaciones Finales

- **Experimentar con diseños diferentes.**
- **Give column bars a chance.** Agregar barras a las palabras, alinear en columnas y permitir al usuarios cierta interacción.
- **Probar otras disposiciones espaciales.** Manteniendo tamaño de fuente e intensidad de color parece funcionar bien para algunas tareas, pero se puede experimentar con otros *layout*.
- **Listas simples de palabras funcionan bien.** No se ven muy fashion, pero especialmente en tareas como encontrar tópicos o temas, parecen funcionar bien.
- **Pensar en ordenar.** En una aplicación interactiva, puede ser buena idea agregar funcionalidad para ordenar alfabéticamente o por tamaño. Esto puede ayudar a responder diferentes preguntas en un ambiente de análisis de datos.

# Espacio de Diseño Combinado

told  
supposed

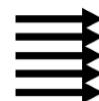
told  
paid

**told**  
mistake

told  
poor

insurance  
told

Value Encoding												
	No Encoding		Font Channels				Additional Mark Channels					
	Control		Color Intensity		Font Size		Bar Length		Circle Area			
Keyword Position	Column	unprofessional	arrogant	unprofessional	arrogant	unprofessional	<b>arrogant</b>	unprofessional	arrogant	unprofessional	arrogant	
	Row	price	long	price	long	price	long	price	long	price	long	
	Spatial	overpriced	rude	overpriced	rude	overpriced	rude	overpriced	rude	overpriced	rude	
		time	wrong	time	wrong	time	wrong	time	wrong	time	wrong	
		unprofessional	price	overpriced	unprofessional	price	overpriced	unprofessional	price	unprofessional	price	
		time	arrogant	long	rude	time	arrogant	long	rude	overpriced	time	
		wrong			wrong			long	rude	arrogant	long	
		rude			rude			rude		rude		
		time	arrogant	price	time	arrogant	price	time	arrogant	time	arrogant	
		unprofessional			unprofessional			unprofessional		unprofessional		
		wrong	long	overpriced	wrong	long	overpriced	wrong	long	wrong	long	



**¿Cómo medir asociación  
entre palabras y conceptos ?  
(para usarlos en visualización)**

# Ejemplos

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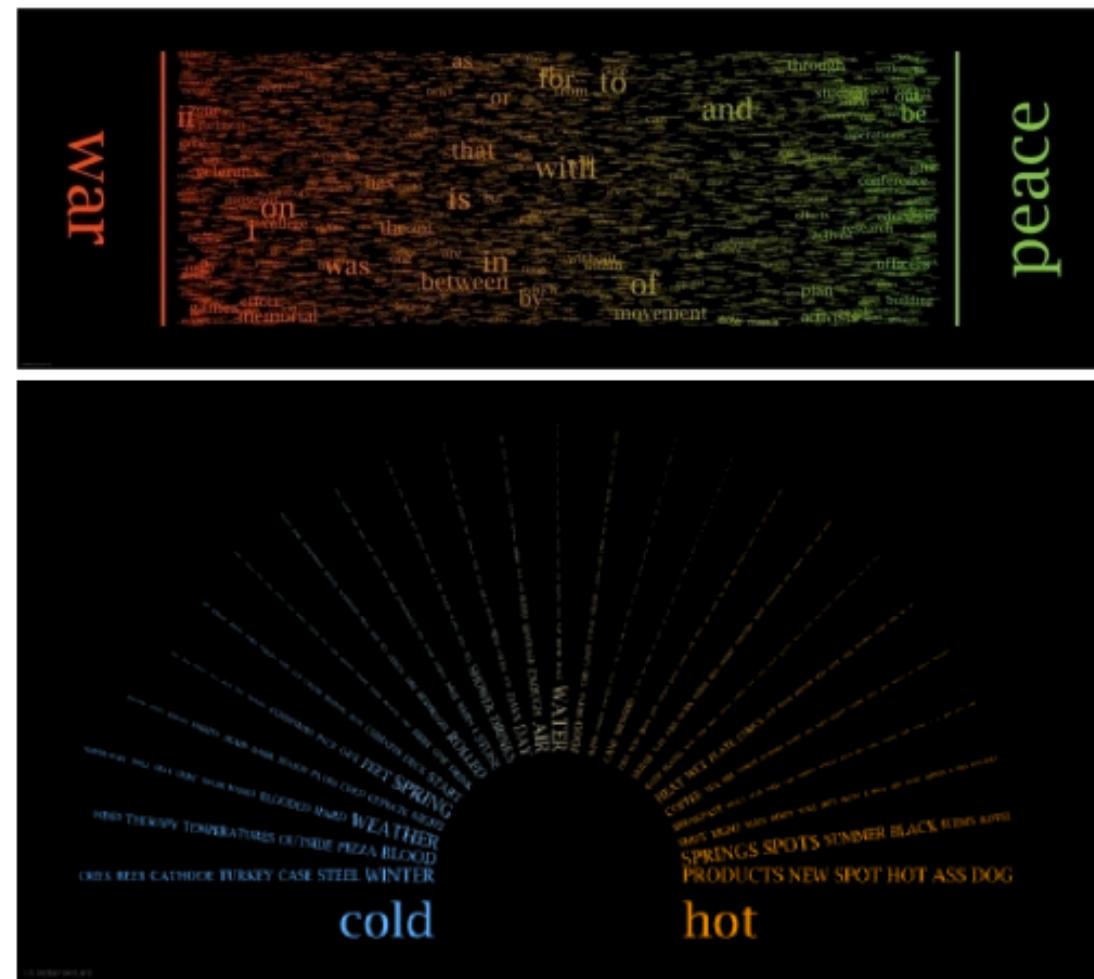
**Author/Source:** [chrisharrison.net](http://chrisharrison.net)

**Implementation:** NA

**Date:** 2010

From Chris Harrison's page [Using Google's enormous bigram dataset, I produced a series of visualizations that explore word associations. Each visualization pits two primary terms against each other. Then, the use frequency of words that follow these two terms are analyzed. For example, "war memorial" occurs 531,205 times, while "peace memorial" occurs only 25,699. A position for each word is generated by looking at the ratio of the two frequencies.](#)

If they are equal, the word is placed in the middle of the scale. However, if there is a imbalance in the uses, the word is drawn towards the more frequently related term. This process is repeated for thousands of other word combinations, creating a spectrum of word associations. Font size is based on a inverse power function (uniquely set for each visualization, so you can't compare across pieces). Vertical positioning is random.



# Ejemplos

- Wagner, C., Graells-Garrido, E., Garcia, D., & Menczer, F. (2016). Women through the glass ceiling: gender asymmetries in Wikipedia. *EPJ Data Science*, 5(1), 5.



**Figure 4 Topical bias.** Word clouds for biographies of women (top) and men (bottom), with birth date before 1900 (left) and since 1900 (right). Spaces in bi-grams are replaced with an underscore. Font size is proportional to PMI with each gender. Colors depict the four categories: *gender* in orange, *family* in green, *relationship* in violet, and *other* in blue. Beside professional and topical areas, words in the gender, relationship, and family categories are more dominant in articles about women born before 1900. Gender-specific differences are much less pronounced in articles about people born since 1900.

# PMI

- Frecuencia de las palabras no es una buena medida de asociación entre palabras (sesgada) – “el” y “de” pueden ser frecuentes, pero poco asociadas
- Medida de asociación entre dos eventos
- Dos eventos co-ocurren más que si fueran independientes?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

Vector Semantics

Positive Pointwise  
Mutual Information  
(PPMI)

# Pointwise Mutual Information

**Pointwise mutual information:**

Do events x and y co-occur more than if they were independent?

$$\text{PMI}(X, Y) = \log_2 \frac{P(x, y)}{P(x)P(y)}$$

**PMI between two words:** (Church & Hanks 1989)

Do words x and y co-occur more than if they were independent?

$$\text{PMI}(\textit{word}_1, \textit{word}_2) = \log_2 \frac{P(\textit{word}_1, \textit{word}_2)}{P(\textit{word}_1)P(\textit{word}_2)}$$

# Positive Pointwise Mutual Information

- PMI ranges from  $-\infty$  to  $+\infty$
- But the negative values are problematic
  - Things are co-occurring **less than** we expect by chance
  - Unreliable without enormous corpora
    - Imagine w1 and w2 whose probability is each  $10^{-6}$
    - Hard to be sure  $p(w1, w2)$  is significantly different than  $10^{-12}$
  - Plus it's not clear people are good at “unrelatedness”

# Positive Pointwise Mutual Information

- So we just replace negative PMI values by 0
- Positive PMI (PPMI) between word1 and word2:

$$\text{PPMI}(\textit{word}_1, \textit{word}_2) = \max \left( \log_2 \frac{P(\textit{word}_1, \textit{word}_2)}{P(\textit{word}_1)P(\textit{word}_2)}, 0 \right)$$

# Computing PPMI on a term-context matrix

- Matrix F with W rows (words) and C columns (contexts)

- $f_{ij}$  is # of times  $w_i$  occurs in context  $c_j$

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^W \sum_{j=1}^C f_{ij}}$$

$$p_{i^*} = \frac{\sum_{j=1}^C f_{ij}}{\sum_{i=1}^W \sum_{j=1}^C f_{ij}}$$

$$p_{*j} = \frac{\sum_{i=1}^W f_{ij}}{\sum_{i=1}^W \sum_{j=1}^C f_{ij}}$$

apricot  
pineapple  
digital  
information

aardvark	computer	data	pinch	result	sugar
0	0	0	1	0	1
0	0	0	1	0	1
0	2	1	0	1	0
0	1	6	0	4	0

$$pmi_{ij} = \log_2 \frac{p_{ij}}{p_{i^*} p_{*j}}$$

$$ppmi_{ij} = \begin{cases} pmi_{ij} & \text{if } pmi_{ij} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^W \sum_{j=1}^C f_{ij}}$$

	Count(w,context)				
	computer	data	pinch	result	sugar
apricot	0	0	1	0	1
pineapple	0	0	1	0	1
digital	2	1	0	1	0
information	1	6	0	4	0

$$p(w=\text{information}, c=\text{data}) = 6/19 = .32$$

$$p(w=\text{information}) = 11/19 = .58$$

$$p(c=\text{data}) = 7/19 = .37$$

$$p(w_i) = \frac{\sum_{j=1}^C f_{ij}}{N}$$

$$p(c_j) = \frac{\sum_{i=1}^W f_{ij}}{N}$$

	p(w,context)					p(w)
	computer	data	pinch	result	sugar	
apricot	0.00	0.00	0.05	0.00	0.05	0.11
pineapple	0.00	0.00	0.05	0.00	0.05	0.11
digital	0.11	0.05	0.00	0.05	0.00	0.21
information	0.05	0.32	0.00	0.21	0.00	0.58
<b>p(context)</b>	0.16	0.37	0.11	0.26	0.11	

$$pmi_{ij} = \log_2 \frac{p_{ij}}{p_{i*}p_{*j}}$$

	<b>p(w,context)</b>					<b>p(w)</b>
	computer	data	pinch	result	sugar	
apricot	0.00	0.00	0.05	0.00	0.05	0.11
pineapple	0.00	0.00	0.05	0.00	0.05	0.11
digital	0.11	0.05	0.00	0.05	0.00	0.21
information	0.05	0.32	0.00	0.21	0.00	0.58
<b>p(context)</b>	0.16	0.37	0.11	0.26	0.11	

•  $pmi(\text{information}, \text{data}) = \log_2 ( .32 / (.37 * .58) ) = .58$  (*.57 using full precision*)

	<b>PPMI(w,context)</b>				
	computer	data	pinch	result	sugar
apricot	-	-	2.25	-	2.25
pineapple	-	-	2.25	-	2.25
digital	1.66	0.00	-	0.00	-
information	0.00	0.57	-	0.47	-

## Weighting PMI

- PMI is biased toward infrequent events
  - Very rare words have very high PMI values
- Two solutions:
  - Give rare words slightly higher probabilities
  - Use add-one smoothing (which has a similar effect)

## Weighting PMI: Giving rare context words slightly higher probability

- Raise the context probabilities to  $\alpha = 0.75$ :

$$\text{PPMI}_\alpha(w, c) = \max\left(\log_2 \frac{P(w, c)}{P(w)P_\alpha(c)}, 0\right)$$

$$P_\alpha(c) = \frac{\text{count}(c)^\alpha}{\sum_c \text{count}(c)^\alpha}$$

- This helps because  $P_\alpha(c) > P(c)$  for rare  $c$
- Consider two events,  $P(a) = .99$  and  $P(b) = .01$

$$\bullet P_\alpha(a) = \frac{.99^{.75}}{.99^{.75} + .01^{.75}} = .97 \quad P_\alpha(b) = \frac{.01^{.75}}{.01^{.75} + .01^{.75}} = .03$$

Use Laplace (add-1) smoothing

**Add-2 Smoothed Count(w,context)**

	computer	data	pinch	result	sugar
apricot	2	2	3	2	3
pineapple	2	2	3	2	3
digital	4	3	2	3	2
information	3	8	2	6	2

**$p(w, \text{context}) [\text{add-2}]$**

	computer	data	pinch	result	sugar	$p(w)$
apricot	0.03	0.03	0.05	0.03	0.05	0.20
pineapple	0.03	0.03	0.05	0.03	0.05	0.20
digital	0.07	0.05	0.03	0.05	0.03	0.24
information	0.05	0.14	0.03	0.10	0.03	0.36
$p(\text{context})$	0.19	0.25	0.17	0.22	0.17	

# PPMI versus add-2 smoothed PPMI

	PPMI(w,context)				
	computer	data	pinch	result	sugar
apricot	-	-	2.25	-	2.25
pineapple	-	-	2.25	-	2.25
digital	1.66	0.00	-	0.00	-
information	0.00	0.57	-	0.47	-

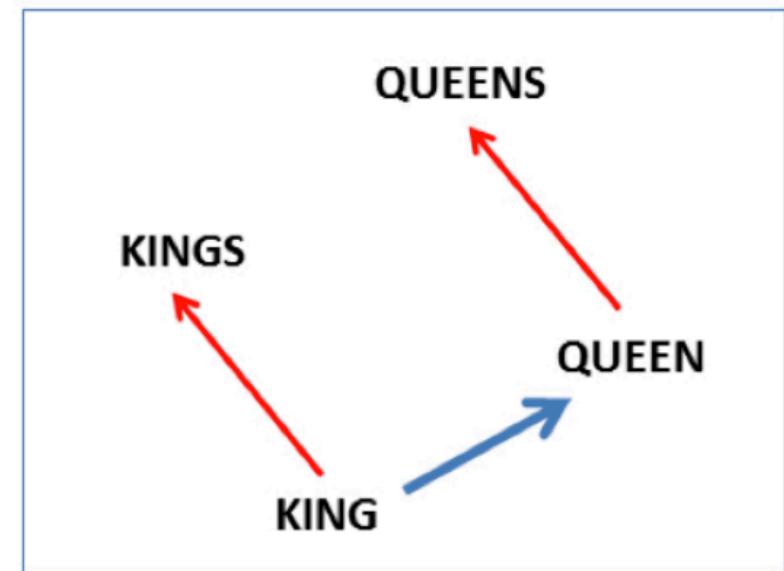
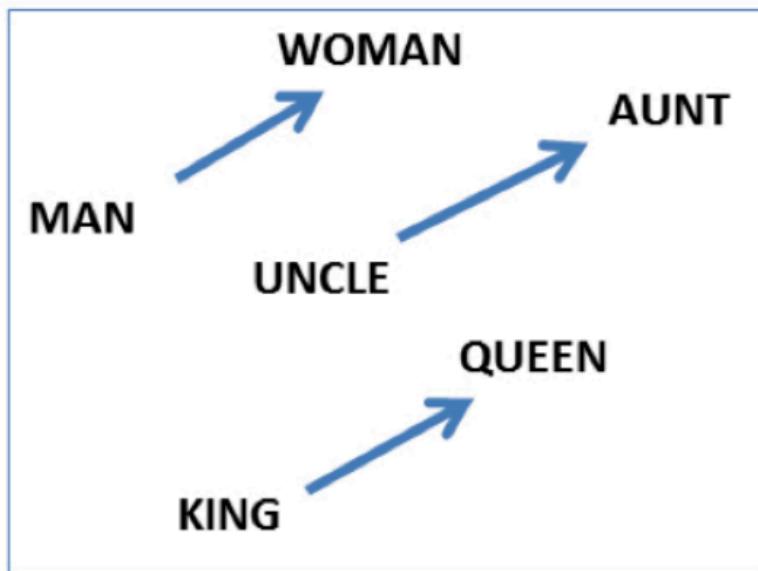
	PPMI(w,context) [add-2]				
	computer	data	pinch	result	sugar
apricot	0.00	0.00	0.56	0.00	0.56
pineapple	0.00	0.00	0.56	0.00	0.56
digital	0.62	0.00	0.00	0.00	0.00
information	0.00	0.58	0.00	0.37	0.00

¿Puede obtenerse y visualizarse semántica?

# Word2vec Embeddings (Mikolov, 2010)

$\text{vector('king')} - \text{vector('man')} + \text{vector('woman')} \approx \text{vector('queen')}$

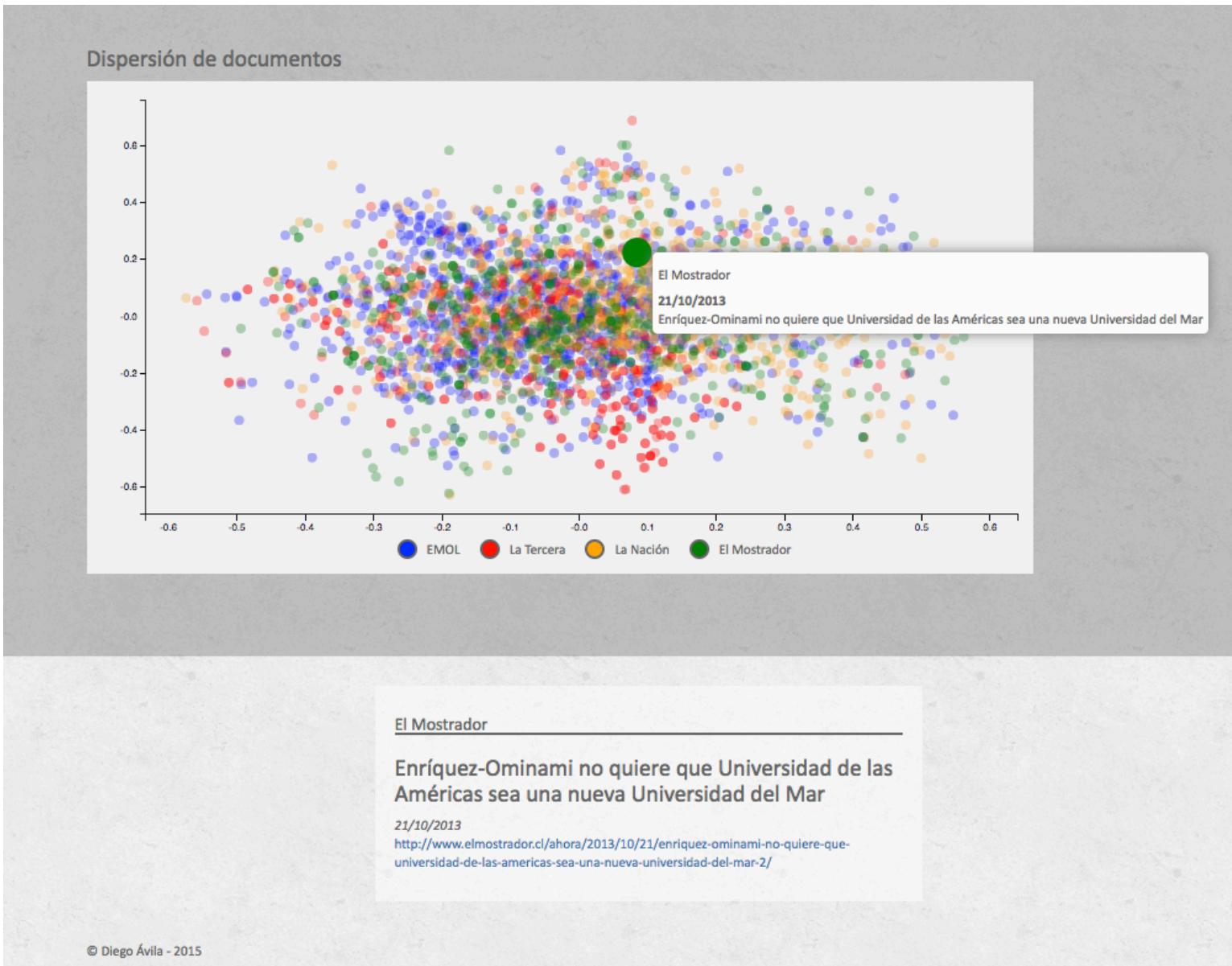
$\text{vector('Paris')} - \text{vector('France')} + \text{vector('Italy')} \approx \text{vector('Rome')}$



¿Cómo visualizar un corpus?

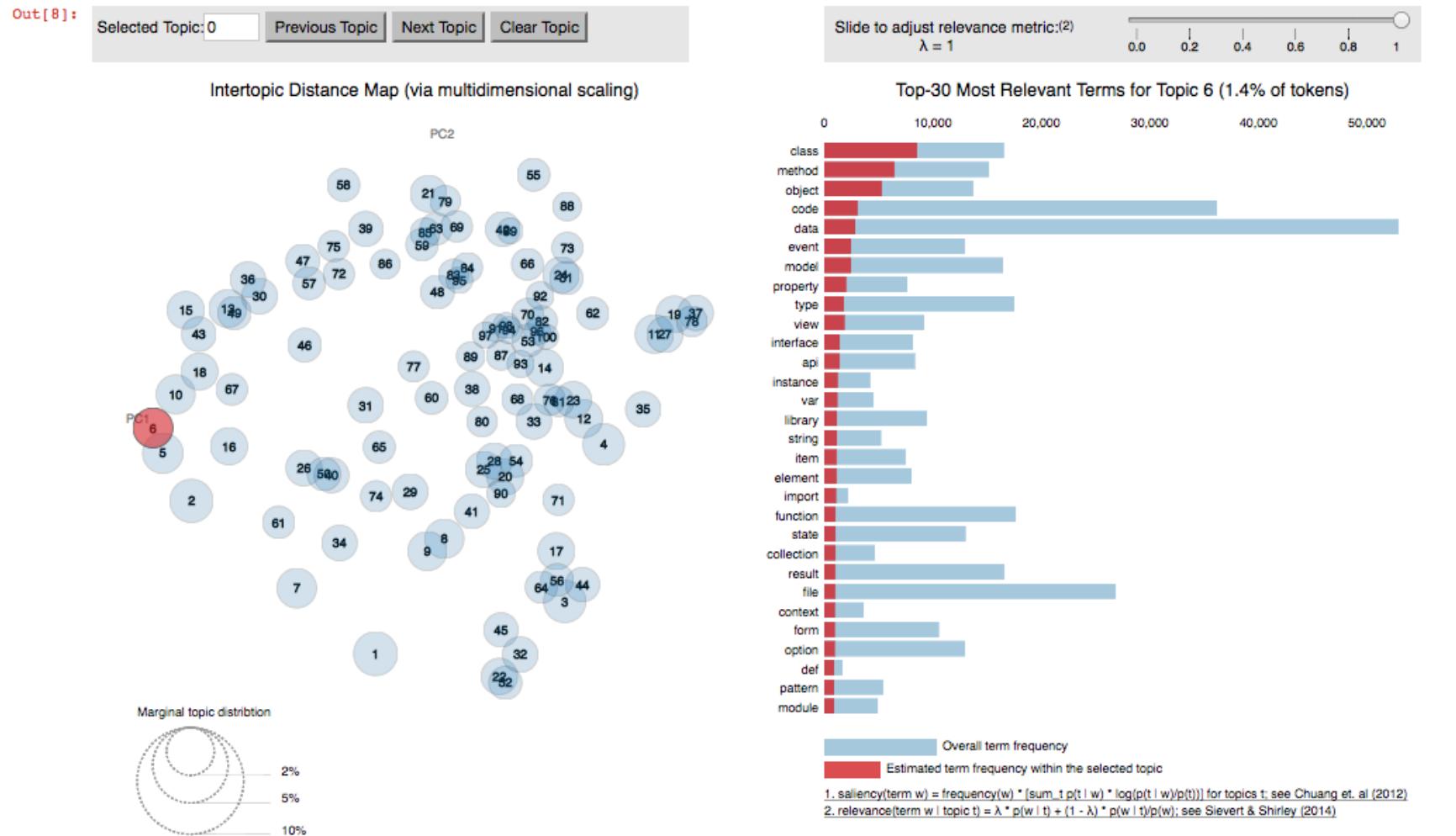
# LSA (SVD)

<http://dfaο-uc.github.io/#articulo>



# Topic Modeling

[http://nbviewer.ipython.org/github/bmabey/hacker\\_news\\_topic\\_modelling/blob/master/HN%20Topic%20Model%20Talk.ipynb](http://nbviewer.ipython.org/github/bmabey/hacker_news_topic_modelling/blob/master/HN%20Topic%20Model%20Talk.ipynb)

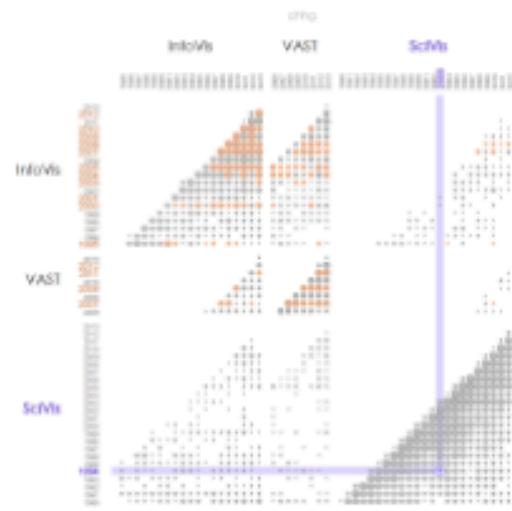


# Interacción

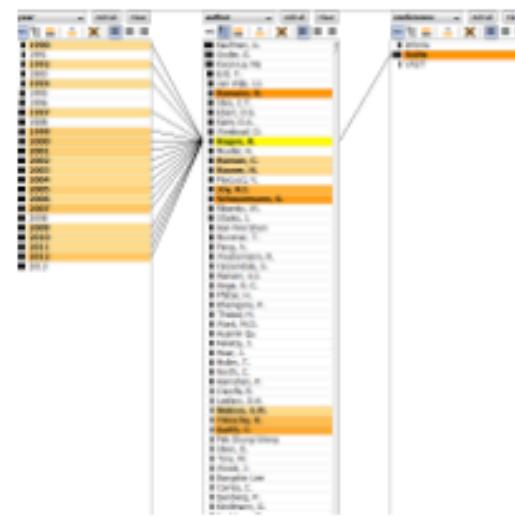
<https://www.cc.gatech.edu/gvu/ii/citevis/VIS25/>



CiteVis2



CiteMatrix



VISLists

# IEEE VIS Citations

Authors: Tamara Munzner

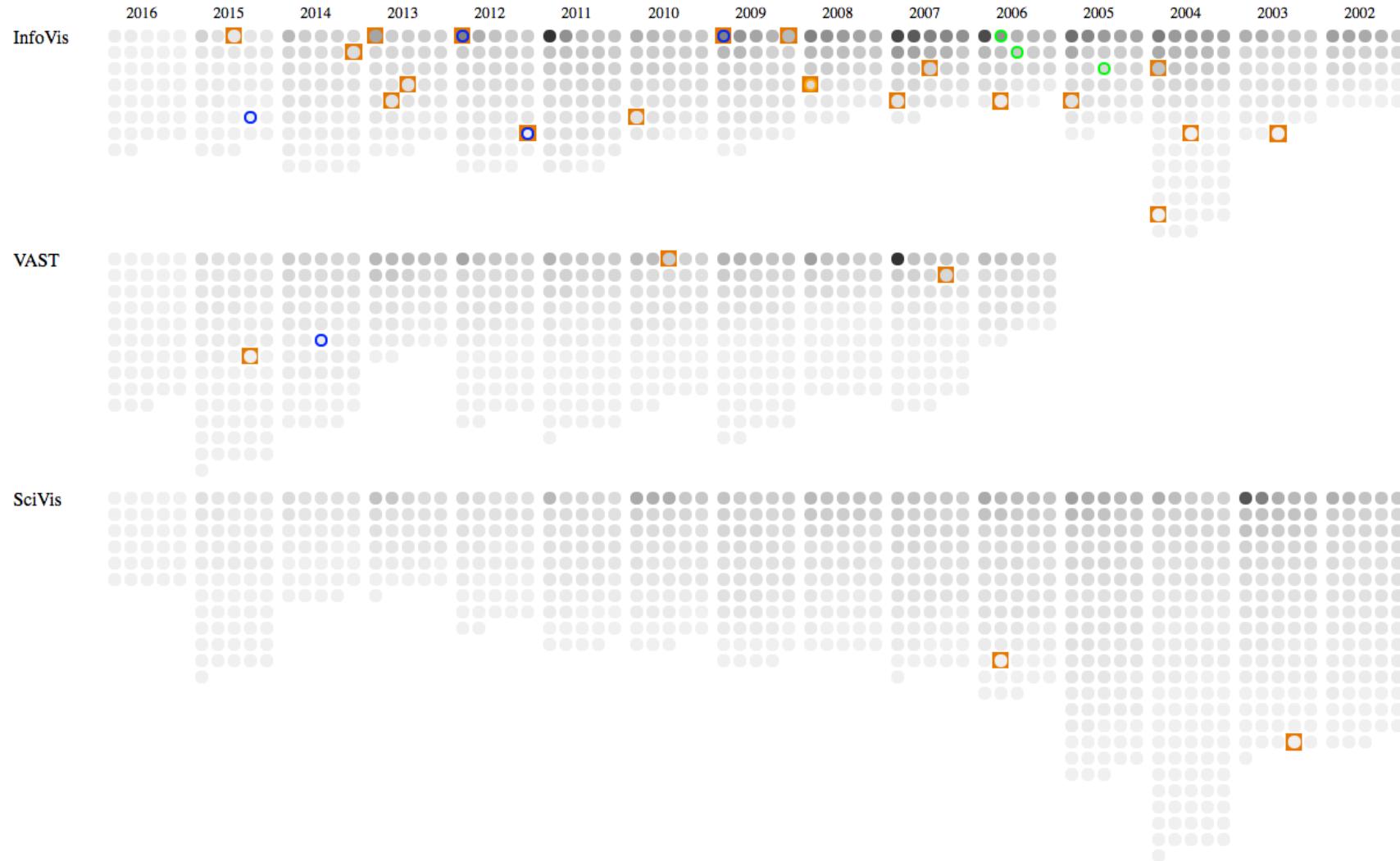
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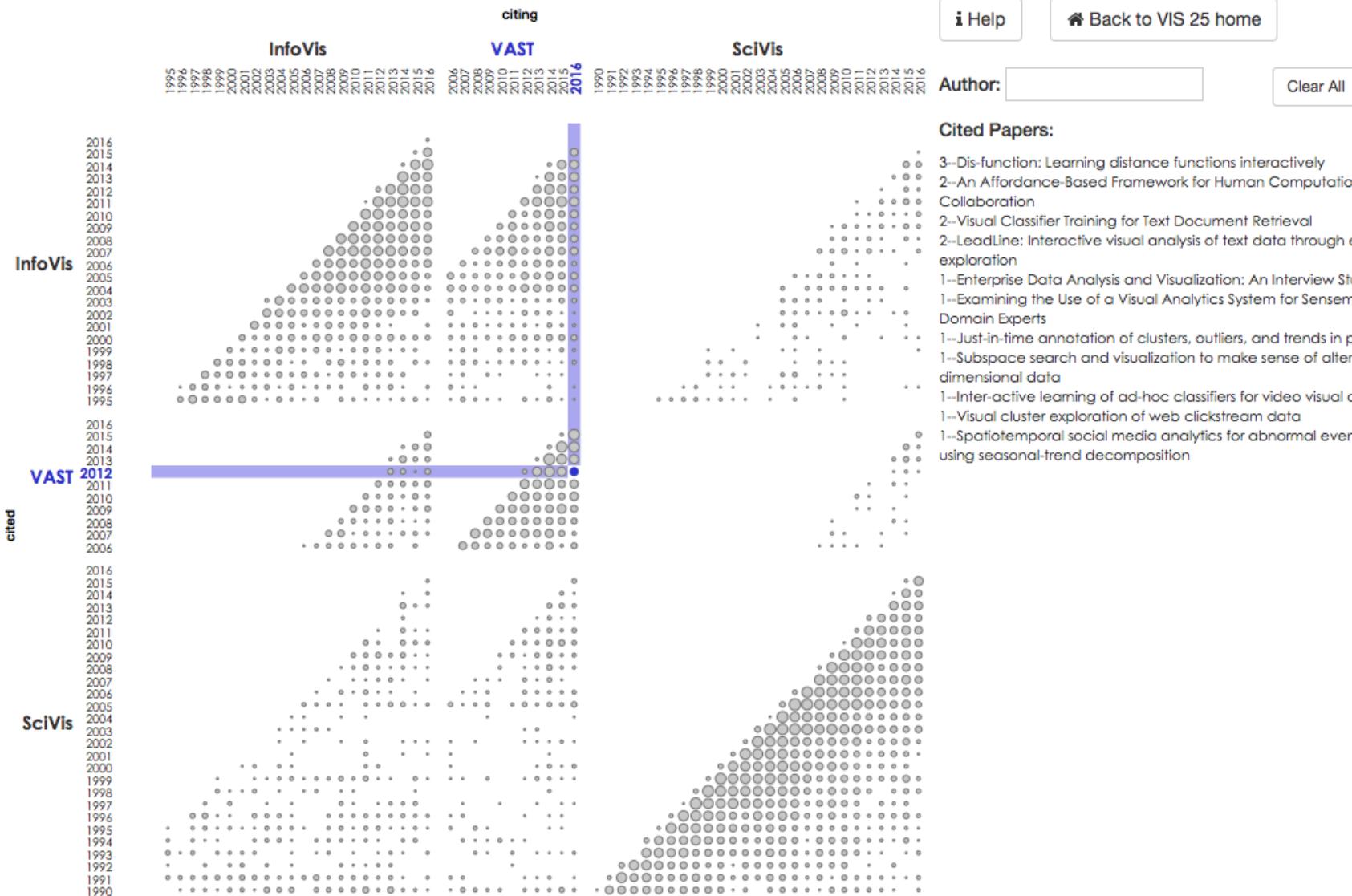
Group:  All  By Conference  By Conference and Year

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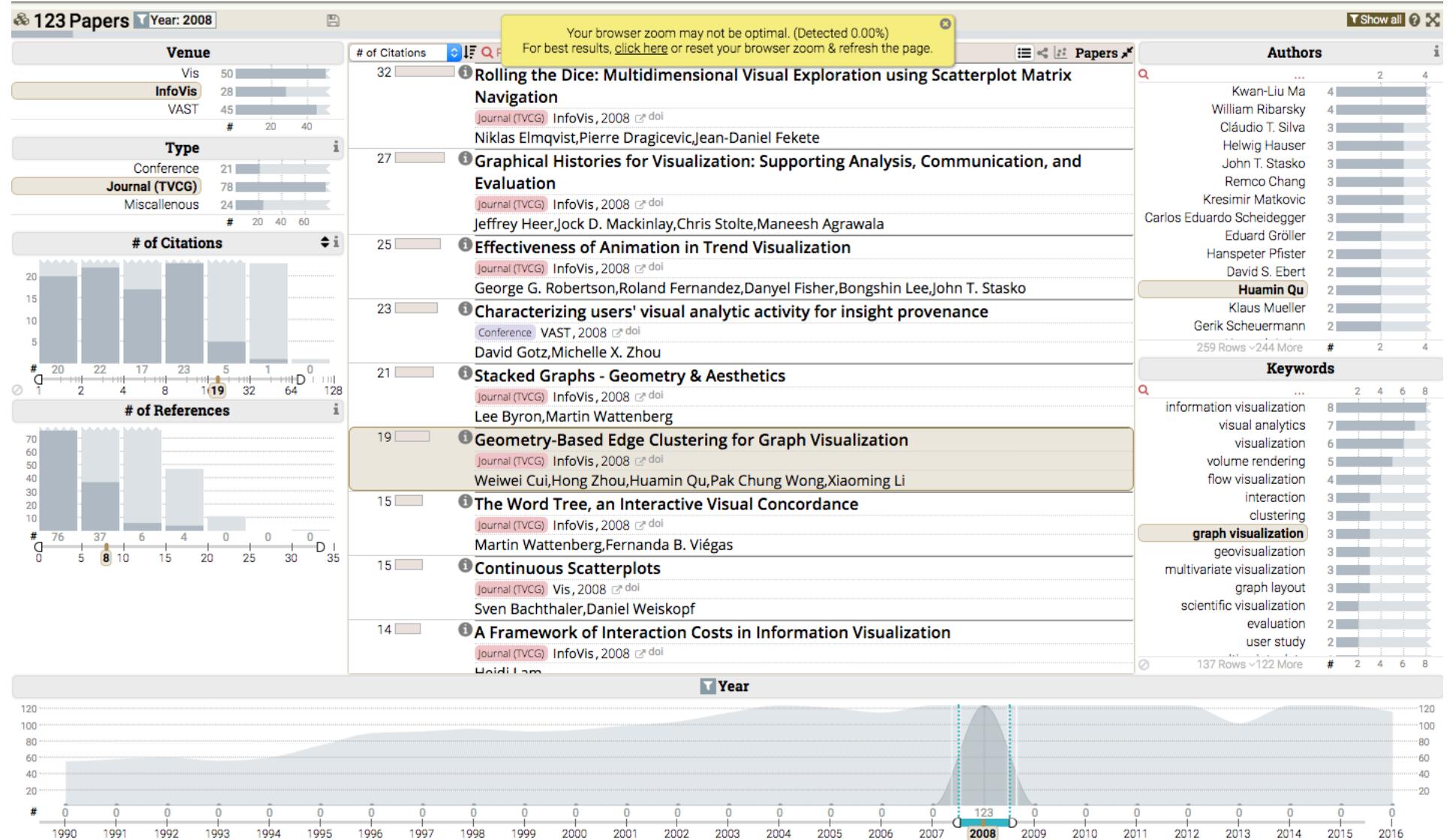
- 3--Dis-function: Learning distance functions interactively
- 2--An Affordance-Based Framework for Human Computation and Human-Computer Collaboration
- 2--Visual Classifier Training for Text Document Retrieval
- 2--LeadLine: Interactive visual analysis of text data through event identification and exploration
- 1--Enterprise Data Analysis and Visualization: An Interview Study
- 1--Examining the Use of a Visual Analytics System for Sensemaking Tasks: Case Studies with Domain Experts
- 1--Just-in-time annotation of clusters, outliers, and trends in point-based data visualizations
- 1--Subspace search and visualization to make sense of alternative clusterings in high-dimensional data
- 1--Inter-active learning of ad-hoc classifiers for video visual analytics
- 1--Visual cluster exploration of web clickstream data
- 1--Spatiotemporal social media analytics for abnormal event detection and examination using seasonal-trend decomposition

Author
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A. J. S. Wilson
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A. Johannes Pretorius
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Abish Malik
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Abraham Stephens
Adam B. Forgánc
Adam Bodnar

Conference
InfoVis
SciVis
VAST
Vis

Year
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17	Zhou, M.X.	1	4	2	2	2
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