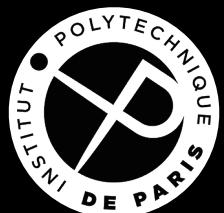


Visual Mappings

James EAGAN



Includes slides adapted from John Stasko
(Georgia Tech), Petra Isenberg & Jean-Daniel
Fekete (INRIA), Nadia Boukhefifa (INRA),
Chris North (Virginia Tech), Tamara Munzner (UBC)



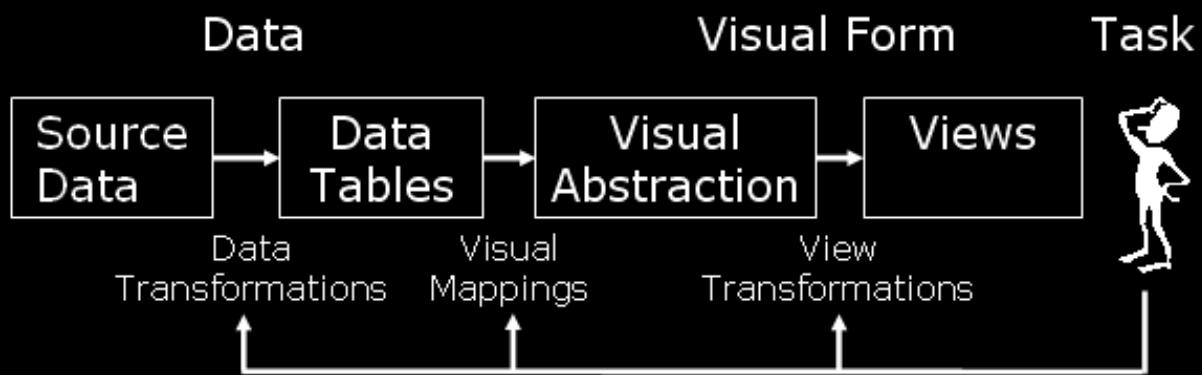
Updated: April 2020

1

How do we show the data?

2

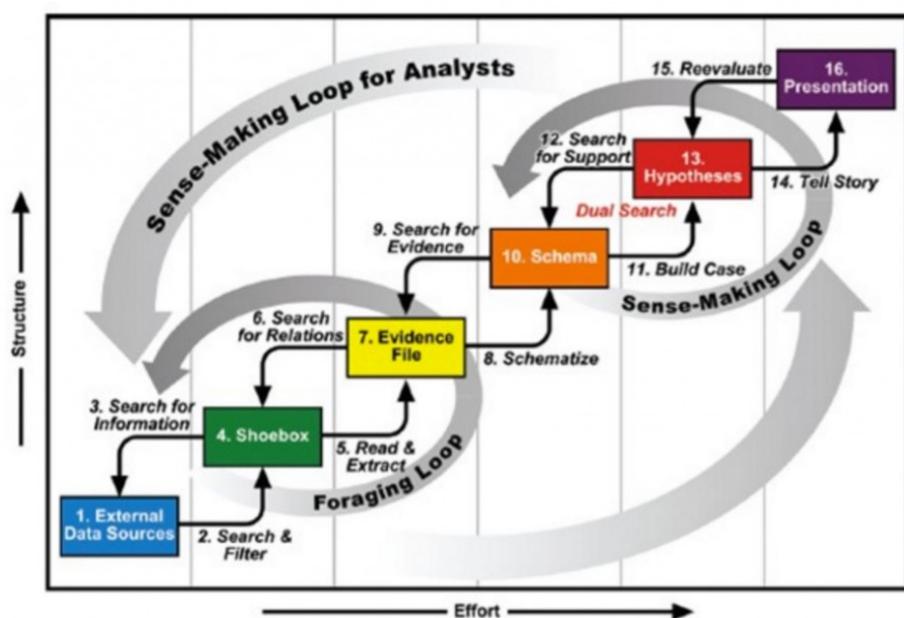
InfoVis Pipeline



3

3

Pirolli-Card Sensemaking Loop



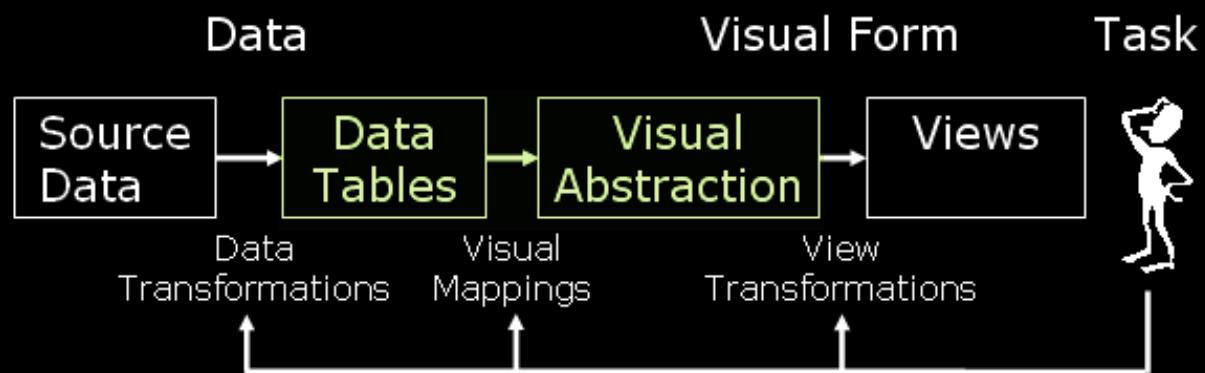
Model: Pirolli, Peter, and Stuart Card. "The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis." *Proceedings of International Conference on Intelligence Analysis*. Vol. 5. McLean, VA: Mitre, 2005.

Image source: Thomas, James J. and Kristin A. Cook "Illuminating The Path" (2005): pp. 44

4

4

InfoVis Pipeline



5

5

Map *data* to a *representation*

- Data is abstract
- Representation is more conceptual
- Use a space
- Create an *implantation* of *data* into the space

6

6

Visual Structures

- Composed of
 - Spatial substrate
 - Marks
 - Graphical properties of marks

[Bertin, Sémiologie Graphique 1967]

7

7

Space

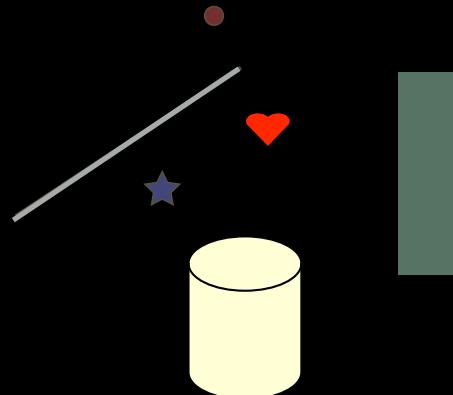
- Visually dominant
- Often put axes on space to assist
- Use techniques of
 - composition, alignment, folding,
 - recursion, overloading to
 1. increase use of space
 2. do data encodings

8

8

Marks

- Things that occur in space
 - Points
 - Lines
 - Areas
 - Volumes



9

9

Graphical Properties

also called Visual Variables

	Spatial properties	Object properties
Expressing extent	position size	greyscale
Differentiating marks	orientation	color shape texture

10

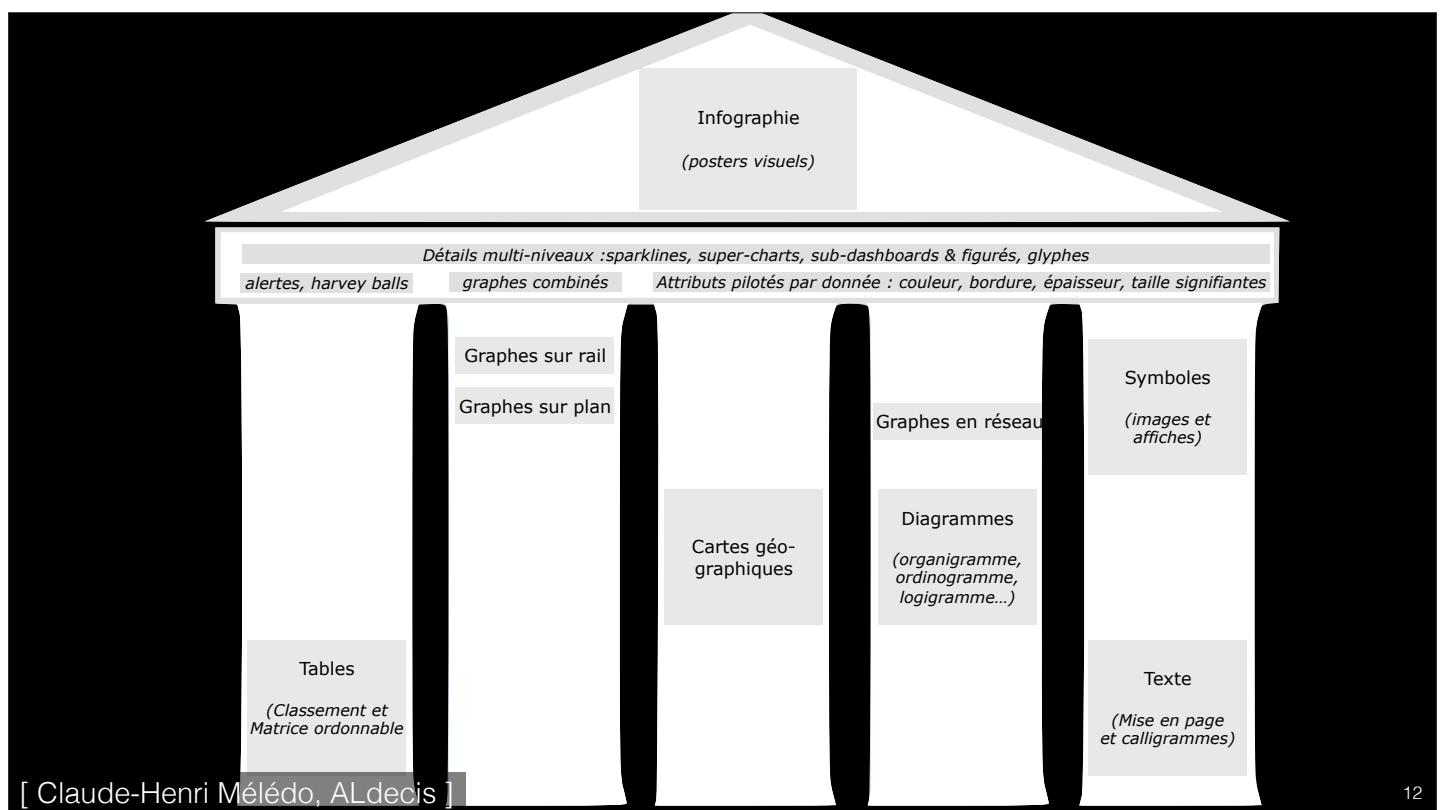
10

There are only 5 graphics

(sort of...)

11

11



12

12

Tables

	Name	At Bats	Hits	Home Run	Runs	Rbi	Walks	Years In M	Career At I	Career Hits	Car
1		INT	INT	INT	INT	INT	INT	INT	INT	INT	INT
2	STRING										
3	Andy Allanson	293	66	1	30	29	14	1	293	66	
4	Alan Ashby	315	81	7	24	38	39	14	3449	835	
5	Alvin Davis	479	130	18	66	72	76	3	1624	457	
6	Andre Dawson	496	141	20	65	78	37	11	5628	1575	
7	Andres Galarraga	321	87	10	39	42	30	2	396	101	
8	Alfredo Griffin	594	169	4	74	51	35	11	4408	1133	
9	Al Newman	185	37	1	23	8	21	2	214	42	
10	Argenis Salaza	298	73	0	24	24	7	3	509	108	
11	Andres Thomas	323	81	6	26	32	8	2	341	86	
12	Andre Thornton	401	92	17	49	66	65	13	5206	1332	
13	Alan Trammell	574	159	21	107	75	59	10	4531	1300	
14	Alex Trevino	202	53	4	31	26	27	9	1876	467	
15	Andy Van Slyk	418	113	13	48	61	47	4	1512	392	
16	Alan Wiggins	239	60	0	30	11	22	6	1941	510	
17	Bill Almon	196	43	7	29	27	30	13	3231	825	
18	Billy Beane	183	39	3	20	15	11	3	201	42	
19	Buddy Bell	568	158	20	89	75	73	15	8068	2273	
20	Buddy Biancalca	190	46	2	24	8	15	5	479	102	
21	Bruce Bochte	407	104	6	57	43	65	12	5233	1478	
	baseball	127	32	8	16	22	14	9	707	199	

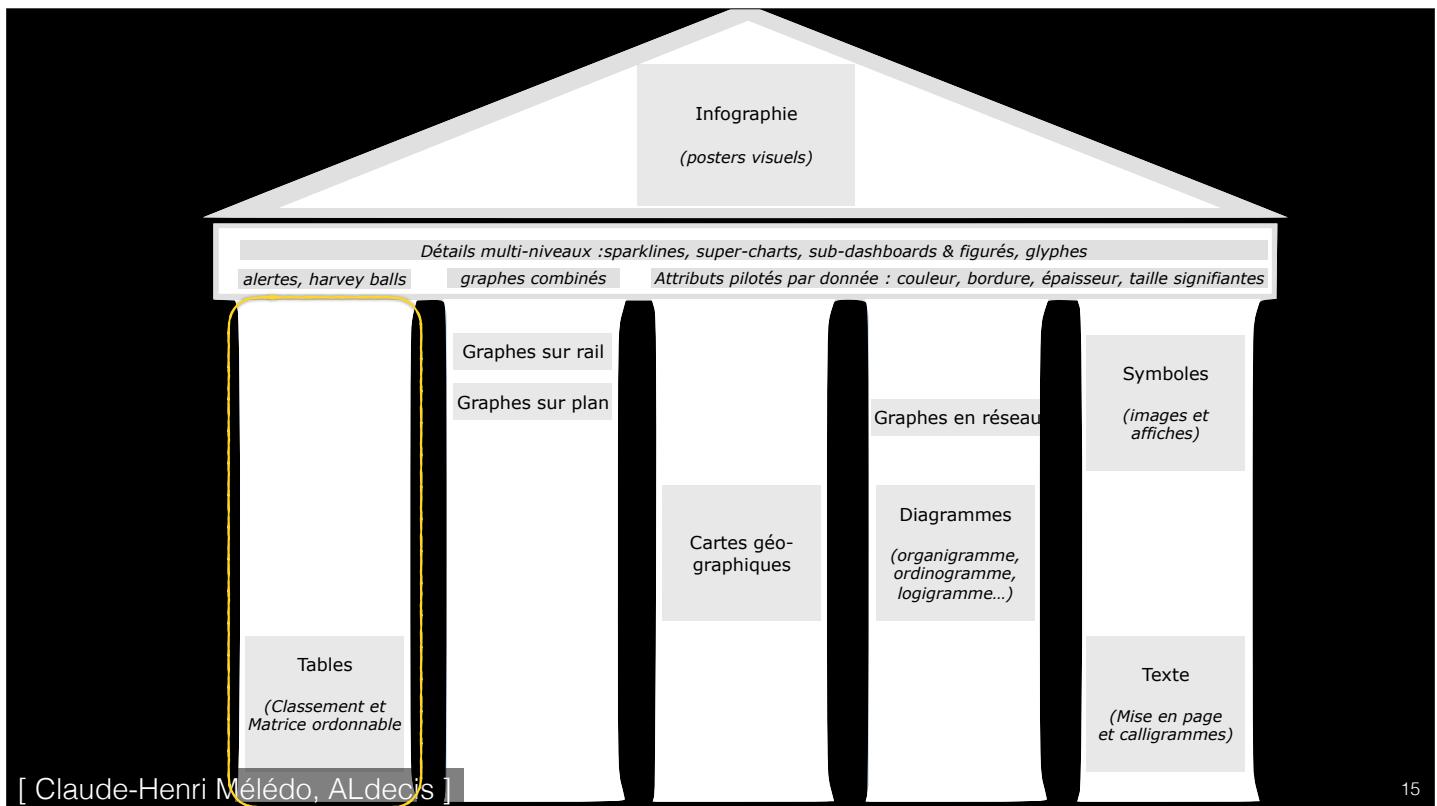
13

13

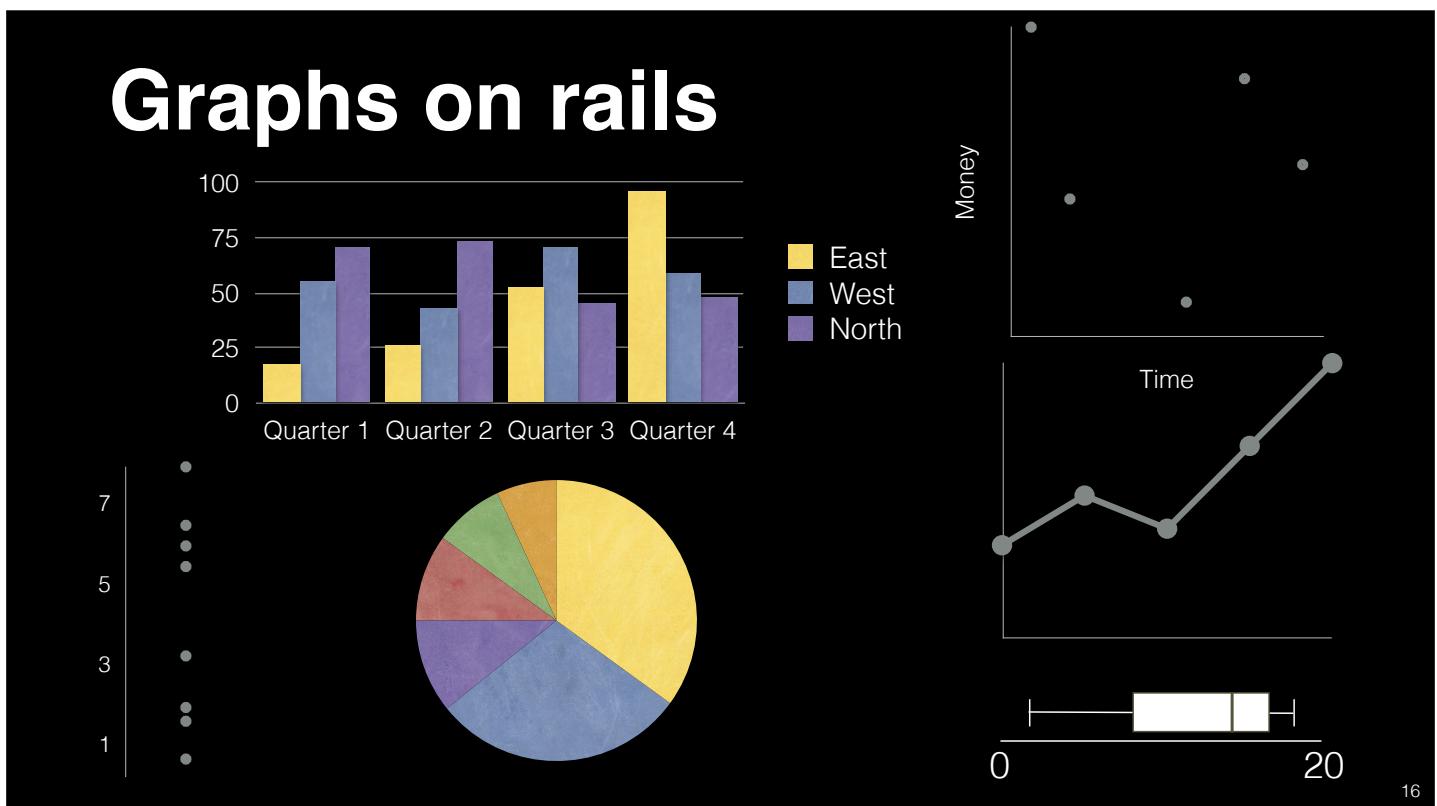
Bullet Train Schedule

14

14

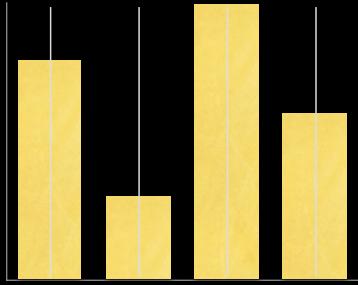


15



16

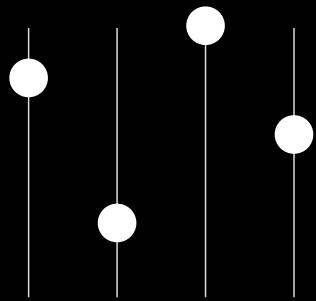
Graphs on rails



17

17

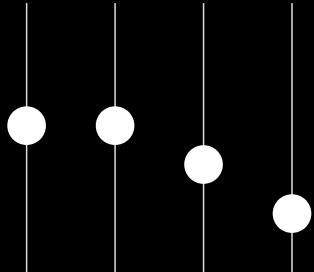
Graphs on rails



18

18

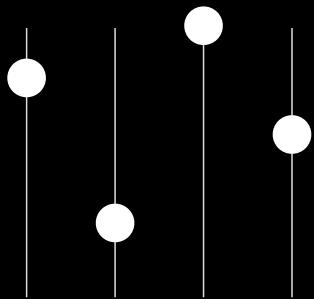
Graphs on rails



19

19

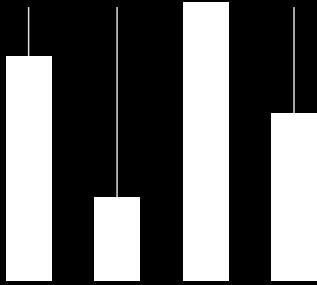
Graphs on rails



20

20

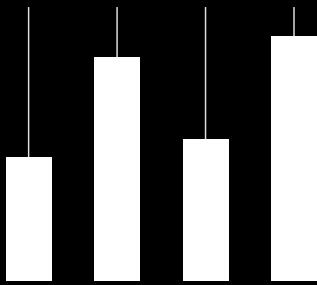
Graphs on rails



21

21

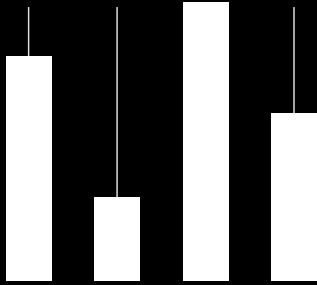
Graphs on rails



22

22

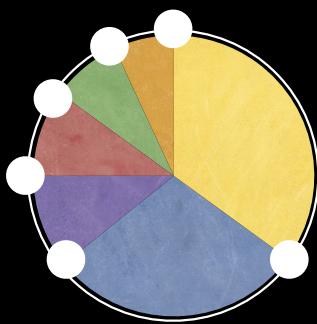
Graphs on rails



23

23

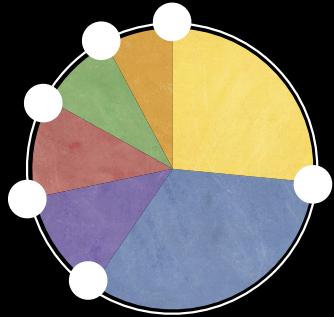
Graphs on rails



24

24

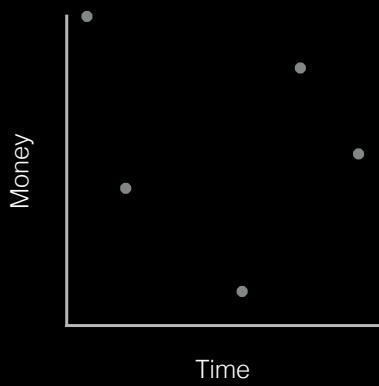
Graphs on rails



25

25

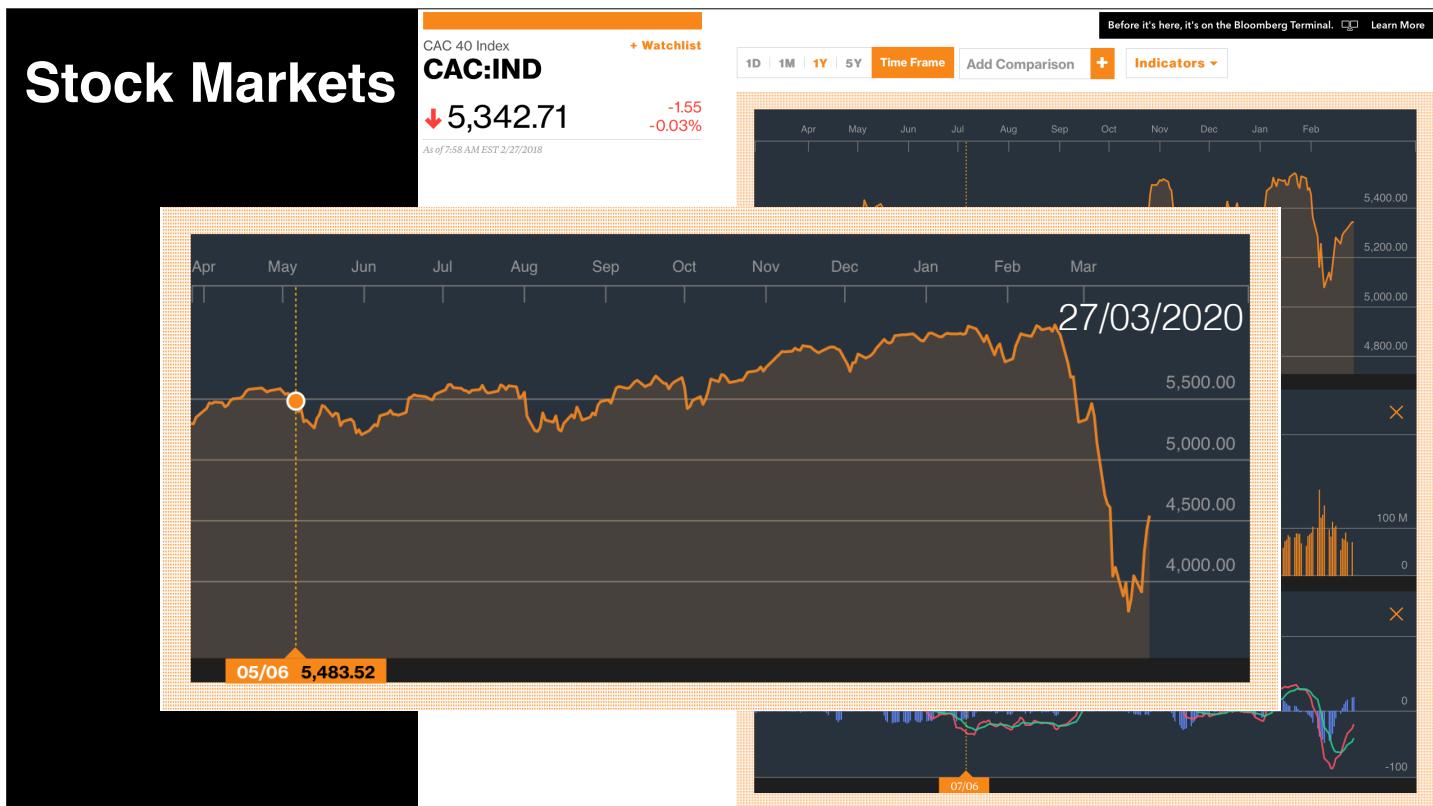
Graphs on the plane



26

26

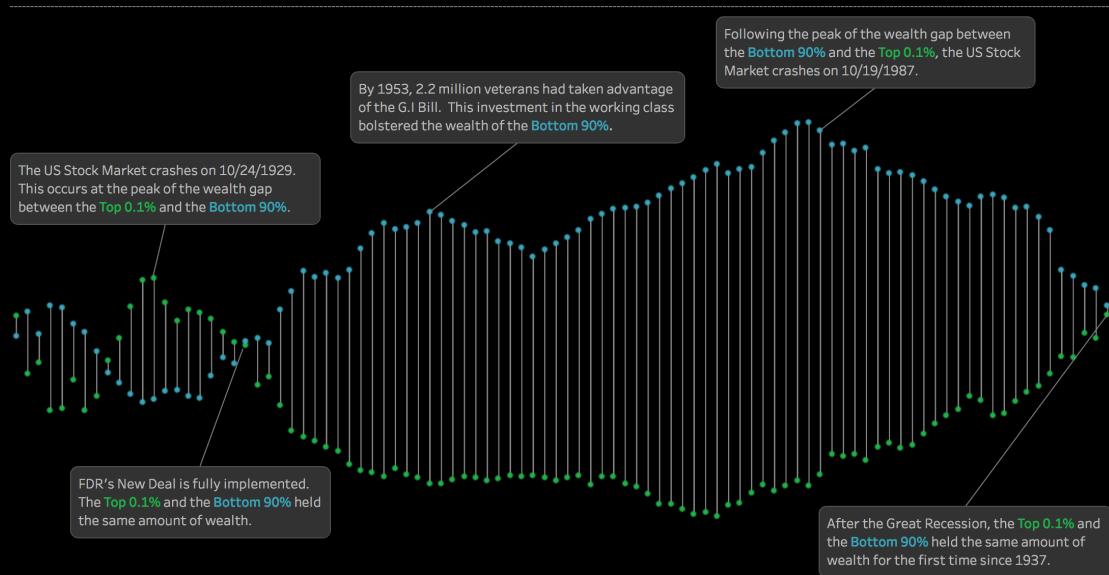
Stock Markets



27

The Wealth Gap

A historical view of wealth ownership within the **Top 0.1%** and the **Bottom 90%** of US households



1921 1924 1927 1930 1933 1936 1939 1942 1945 1948 1951 1954 1957 1960 1963 1966 1969 1972 1975 1978 1981 1984 1987 1990 1993 1996 1999 2002 2005 2008 2011

Source: <http://www.businessinsider.com/share-of-us-household-wealth-by-income-level-2016-11>

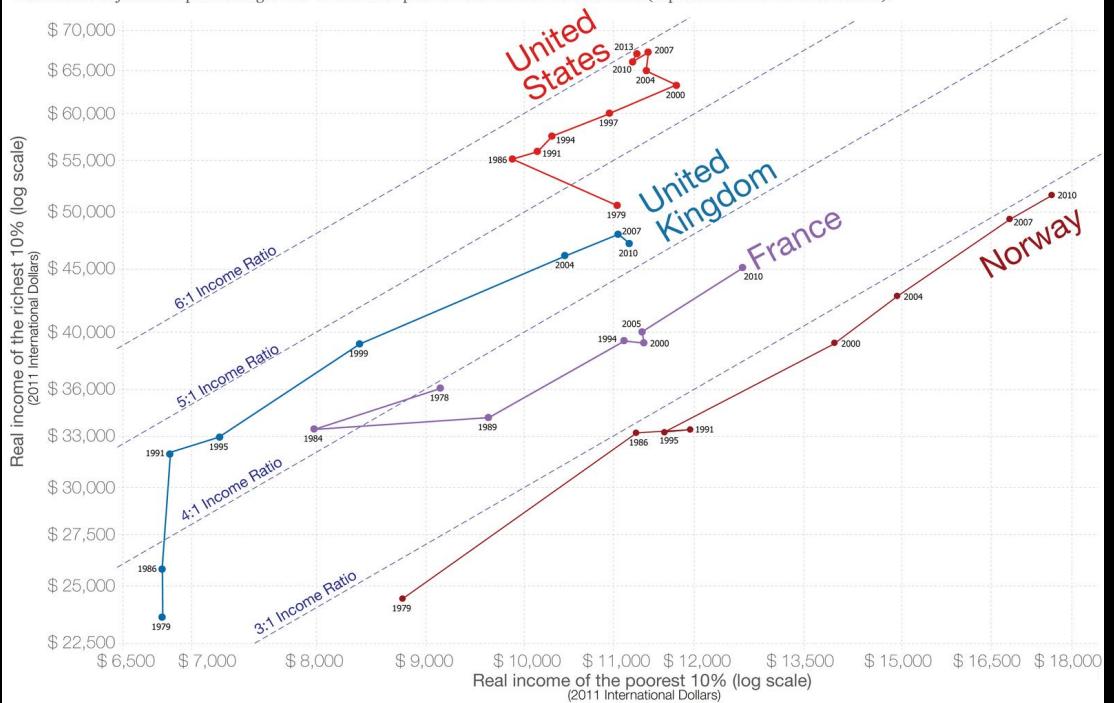
Designer: <https://twitter.com/sirvzialot>

28

Income growth of the poorest 10% vs income growth of the richest 10%

Incomes are real disposable household incomes. Shown is the income cutoff between the richest and poorest 10% and the rest of the population. Incomes are adjusted for price changes over time and for price differences between countries (expressed in international dollars).

OurWorld
in Data



[Max Roser]

Data source: 'Incomes across the Distribution Database' by Stefan Thewissen, Brian Nolan, and Max Roser. Based on LIS data. The data visualization is available at OurWorldinData.org. There you find the raw data and more visualizations on inequality and growth.

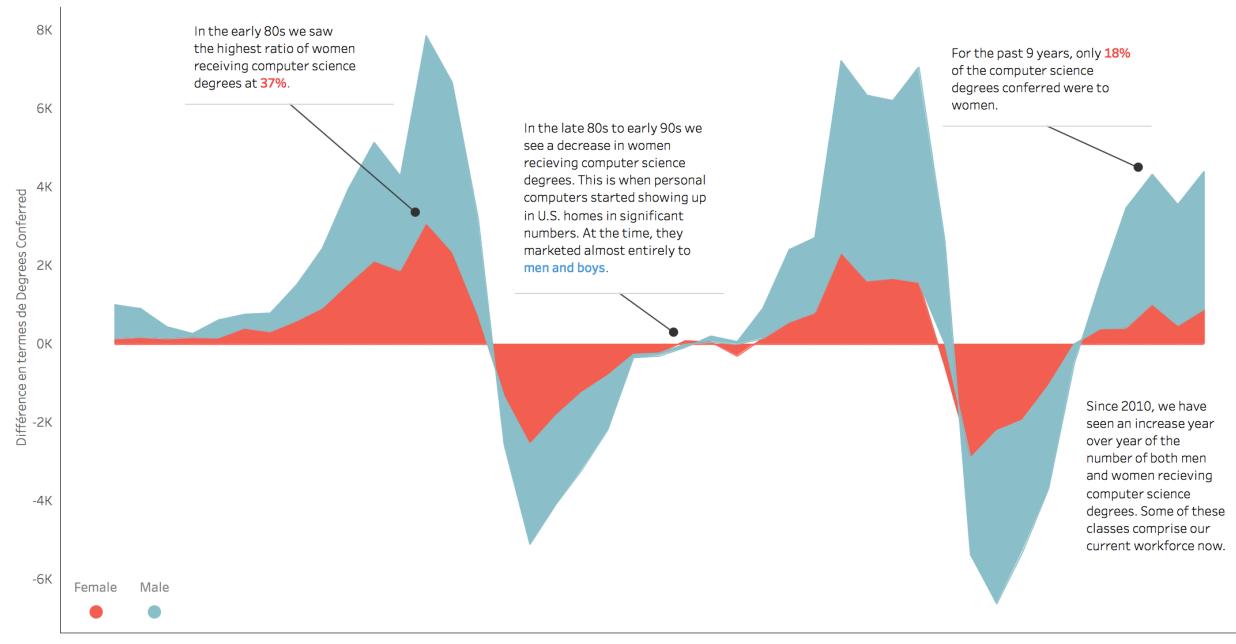
Licensed under CC-BY-SA by the author Max Roser.

29

29

Computer Science Bachelor Degrees in the U.S. - Year/Year Changes

Chart shows the yearly changes by gender annotated for context

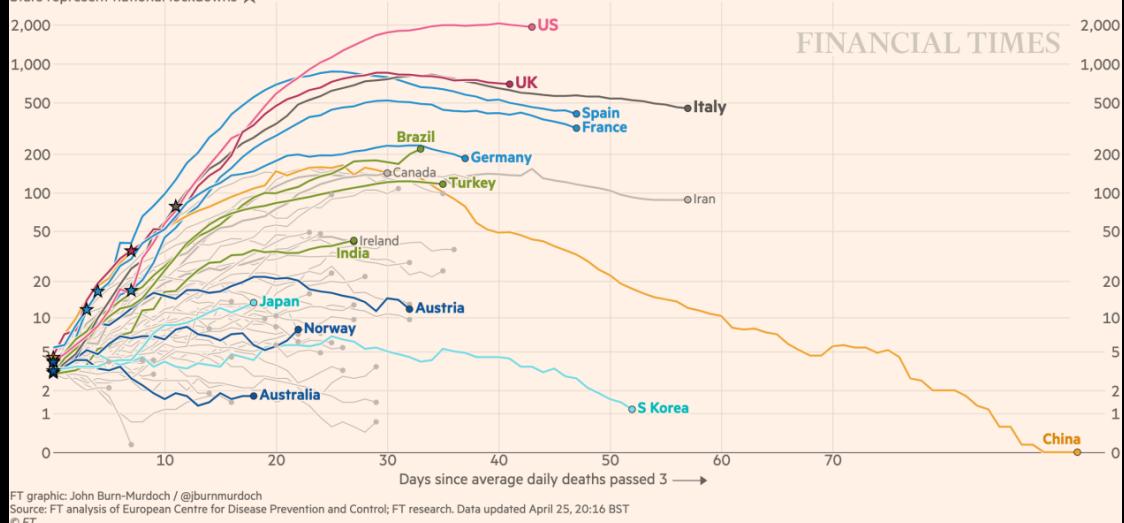


30

Line chart

Daily death tolls are now at their peak or falling in many western countries

Daily deaths with coronavirus (7-day rolling average), by number of days since 3 daily deaths first recorded
Stars represent national lockdowns ★



[Financial Times, 27/04/2020]

31

31

Matrix – Flights

<http://matrix.itasoftware.com/view/flights?session=d6bae5ea-16ef-4e2a-861d-7c892a9a4>

Flight 1: Paris to San Francisco - lun., juin 13

PRICE ▾	FROM/TO ▾	AIRLINE ▾	DEPART ▾	ARRIVE ▾	DURATION ▾	STOPS ▾	ADVISORY ▾								
Paris time San Francisco time	8a 11p	10a 1a	12p 3a	2p 5a	4p 7a	6p 9a	8p 11a	10p 1p	12a 3p	2a 5p	MAR., JUIN 14	4a 7p	6a 9p	8a 11p	10a 1a
From 737 €	CDG to SFO	US					CLT	US							
From 780 €	CDG to SFO	DL					MSP	DL							
From 788 €	CDG to SFO	DL						SLC	DL*						
From 788 €	CDG to SFO	AF													
From 790 €	CDG to SFO	DL*													
From 813 €	CDG to SFO	AF*					MSP	DL							
From 813 €	CDG to SFO		CO*				IAD	CO*							
From 815 €	CDG to SFO	LH	FRA		LH*										
From 815 €	CDG to SFO	LH	FRA		CO*										
From 815 €	CDG to SFO	LH	FRA		UA										
From 815 €	CDG to SFO	LH	FRA	LH*											
From 815 €	CDG to SFO	LH	FRA	UA											
From 815 €	CDG to SFO	LH	FRA	CO*											
From 815 €	CDG to SFO	CO					IAH	CO							
From 815 €	CDG to SFO		IUA	FDA	IUA										

32

Infographie

(posters visuels)

Détails multi-niveaux :sparklines, super-charts, sub-dashboards & figurés, glyphs

[Alertes](#), [Harvey](#), [Bush](#)

Attributs pilotés par donnée : couleur, bordure, épaisseur

Graphes sur rail

Graphes sur plan

Tables

Graphes en réseau

Symboles

Diagrammes
(organigramme,
ordinogramme,

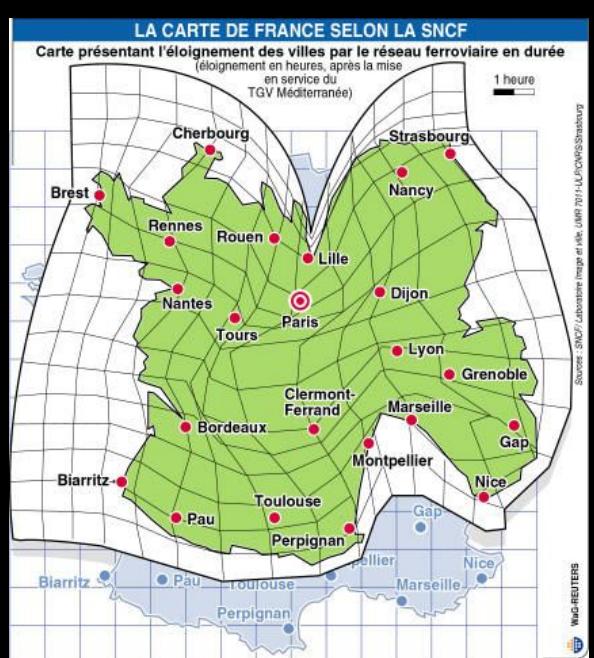
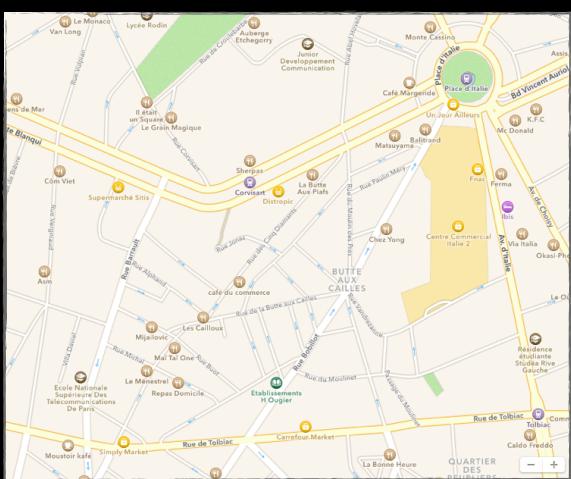
Texte

[Claude-Henri Mélédo, ALdecis]

33

33

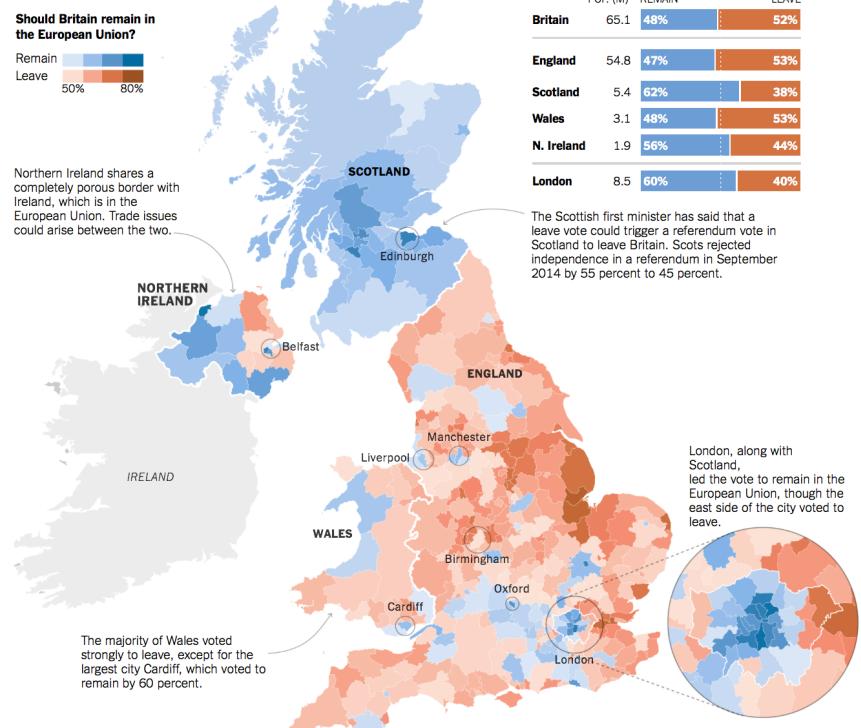
Geospatial maps



34

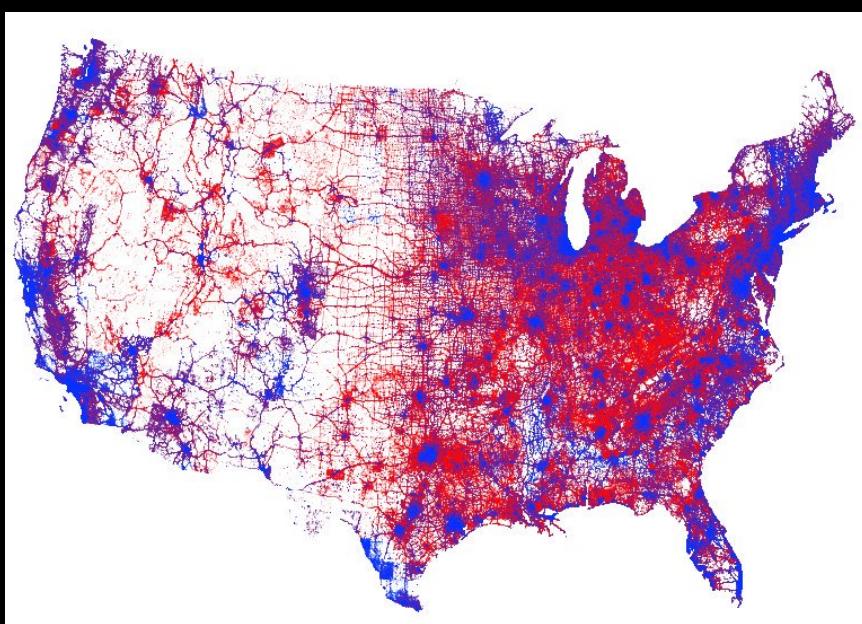
34

Brexit



35

35



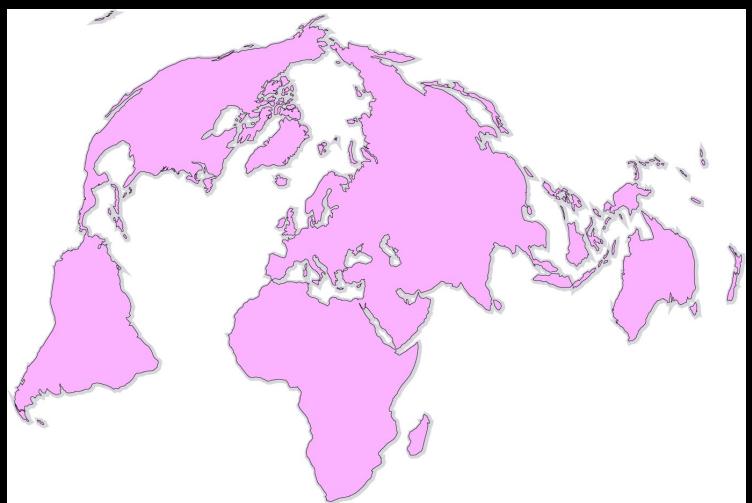
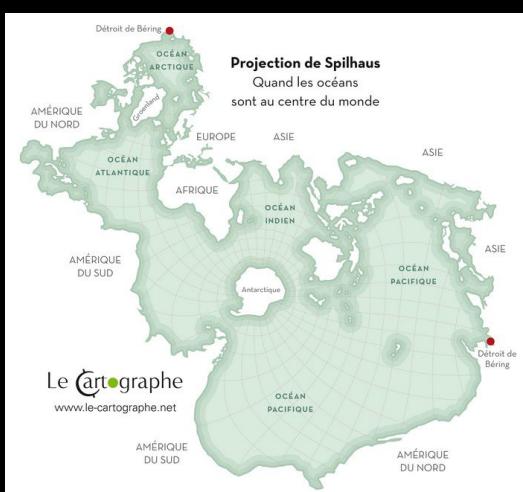
36

36

E.U.



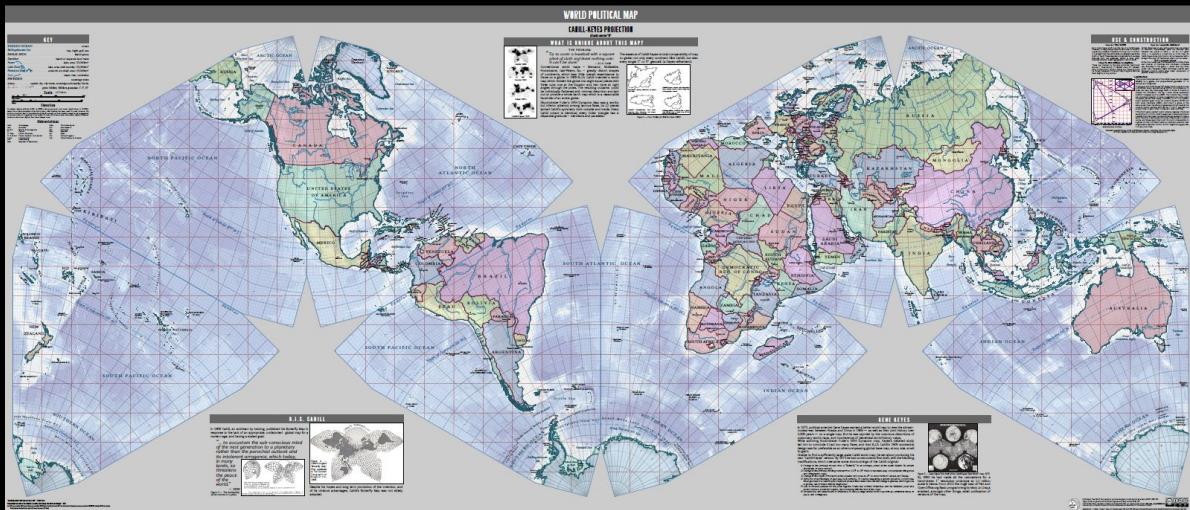
37



38

38

Duncan-Webb



[Source : [Wired](#)]

39

39

Country Music

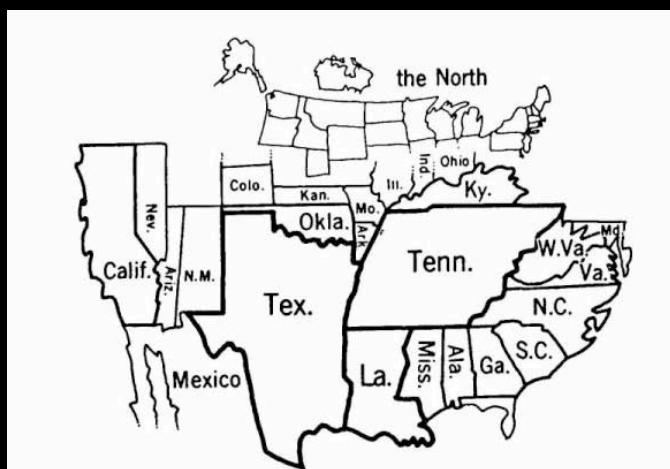


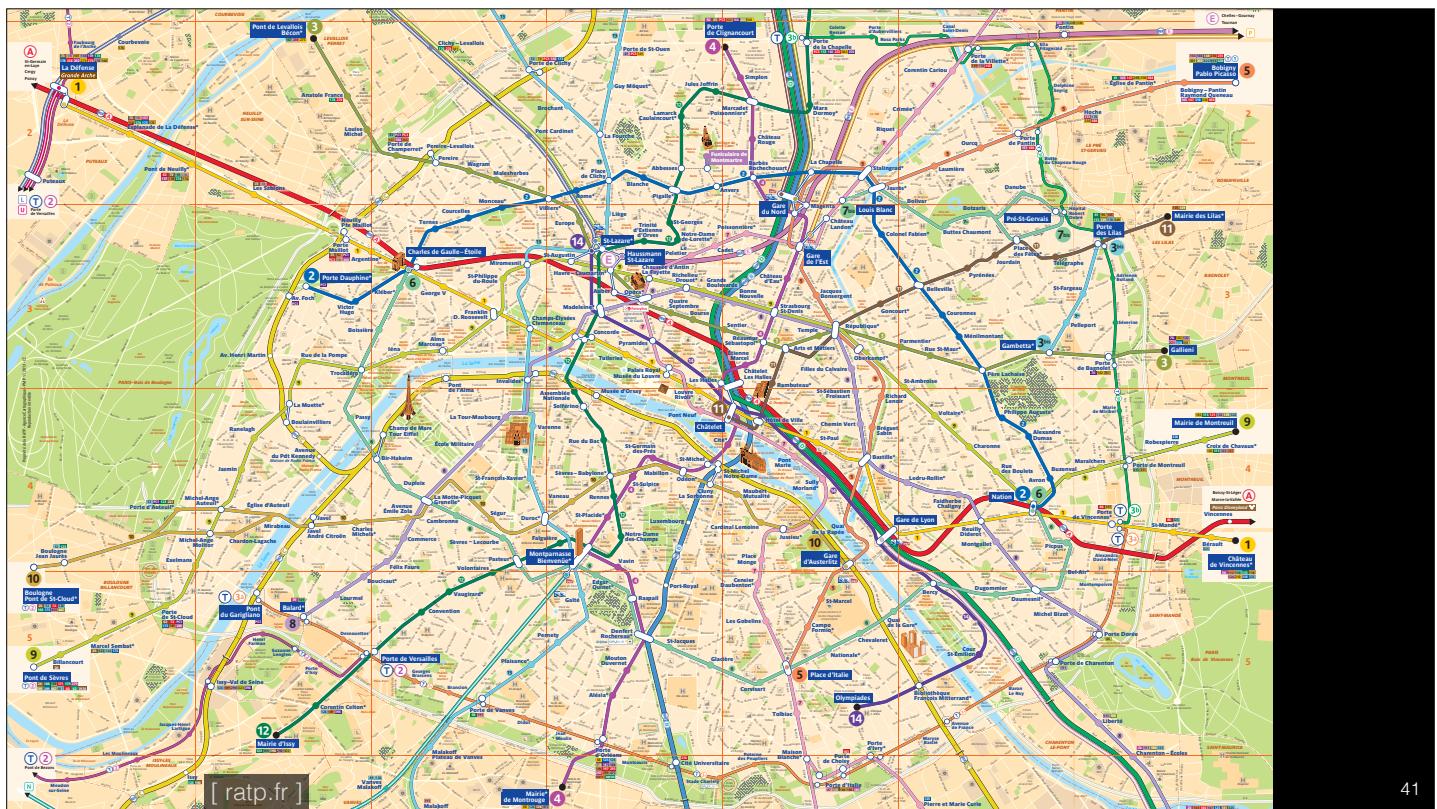
Figure 14. States Mentioned in Country-Music Lyrics

Source: Ben Marsh, "A Rose-Colored Map," *Harper's*, July 1977, 80. Used by permission.

Note: The size of each state is proportional to the number of times it is mentioned.

40

40

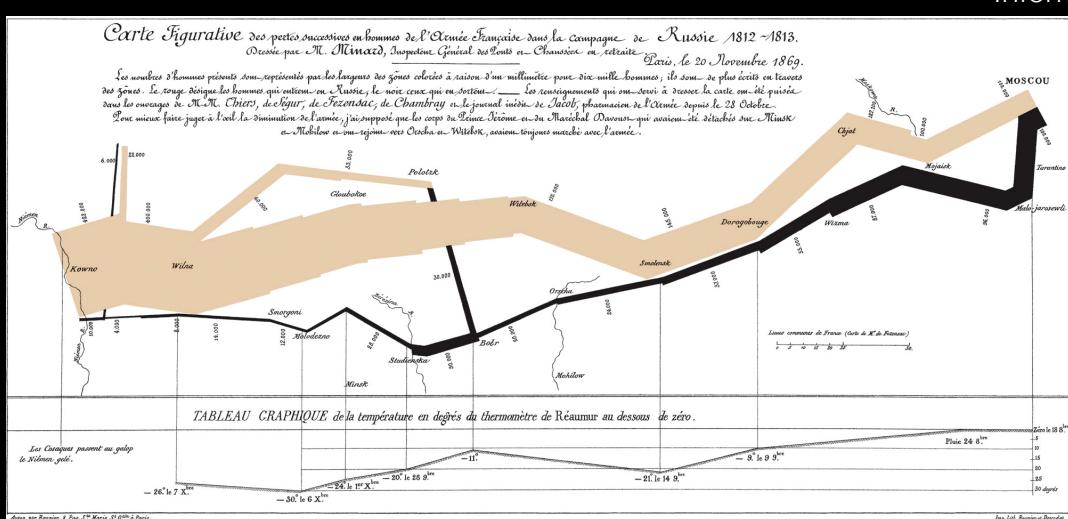


41

41

Napoleonic's March

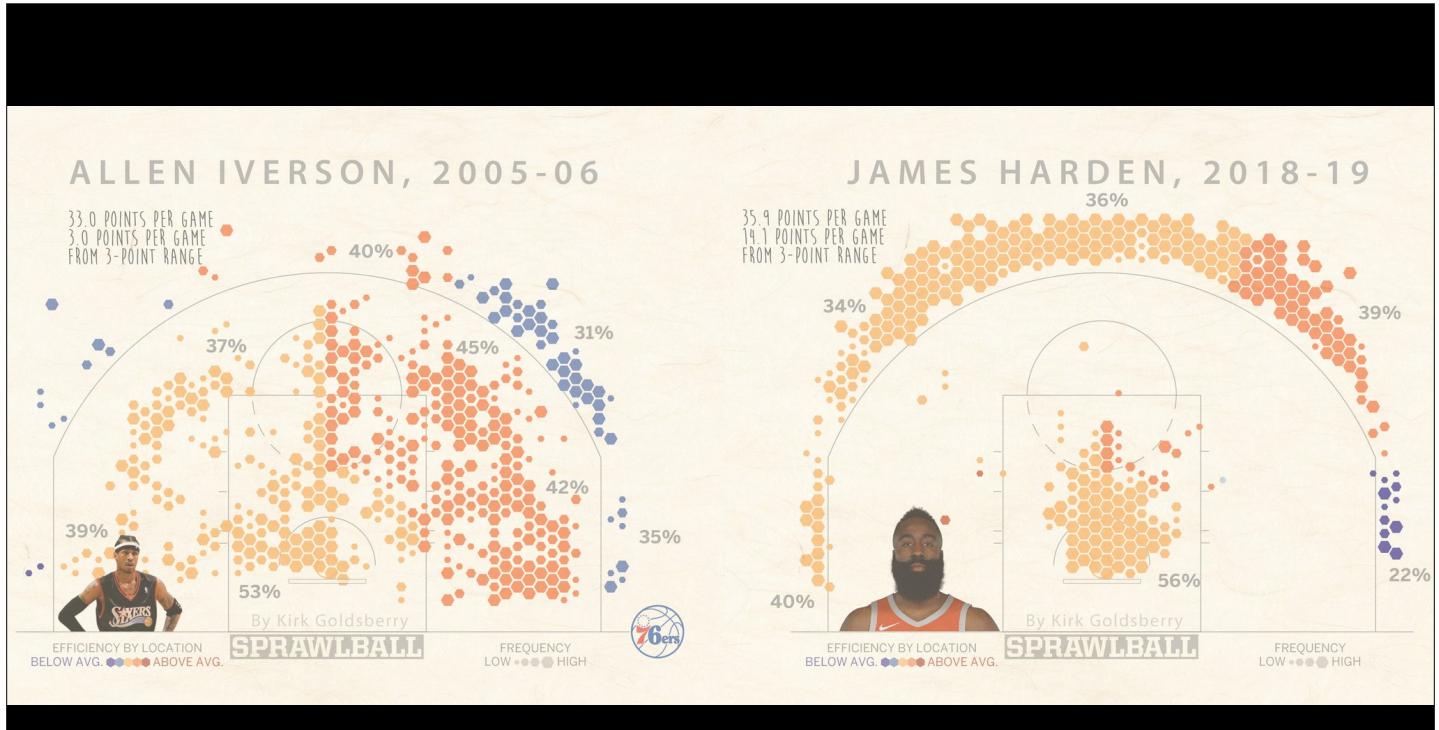
From E. Tufte
The Visual Display of Quantitative Information



Graphic by Minard

size of army
directionlatitude
longitude temperature
date

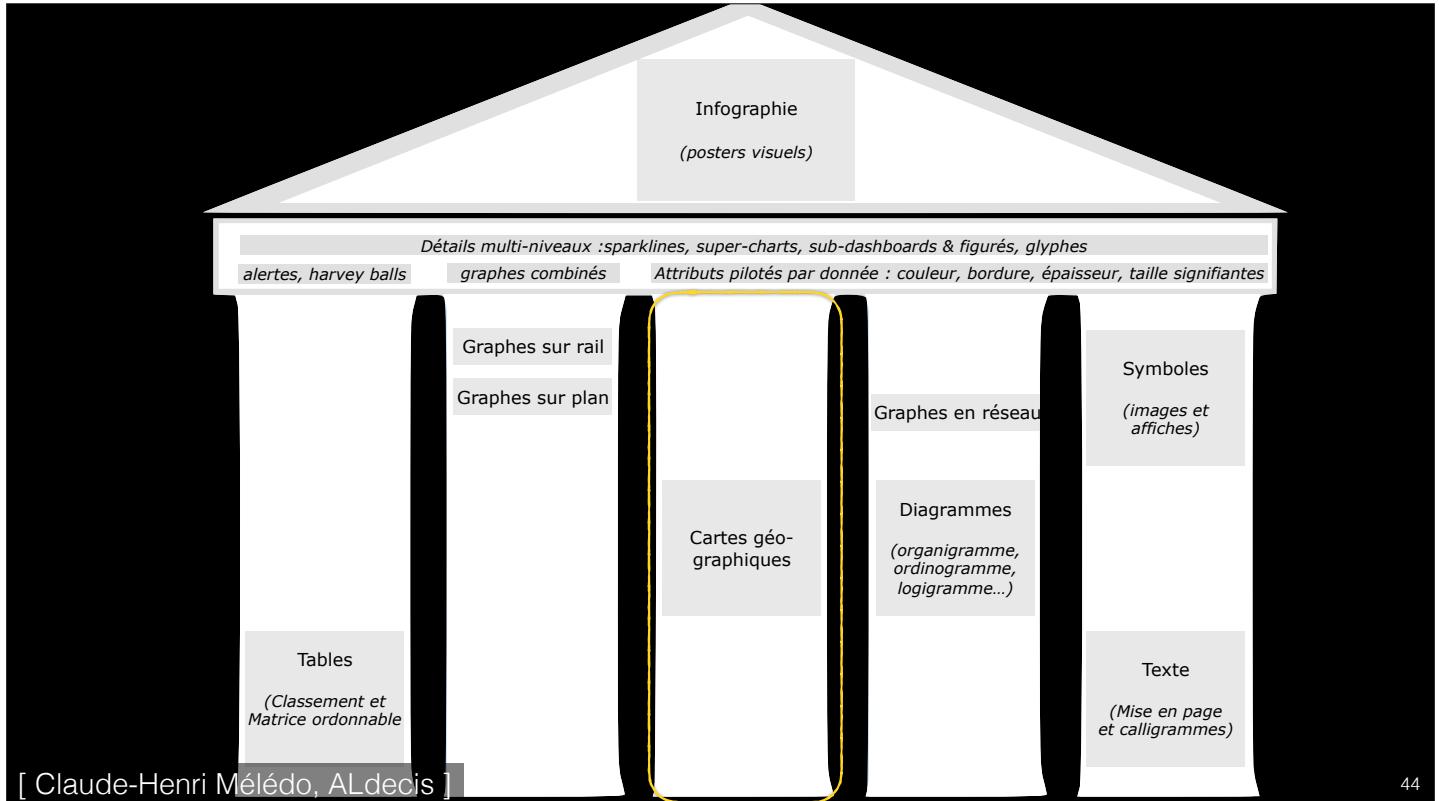
42



[Source : Kirk Goldsberry ([@kirkgoldsberry](#))]

43

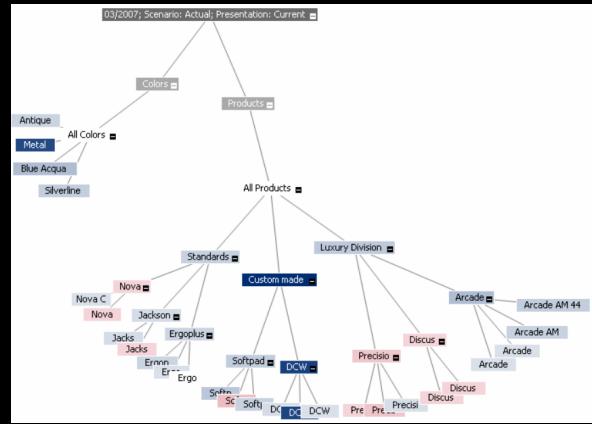
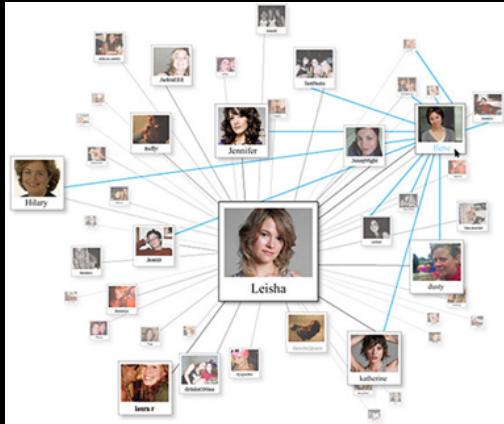
43



[Claude-Henri Mélédo, ALdecis]

44

Networks & Diagrams

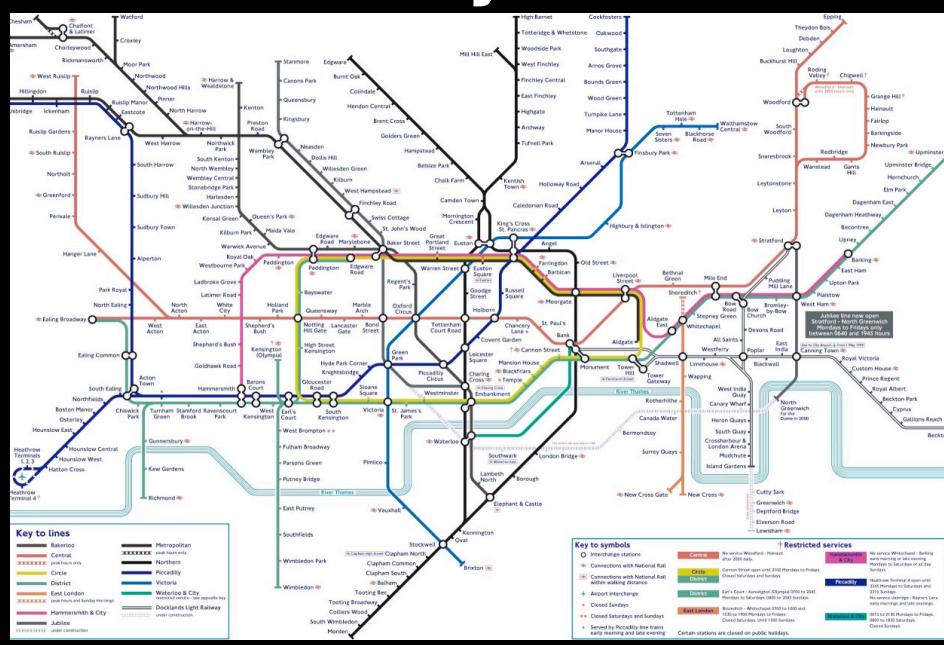


45

45

London Subway

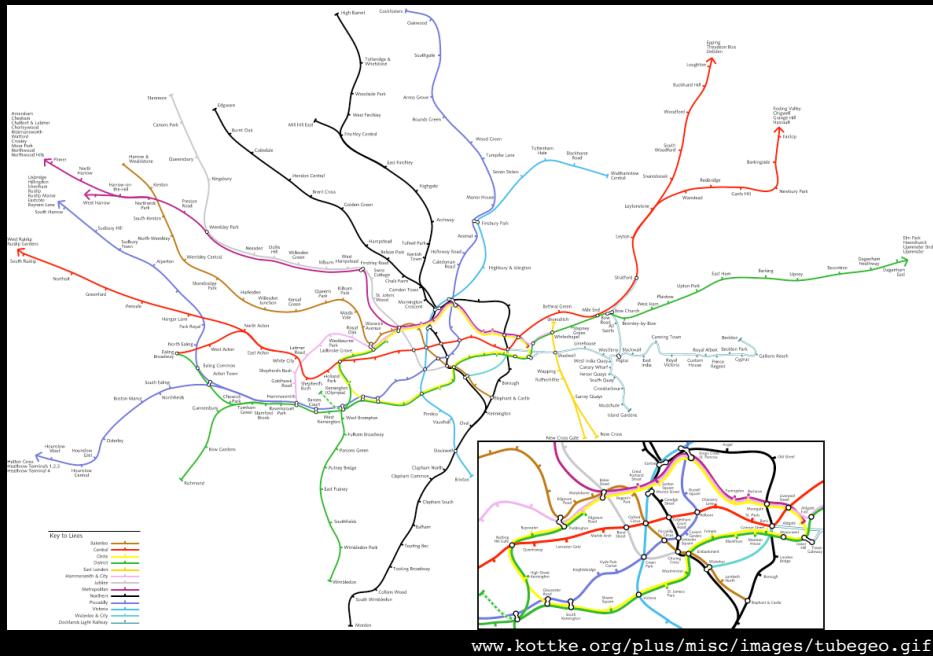
www.thetube.com



46

46

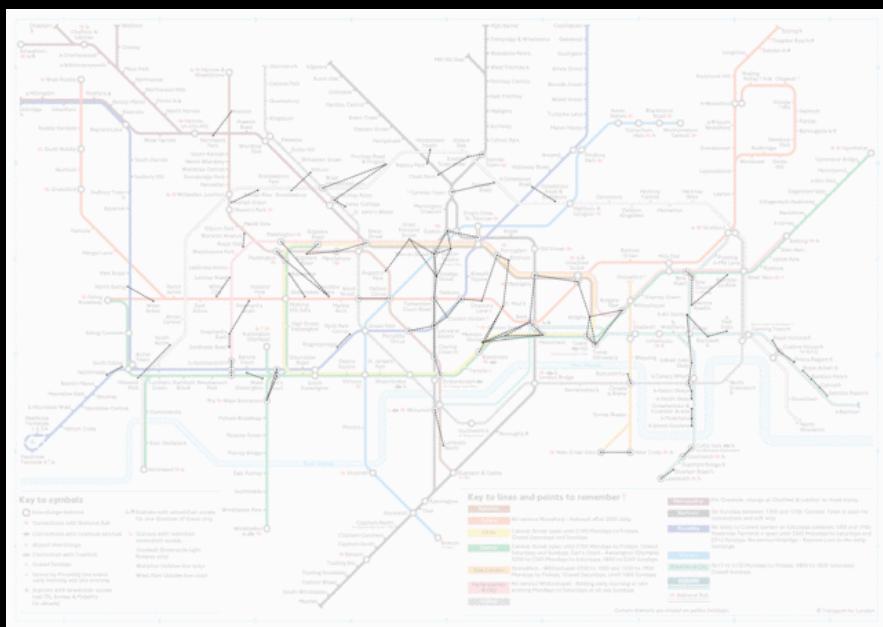
True Geography



47

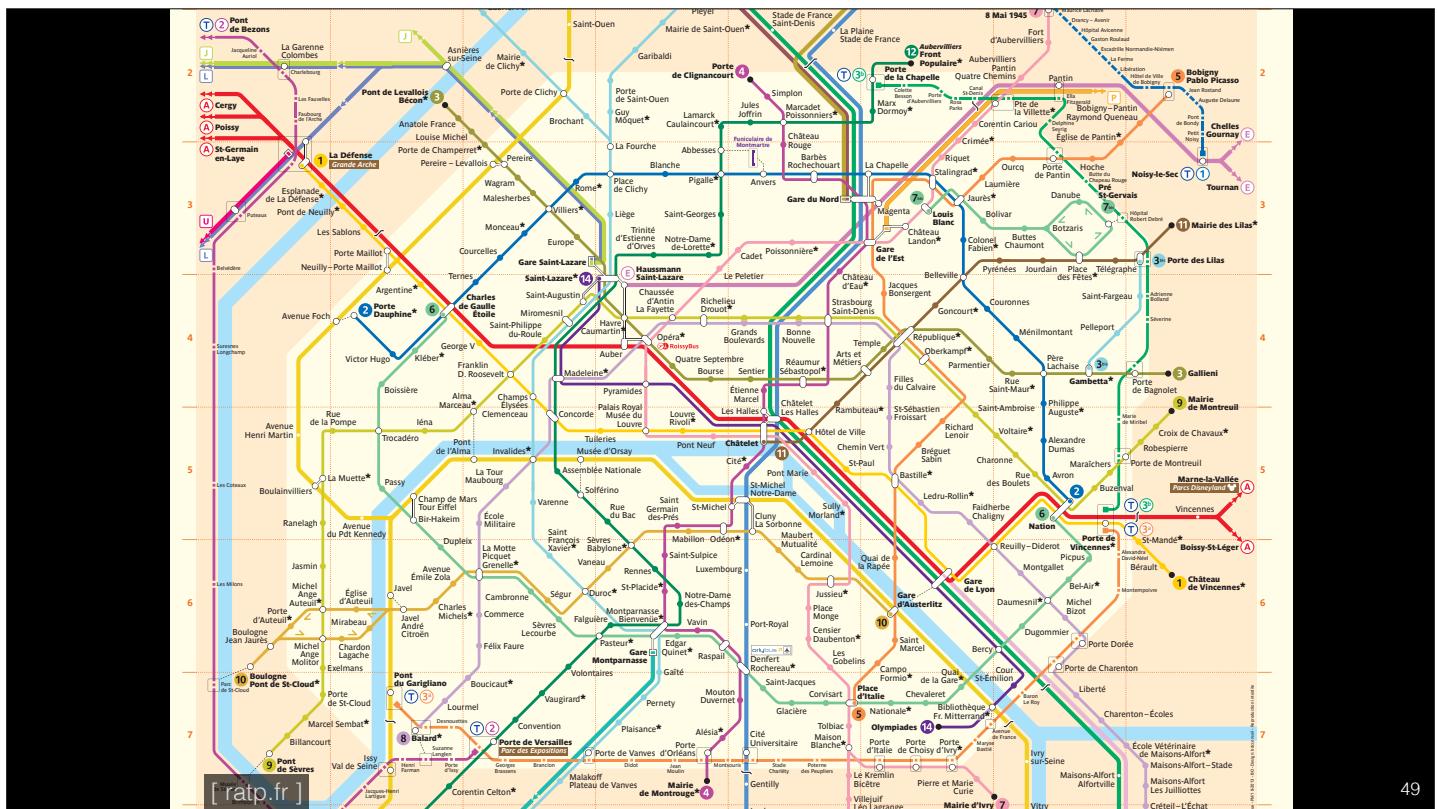
47

Easy Walking Lines Added

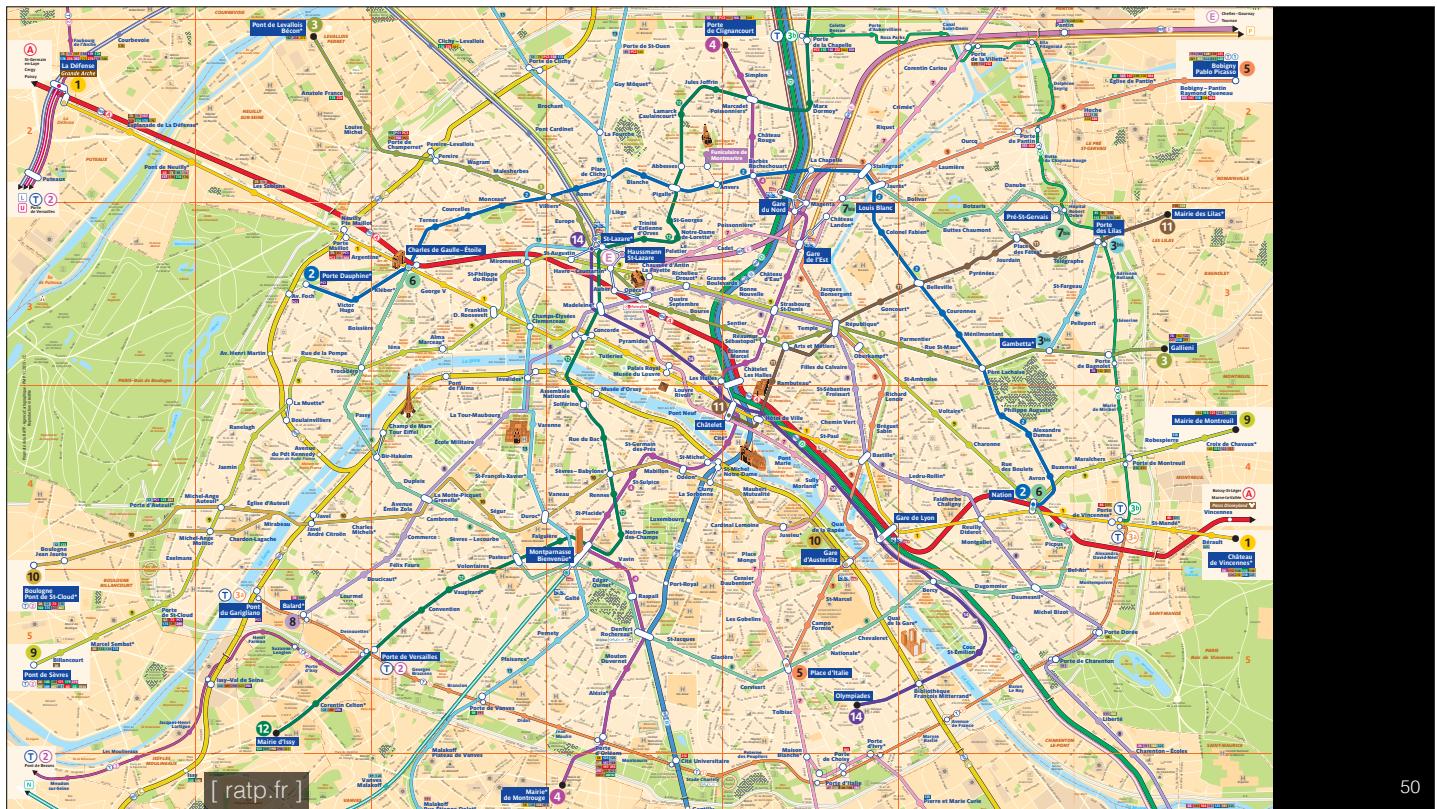


48

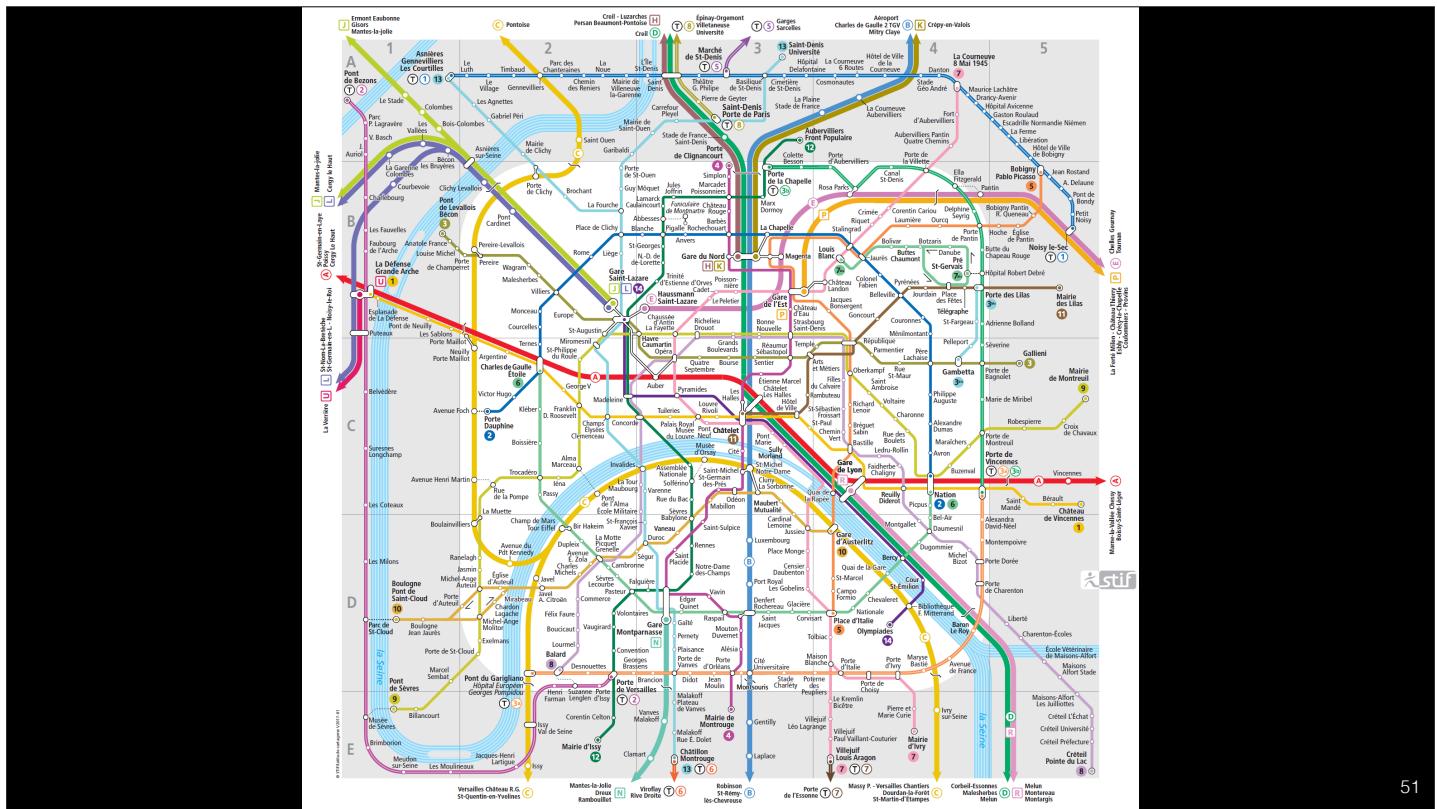
48



49



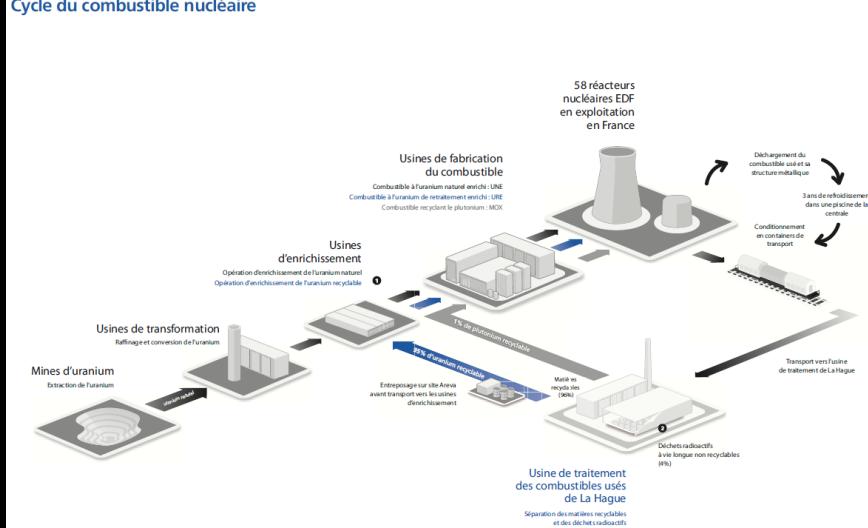
50



51

Networks & Diagrams

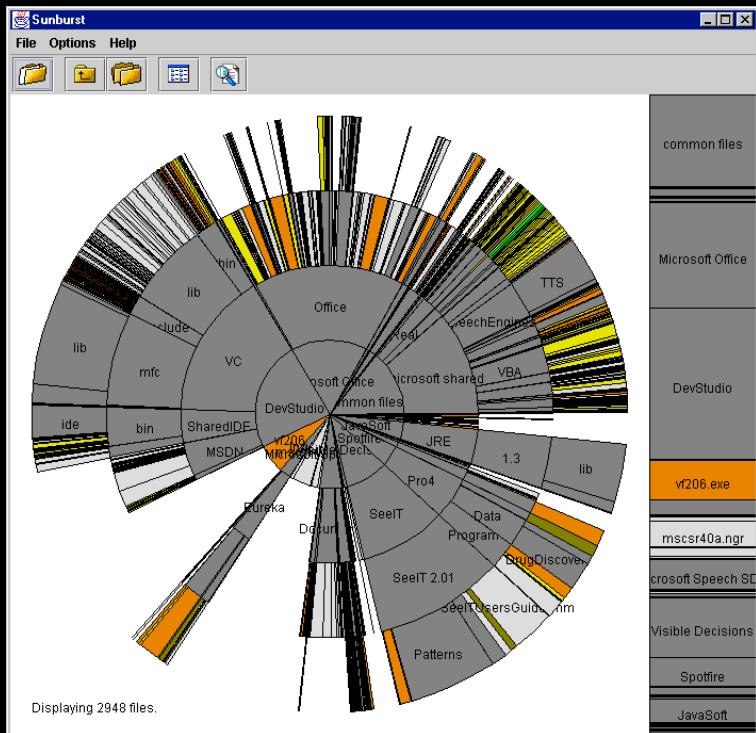
Cycle du combustible nucléaire



52

SunBurst

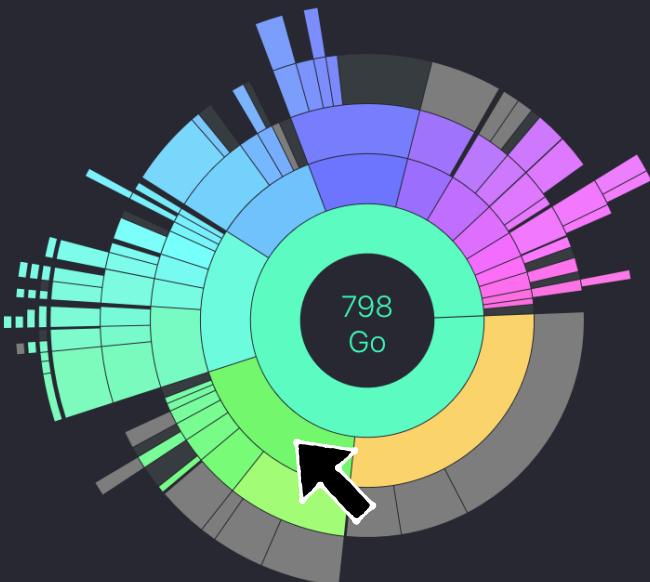
[www.cc.gatech.edu/
gvu/ii/sunburst](http://www.cc.gatech.edu/gvu/ii/sunburst)



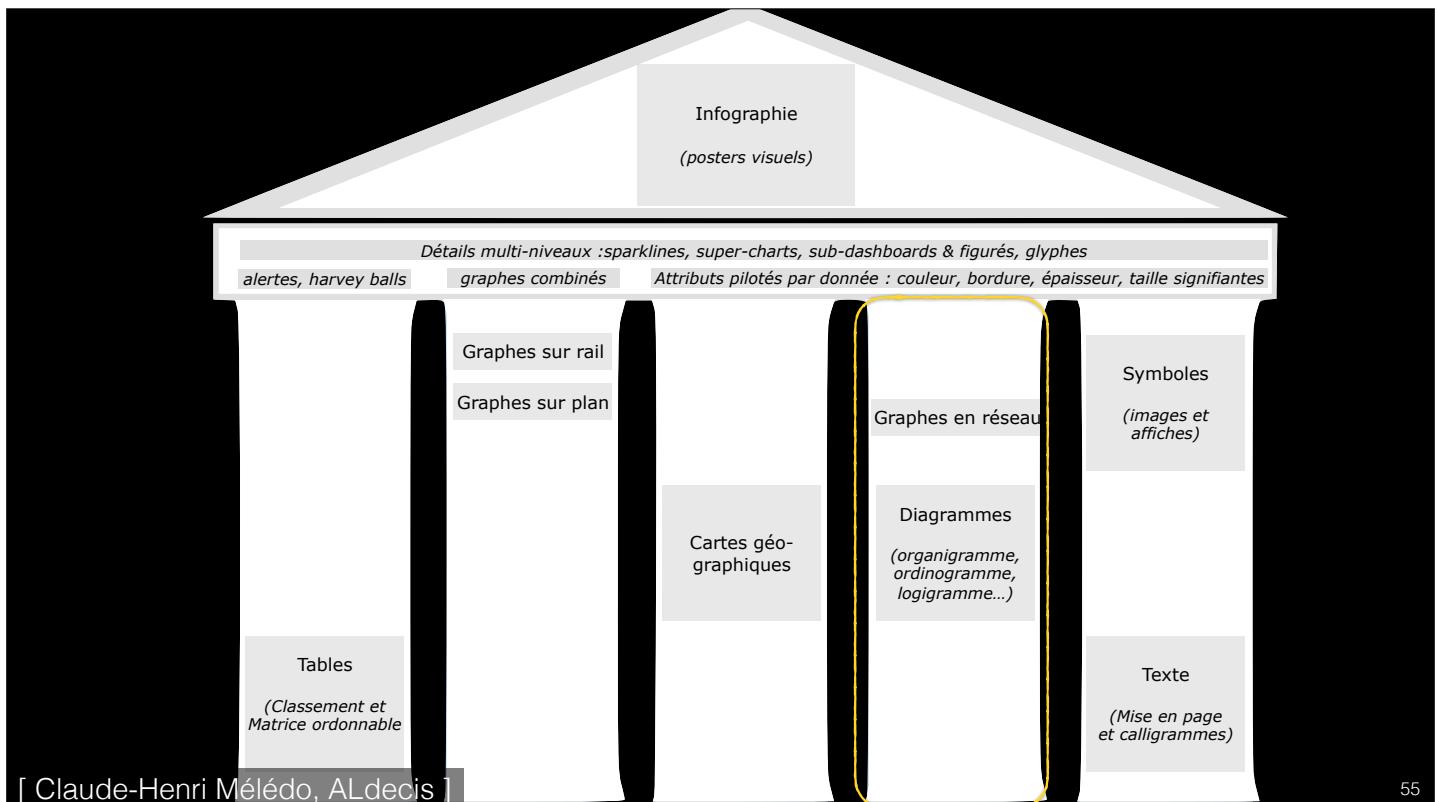
53

53

- Documents 146,2 Go
- Parallels 71,6 Go
- Disc Images 25,7 Go
- Cours 14,6 Go
- Backups 11,1 Go
- Machines Virtuelles 8,3 Go
- Presentations 4,8 Go
- Bibliothèque calibre 3,7 Go
- ... objets plus petits 6,4 Go

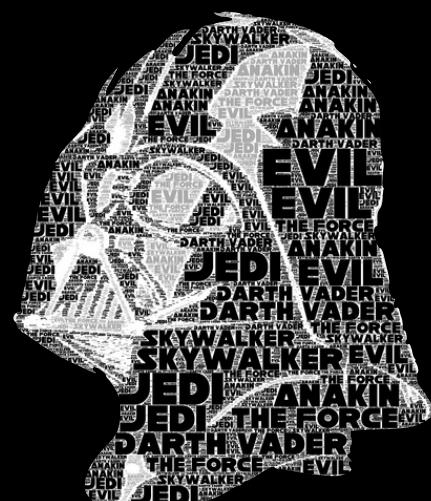


54



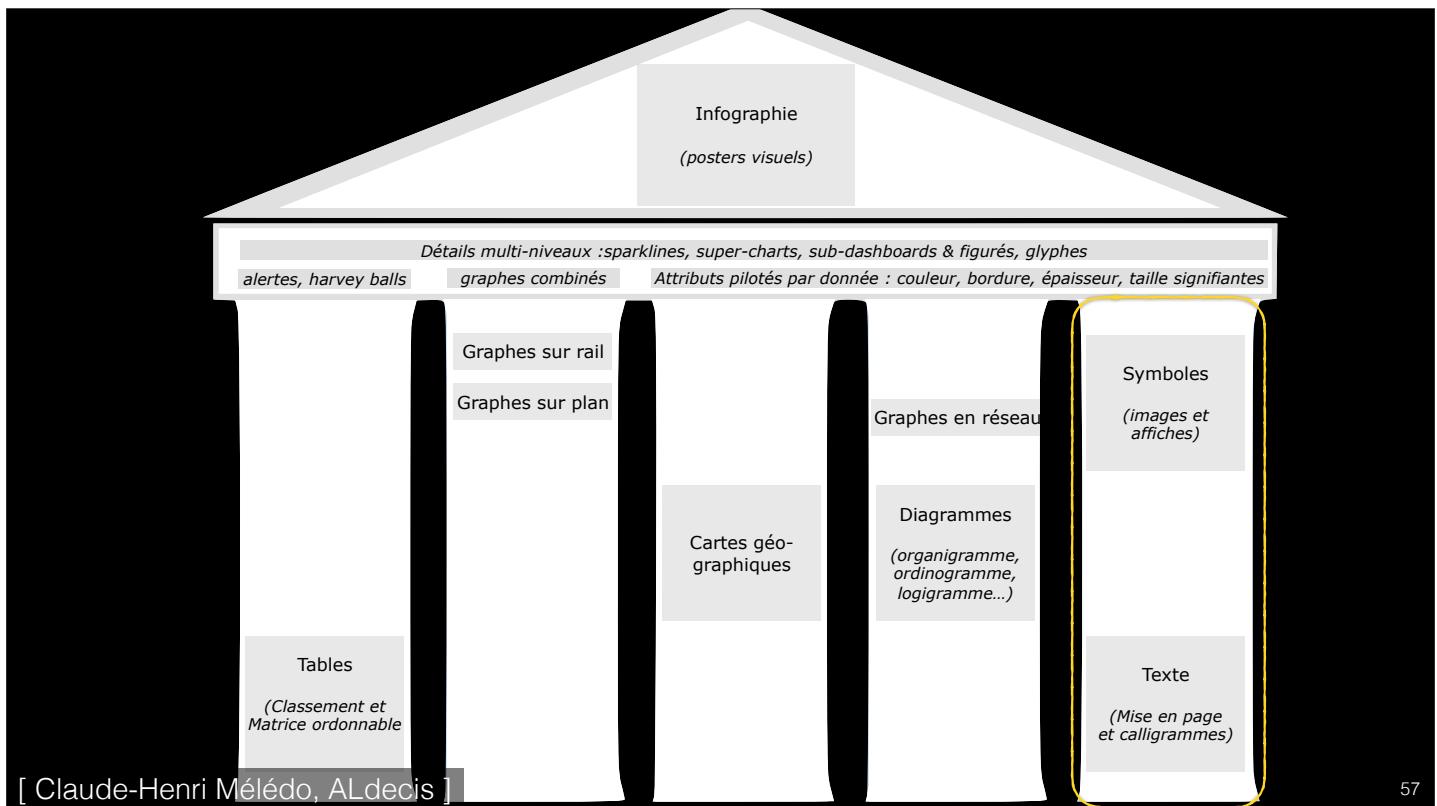
55

Conceptual Images

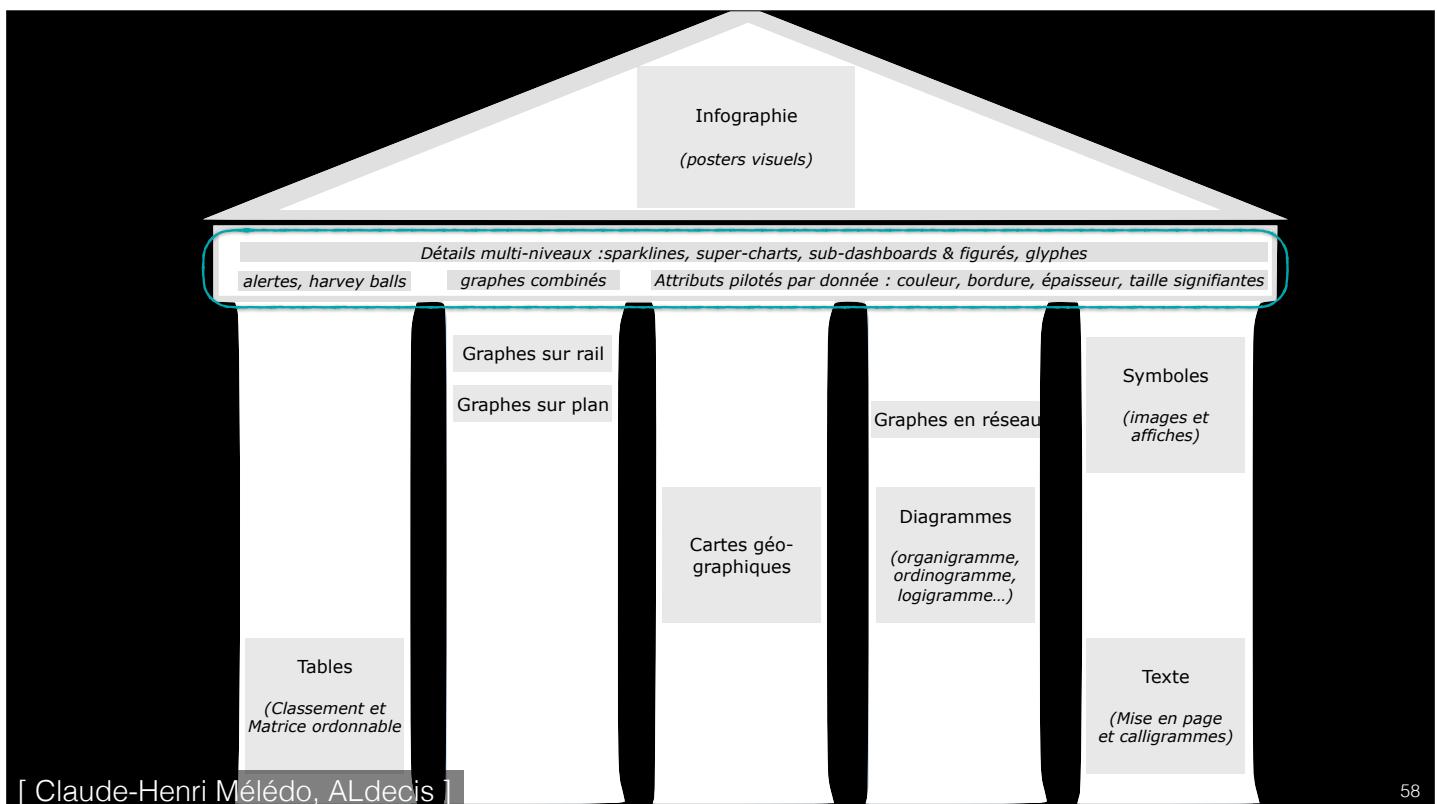


56

56

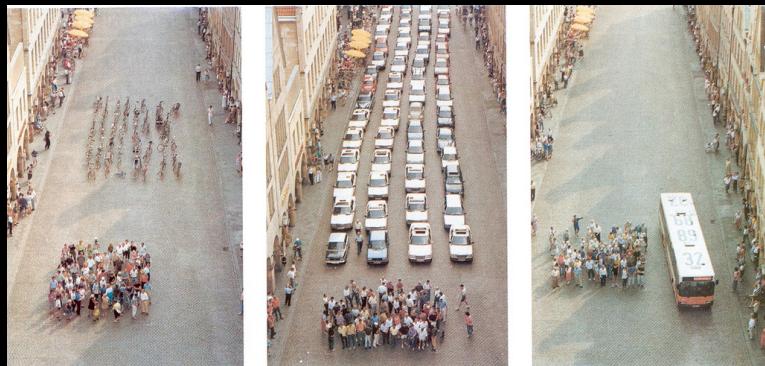


57



58

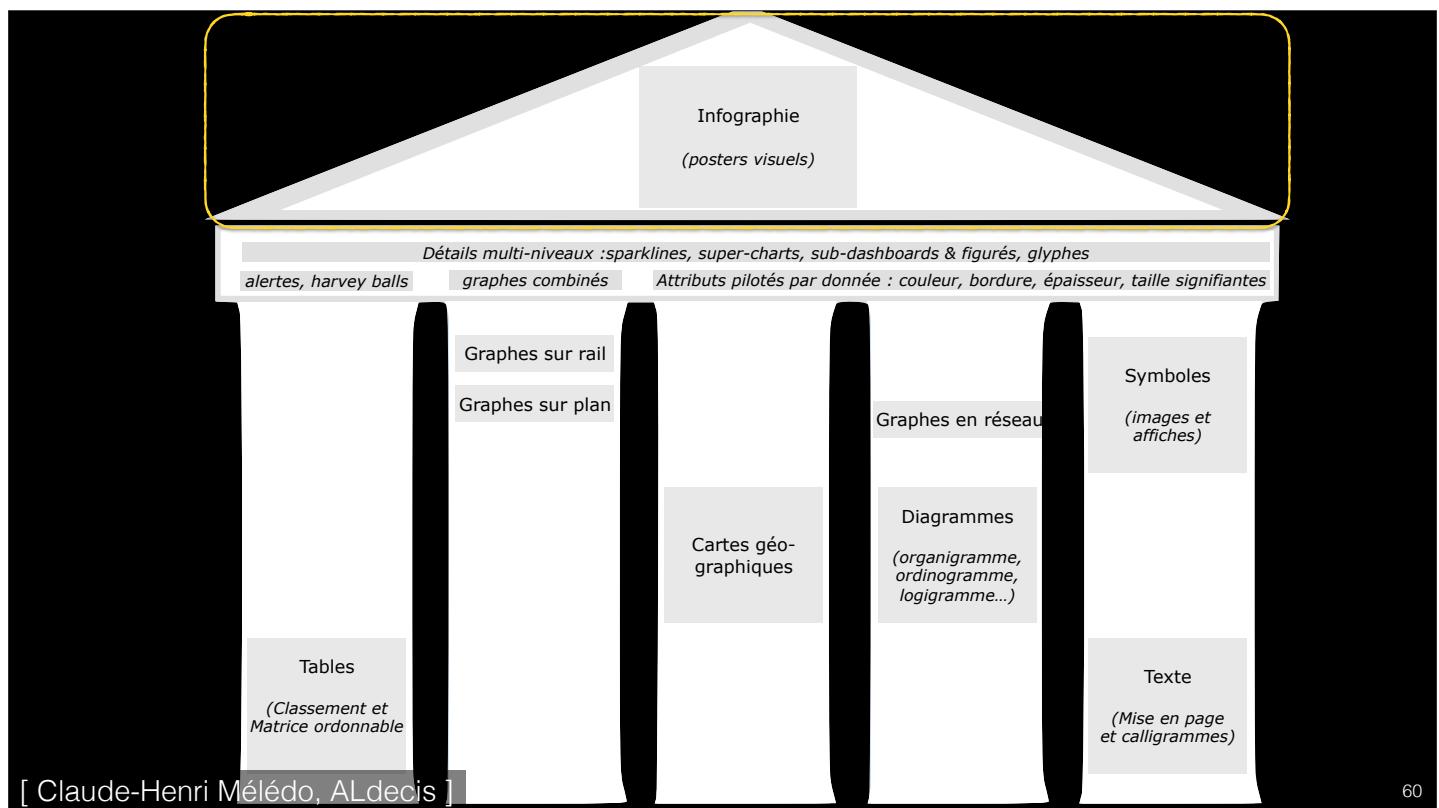
72 people



[www.visualnews.com]

59

59

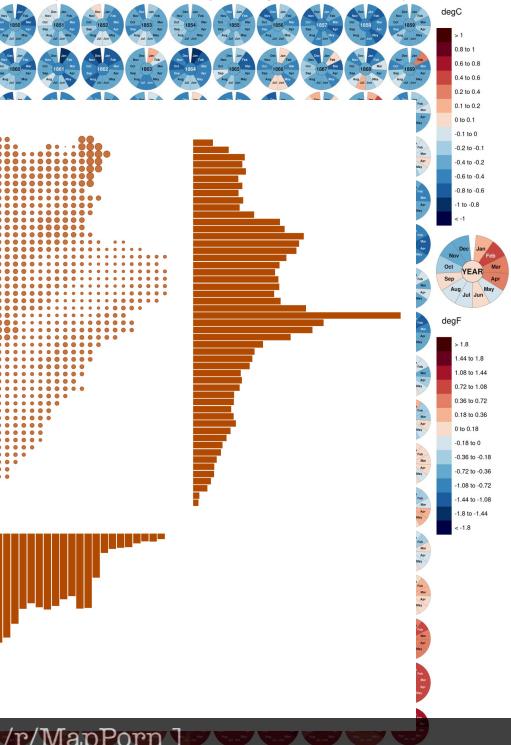


60

60

Infographie

Monthly global mean temperature between 1850 and 2019
(compared to monthly averages for 1961-1990)



61

61

62

62

Back to Data

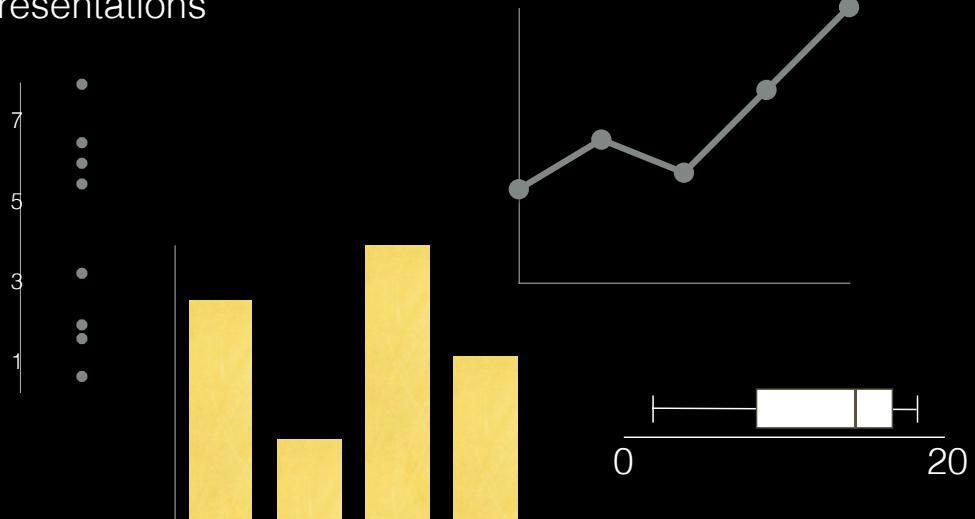
- What were the different types of data sets?
- Number of variables per class
 - 1 – Univariate data
 - 2 – Bivariate data
 - 3 – Trivariate data
 - >3 – Hypervariate data
- But also data types
 - Temporal
 - Geospatial
 - Relational (e.g. Trees, Graphs)
 - Textual

63

63

Univariate Data

- Representations

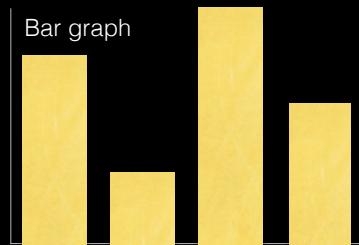
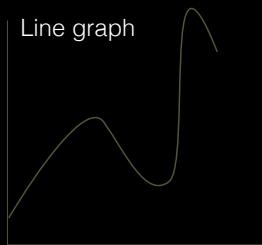


64

64

What Goes Where?

- In univariate representations, we often think of the data case as being shown along one dimension, and the value in another



- Y-axis is quantitative variable
- See changes over consecutive values

- Y-axis is quantitative variable
- Compare relative point values

65

65

Alternative View

- We may think of graph as representing independent (data case) and dependent (value) variables
- Guideline:
 - Independent vs. dependent variables
 - Put independent on x-axis
 - See resultant dependent variables along y-axis

66

66

Bivariate Data

- Representations

Scatterplot is common

Each mark is
now a data
case



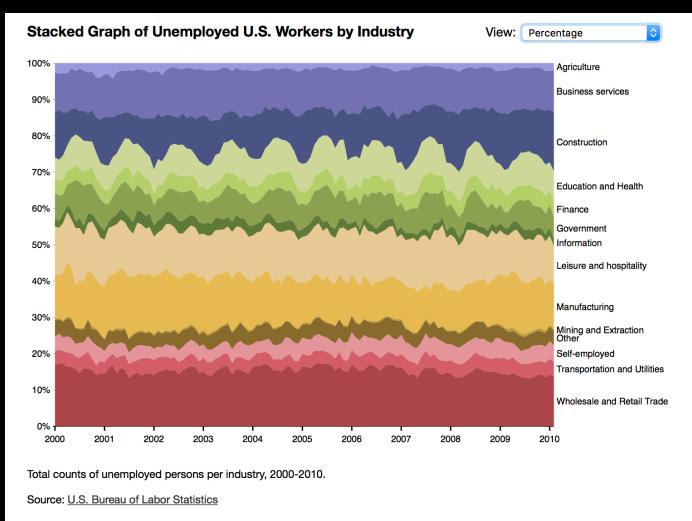
Two variables,
want to see a
relationship

Is there a linear,
curved, or random
relationship?

67

67

Time Series

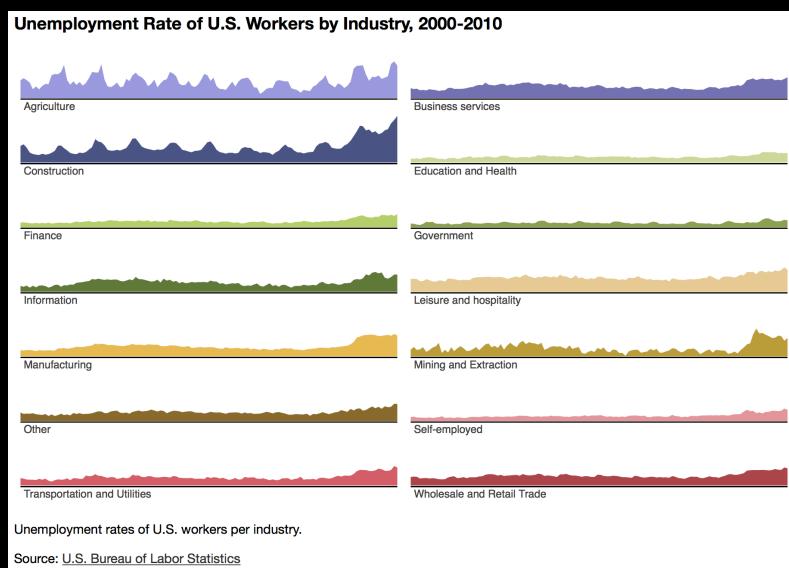


[Source: Heer et al., CACM 2010]

68

68

Time Series (Small multiples)



[Source: Heer et al., CACM 2010]

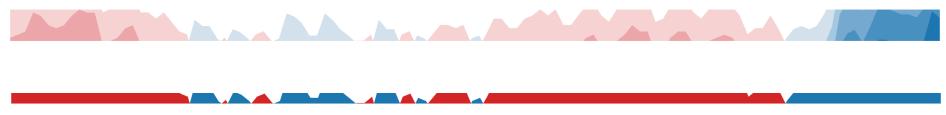
69

69

Horizon Graphs

Horizon Graphs of U.S. Unemployment Rate, 2000-2010

Bands: 5 Negative Values: mirror offset



[Source: Heer et al., CACM 2010]

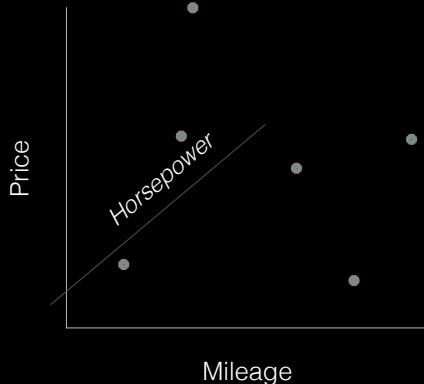
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Trivariate Data

- Representations

3D scatterplot is possible

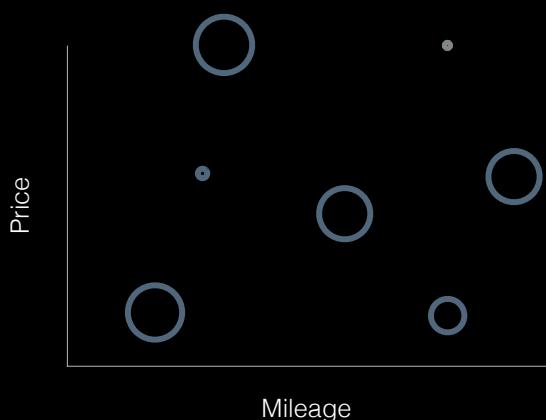


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Alternative Representation

- Representations



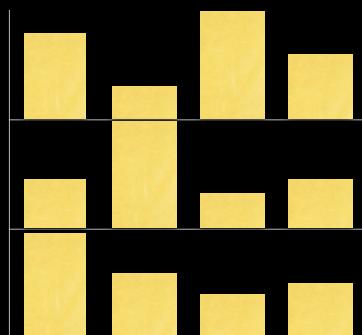
Still use 2D but have
mark property
represent third
variable

72

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Alternative Representation

- Representations



Represent each variable
in its own explicit way

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Hypervariate Data

- Ahhh, the tough one
- Number of well-known visualization techniques exist for data sets of 1-3 dimensions
 - line graphs, bar graphs, scatter plots OK
 - We see a 3-D world (4-D with time)
- What about data sets with more than 3 variables?
 - Often the interesting, challenging ones

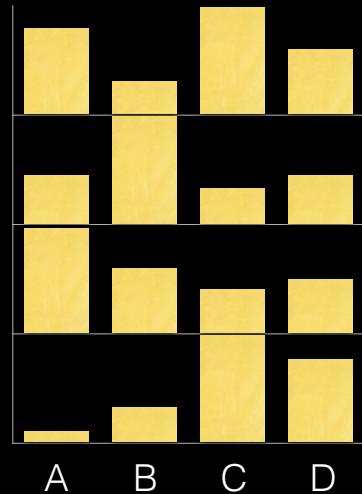
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Multiple Views

- Give each variable its own display

	A	B	C	D
1	8	3	10	6
2	4	9	3	4
3	10	6	4	5
4	1	3	9	7

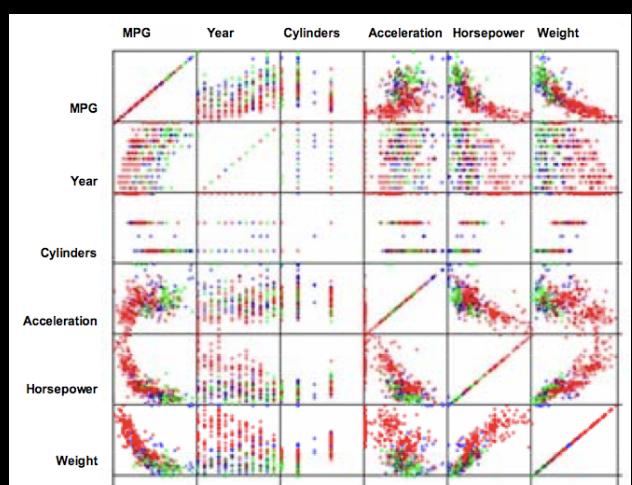


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Scatterplot Matrix

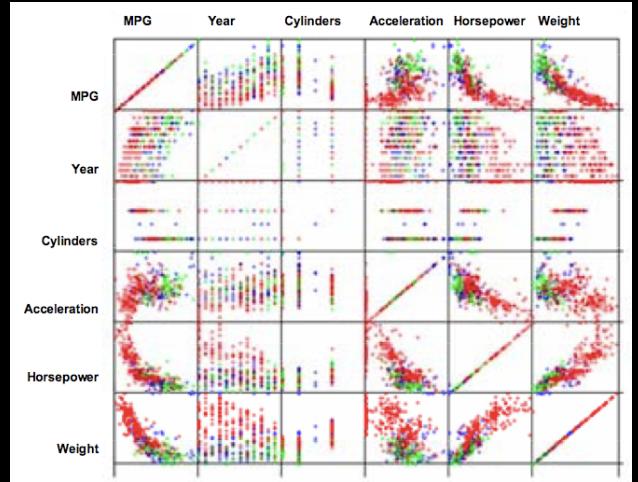
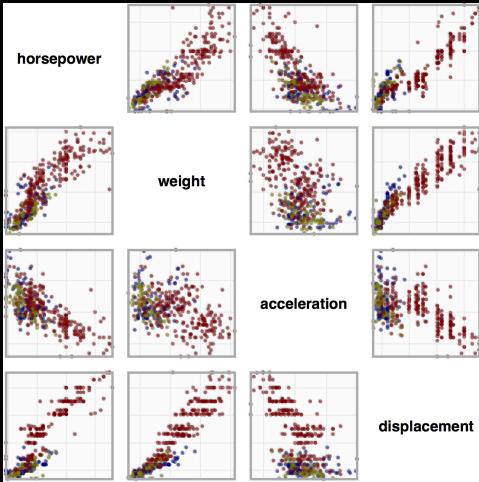
- Represent each possible pair of variables in their own 2-D scatterplot
- Useful for what?
- Misses what?



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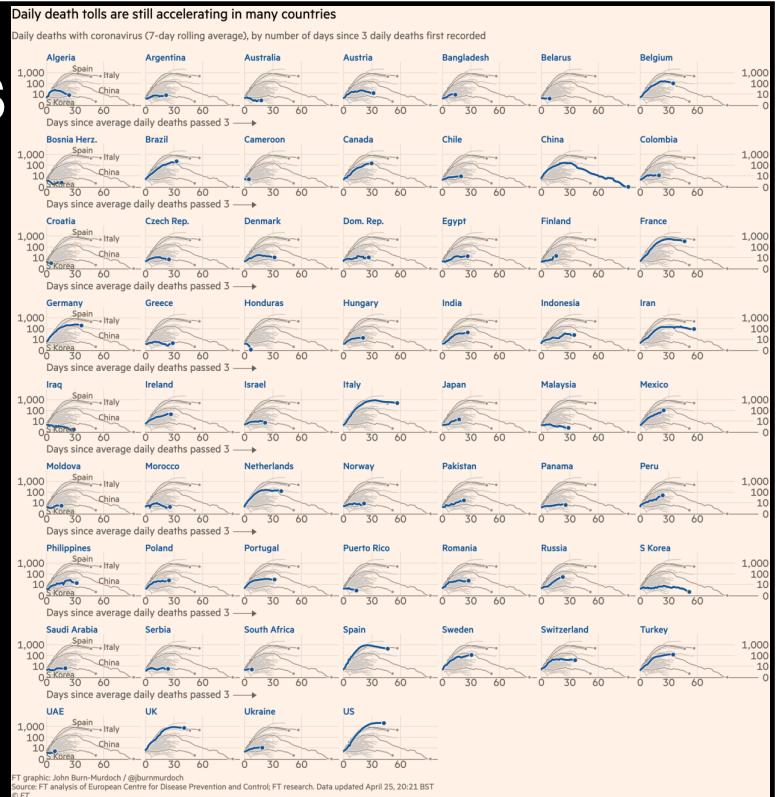
Scatterplot Matrix



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Small Multiples

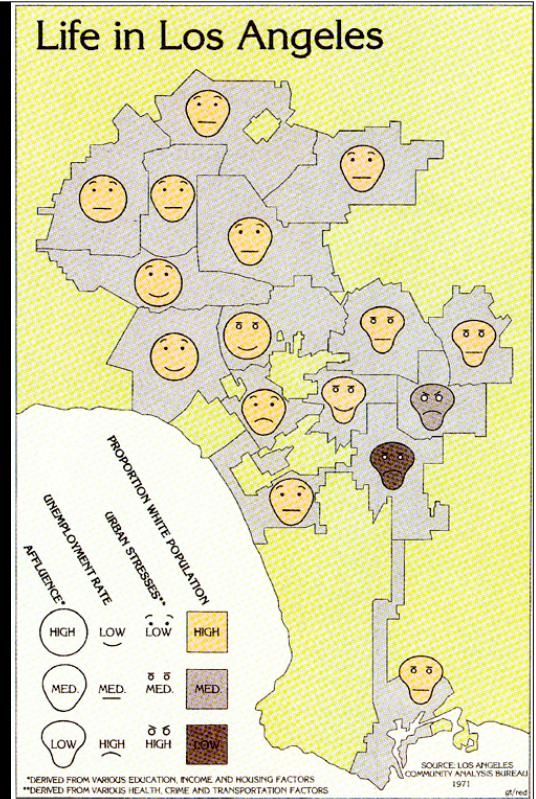
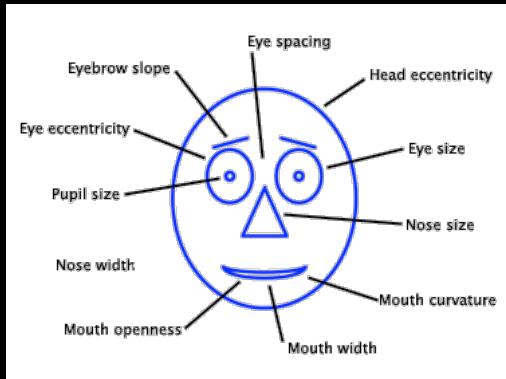


[FT, 27/04/2020]

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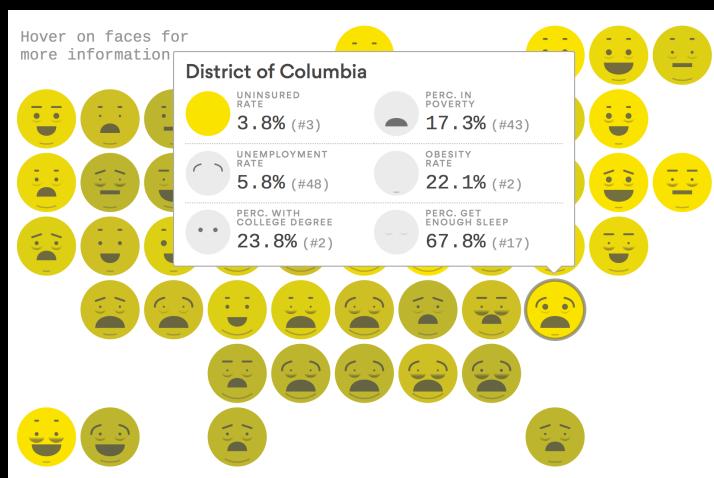
Chernoff Faces

- Encode different variables' values in characteristics of human face



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Emoji Chernoff Faces



[<https://www.axios.com/an-emoji-built-from-data-for-every-state-2408885674.html>]

80

80

So far...

- We examined a number of tried-and-true techniques/visualizations for presenting multivariate (typically ≤ 3) data sets
 - Hinted at how to go above 3 dimensions

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More Dimensions

- Fundamentally, we have 2 display dimensions
- For data sets with > 2 variables, we must project data down to 2D
- Come up with visual mapping that locates each dimension into 2D plane
- Computer graphics 3D \rightarrow 2D projections

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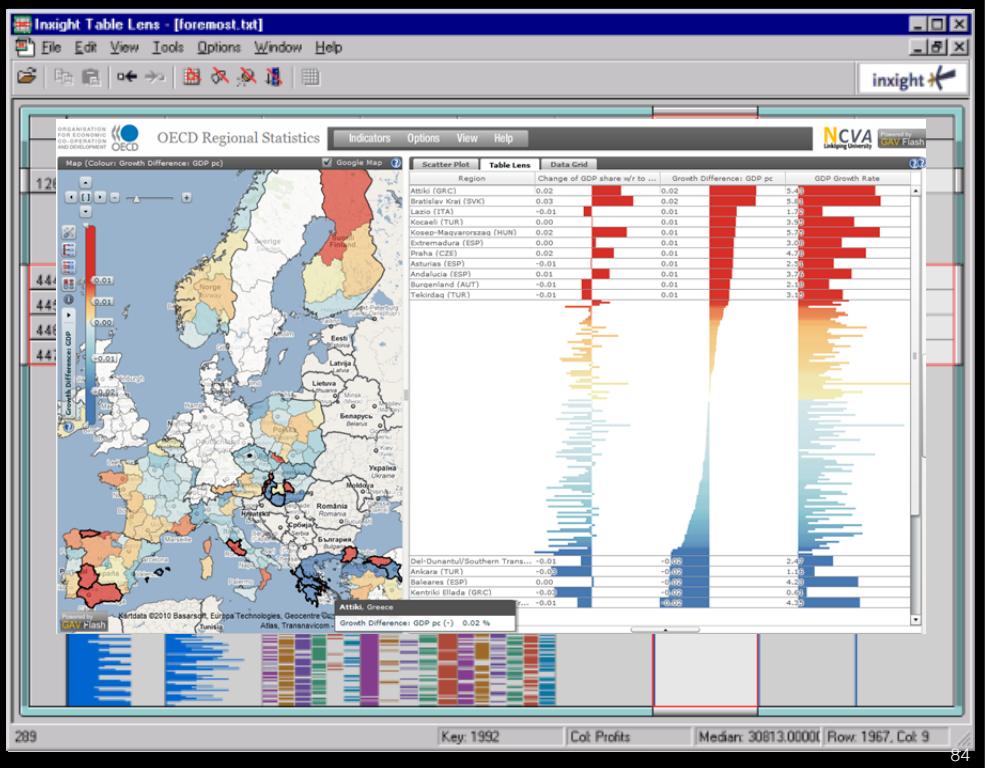
Wait a moment...

- A spreadsheet already does that
 - Each variable is positioned into a column
 - Data cases in rows
 - This is a projection (mapping)

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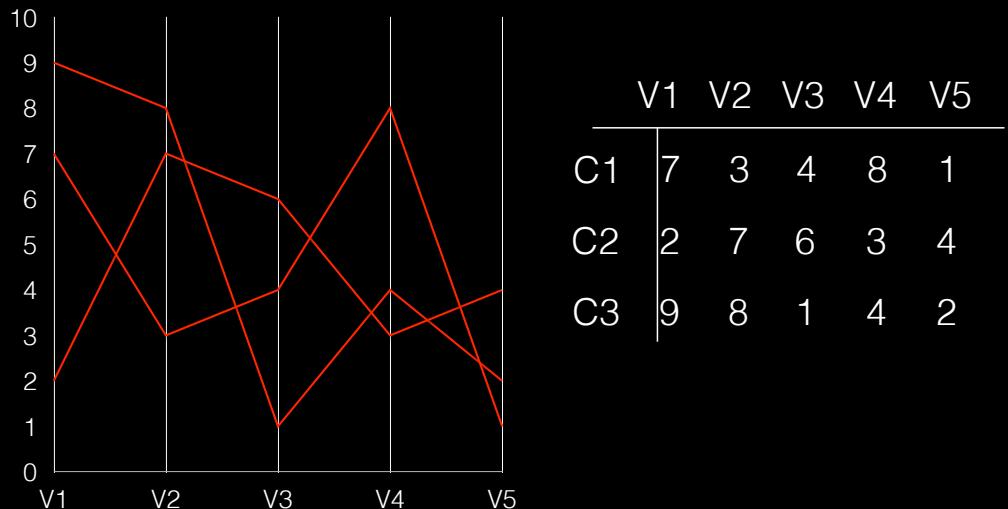
Table Lens



[Rao & Card, CHI '94]

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Parallel Coordinates

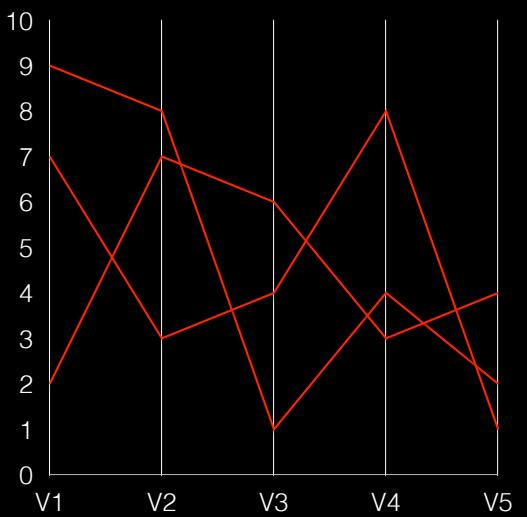


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Parallel Coordinates

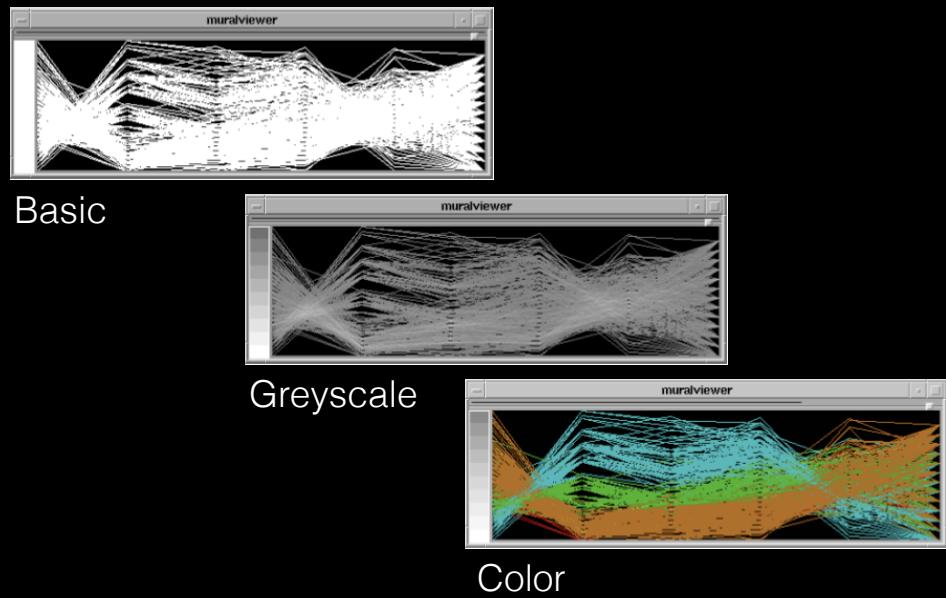
- Encode variables along a horizontal row
- Vertical line specifies different values that variable can take
- Data point represented as a polyline



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Parallel Coordinates Example



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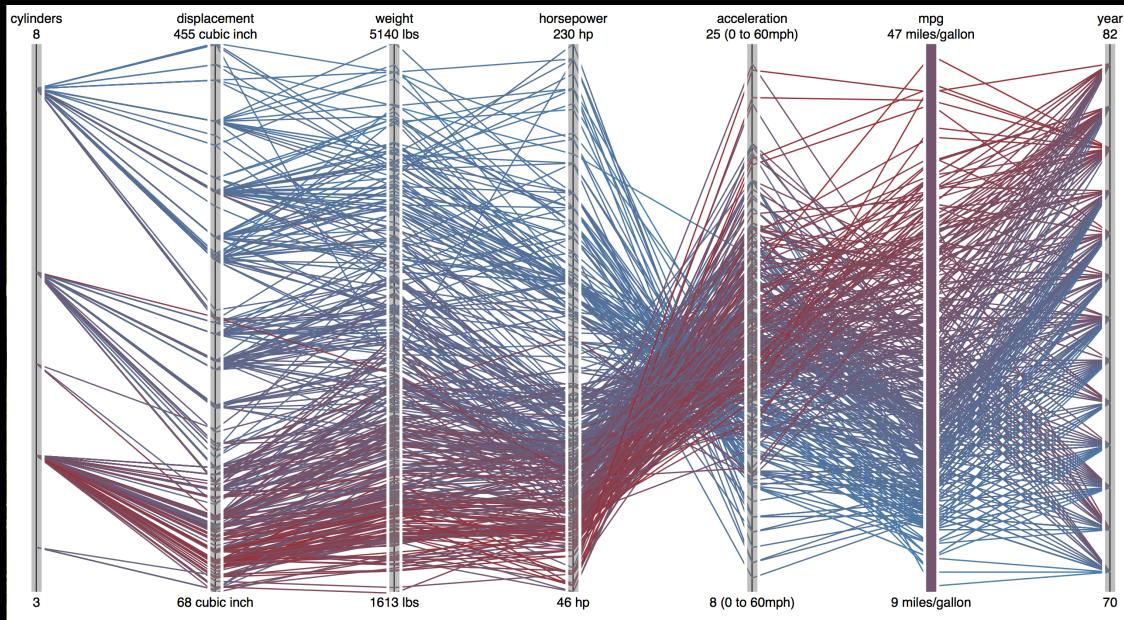
Issue

- Different variables can have values taking on quite different ranges
- Must normalize all down (e.g., $f(x): \mathbb{N} \rightarrow [0, 1]$)

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88

Parallel Coordinates



[Source: Heer et al., CACM 2010]

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Example

- VLSI chip manufacture
- Want high quality chips (high speed) and a high yield batch (% of useful chips)
- Able to track defects
- Hypothesis: No defects gives desired chip types
- 473 batches of data

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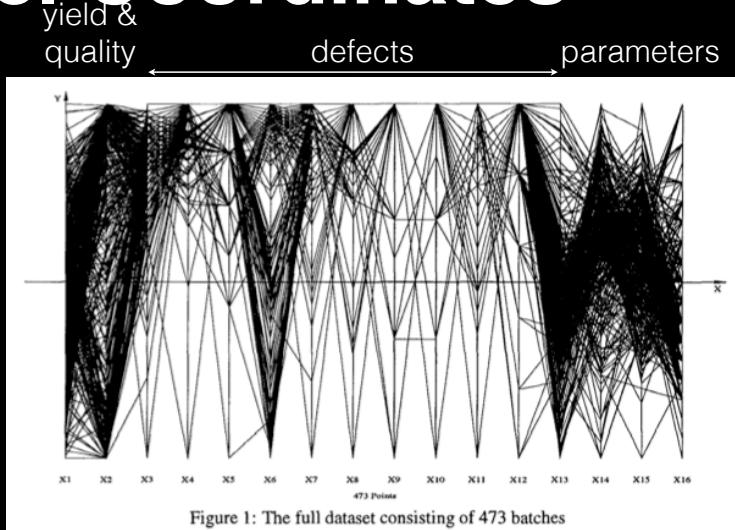
The Data

- 16 variables
- X1 — yield
- X2 — quality
- X3–X12 - # defects (inverted)
- X13–X16 - physical parameters

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Parallel Coordinates



Yikes!
But not
that bad

Distributions
x1 - normal
x2 - bipolar

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Top Yield & Quality

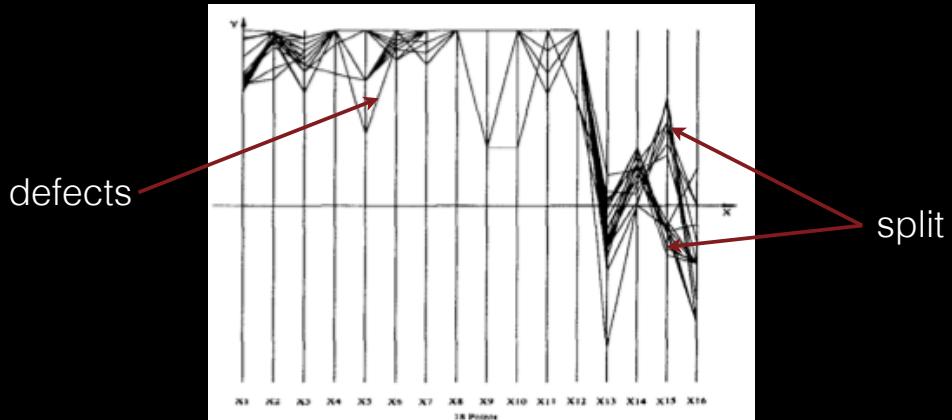


Figure 2: The batches high in Yield, X_1 , and Quality, X_2 .

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Minimal Defects

Not the highest yields and quality

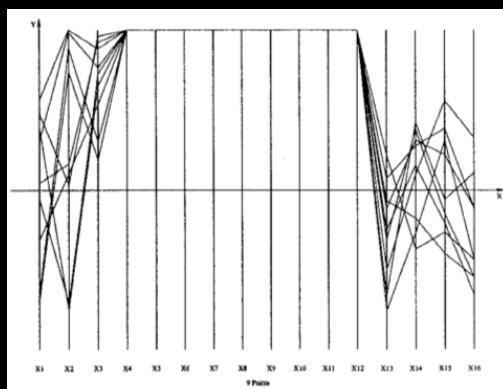


Figure 3: The batches with zero in 9 out of the ten defect types.

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Best Yields

Appears that some defects are necessary to produce the best chips

Non-intuitive!

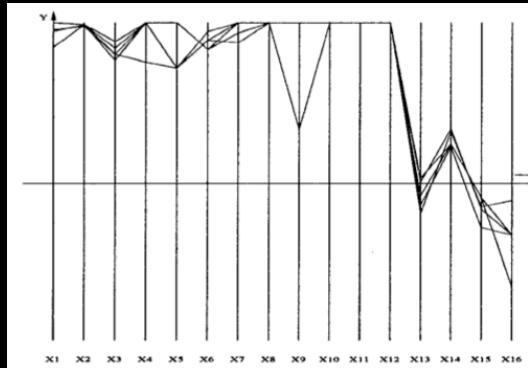
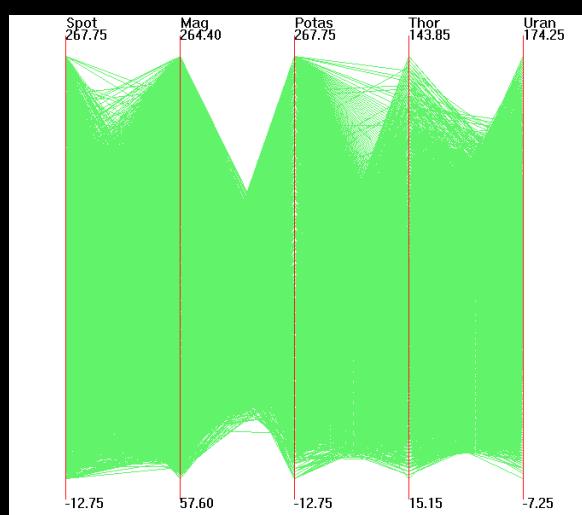


Figure 6: Batches with the highest Yields do not have the lowest defects in $X3$ and $X6$.

95

95

Challenges



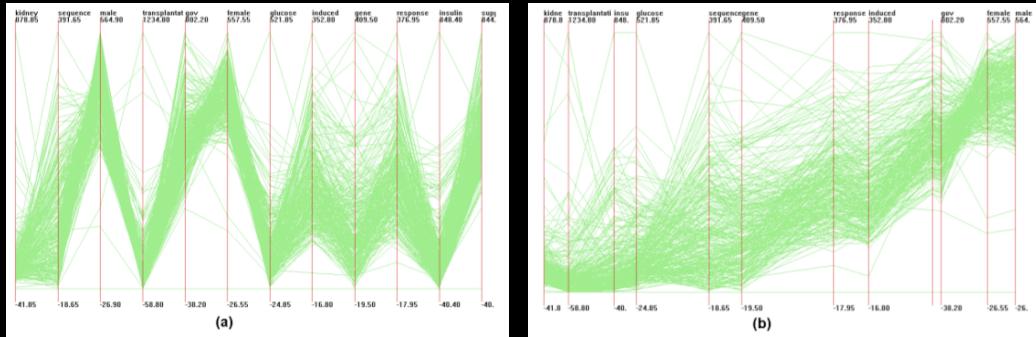
Out5d dataset (5 dimensions, 16384 data items)

96

96

Dimensional Reordering

Which dimensions are most like each other?



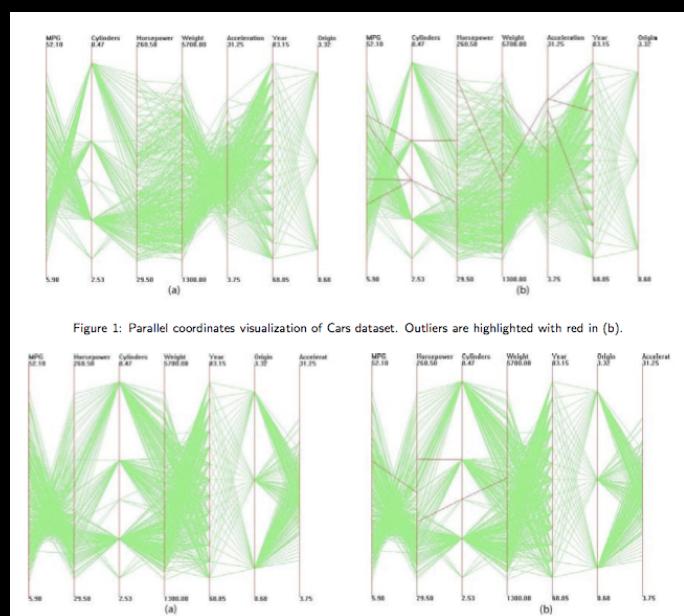
Same dimensions ordered by similarity

97

97

Dimensional Reordering

Can you
reduce clutter
and highlight
other
interesting
features in
data?



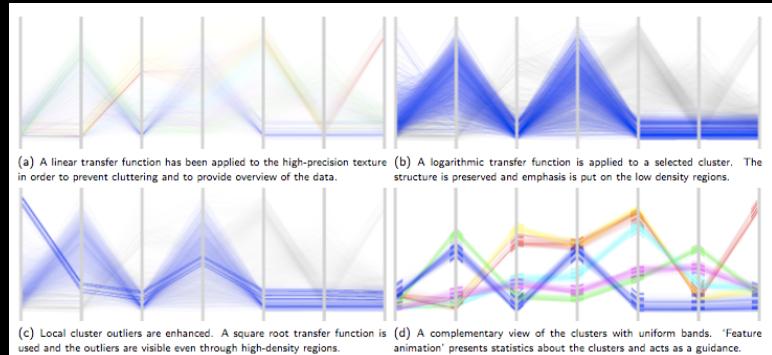
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Reducing Density



[Artero et al, InfoVis 2004]



[Johansson et al, InfoVis 2005]

99

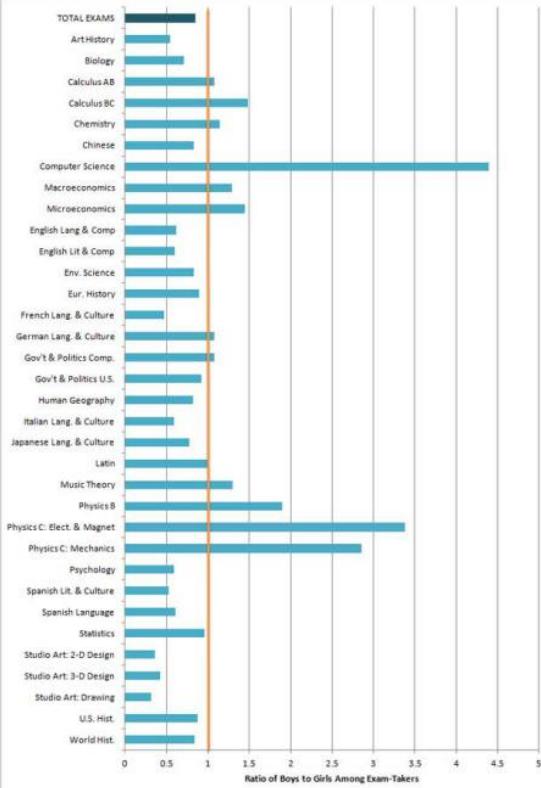
99

Critique du moment

100

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Ratio of boys to girls among exam takers

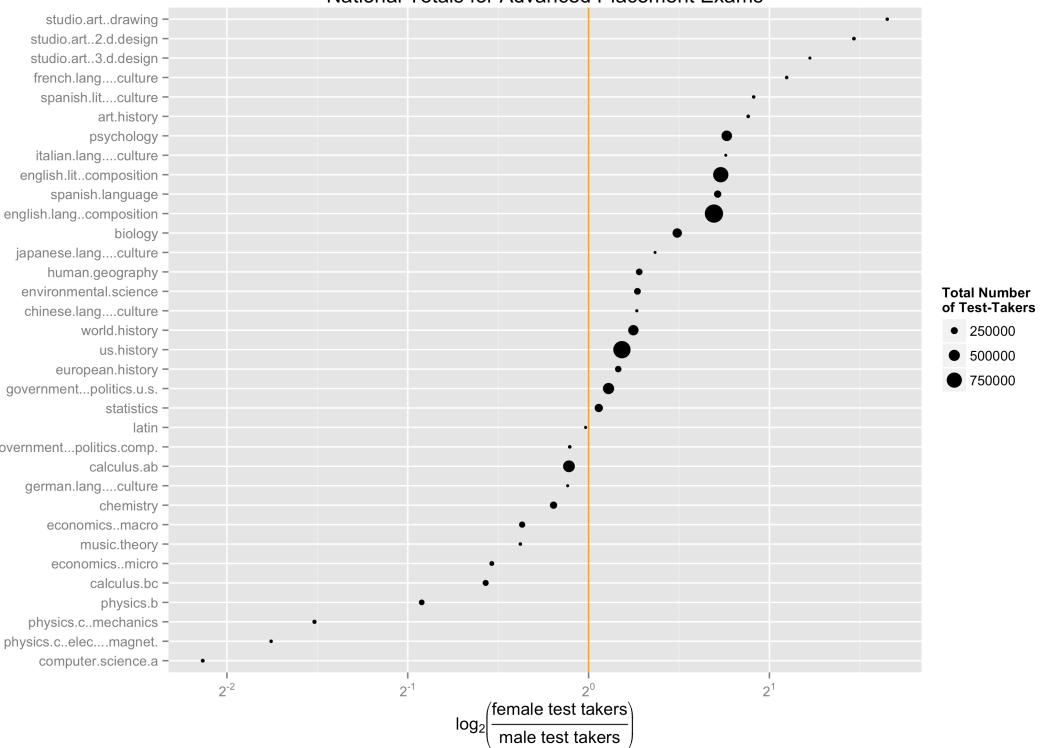


101

101

Advanced Placement (AP) Exam

National Totals for Advanced Placement Exams



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Next time: Tasks