Storytelling With Data

The storytelling process, with images and data graphics

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Conceptual project timeline



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integrating images and words in narrative to create shared meaning

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Edward Tufte, in Visual Explanations — his book about pictures of verbs to show causes and effects, explanations and narratives — cites to **comics** for understanding the idea of "visual narrative".

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Tufte, Edward

A very simple story using only words





A very simple story using words



The same story using only images



Shared meaning of words and images









Shared meaning of words and images









The **balance between text and visualization** becomes an issue when too much text takes away from the data but too little text leaves the viewer confused and unable

to see the connections.



Storyboards are a tool to test narrative containing mixed media types

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The Next Rembrandt, demonstrating our data science skills we can apply to client needs. Storyboard |

Visual narrative

Can we convince clients we are the Rembrandt of data science?

What from his paintings can ve turn into data to create a new solution? A new painting?

Clustering demographics



Written narrative

We should market ourselves as data-driven, forwardthinking, and creative.

To demonstrate our creativity, we attempted to turn paintings into data, analyze it, and create an entirely new painting perhaps indistinguishable from the master, Rembrandt. Did Rembrandt paint this? Or did we?

To answer the challenge, we gathered a extensive pool of data. Perhaps to some, a large collection of paintings are not data. But we partnered with museums to collect many of Rembrandt's works.

Our analysis of these works — these data — helped us understand how to paint like Rembrandt.

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With these paintings, we coded and trained an algorithm to see what we can see through our own eyes, to identify the subject of each painting, to learn the demographics of this master painter's focus.

Visual narrative



Written narrative

That wasn't enough. Then, our algorithm identified the features of his subjects, like the shape of the face and eyes.

To make a painting like Rembrandt, though, we would need it to look and feel like his originals. Paintings have texture and depth. We measured the actual depth of his paint strokes on each of the works we collected, turning messy, real-world information into structured data for our algorithm.

6

After transforming the data generated by our algorithm, we were able to create the new painting by feeding it back into a 3D printer.

We apply this same dedication using technology to inform our customers. We can do even more with data for our clients. Let's make them curious about how we can use data to create solutions for them.

Measuring paint depth

Printing in three dimensions, we are Rembrandt ...

> .. of data science. Let's show clients our creative data solutions.

The Next Rembrandt, demonstrating our data science skills we can apply to client needs.

Can we convince clients ve are the Rembrandt of data science?

We should market ourselves as data-driven, forwardthinking, and creative.

To demonstrate our creativity, we attempted to turn paintings into data, analyze it, and create an entirely new painting perhaps indistinguishable from the master, Rembrandt. Did Rembrandt paint this? Or did *we*?

Vhat from his paintings can ve turn into data to create a new solution? A new painting

Do we think this is a story? Do the visuals add to the written narrative? paintings are no Would it engage the audience? Explain.

Our analysis of these works — these data — helped us understand how to paint like Rembrandt.

Clustering demographics

With these paintings, we coded and trained an algorithm to see what we can see through our own eyes, to identify the subject of each painting, to learn the demographics of this master painter's focus.

Learning his facial shapes

That wasn't enough. Then, our algorithm identified the features of his subjects, like the shape of the face and eyes.

Measuring paint depth

Printing in three dimensions, ve are Rembrandt ...

> .. of data science Let's show clients our creative data solutions

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We apply this same dedication using technology to inform our customers. We can do even more with data for our clients. Let's make them curious about how we can use data to create solutions for them.

use data graphics to support and amplify your narrative

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Why show data graphically?

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Classic example, datasets from Anscombe

1		2		3		4	
X	у	X	у	X	у	X	у
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.10	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.10	4	5.39	19	12.50
12	10.84	12	9.13	12	8.15	8	5.56
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

Anscombe

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Classic example, datasets from Anscombe

1		2		3		4	
X	У	Х	У	Х	У	Х	У
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.10	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.10	4	5.39	19	12.50
12	10.84	12	9.13	12	8.15	8	5.56
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

Summary statistics of data: are they the same?

	1		2			3		4	
	X	у	X	у	X	у	X		
mean	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.	
sd	3.32	2.03	3.32	2.03	3.32	2.03	3.32	2.	

Parameter	Mean	Std Err	t-val	p-val
Dataset 1				
(Intercept)	3.000	1.125	2.667	0.026
X	0.500	0.118	4.241	0.002
Dataset 2				
(Intercept)	3.001	1.125	2.667	0.026
X	0.500	0.118	4.239	0.002
Dataset 3				
(Intercept)	3.002	1.124	2.670	0.026
X	0.500	0.118	4.239	0.002
Dataset 4				
(Intercept)	3.002	1.124	2.671	0.026
X	0.500	0.118	4.243	0.002



Classic example, datasets from Anscombe

1		2		3		4	
X	У	Х	У	Х	У	Х	У
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.10	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.10	4	5.39	19	12.50
12	10.84	12	9.13	12	8.15	8	5.56
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Graphics show how the datasets are different





graphics, the non-data-ink

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graphics, the non-data-ink





graphics, the non-data-ink



<...>

Coding graphic elements, *example in R/GGplot2*

```
# load grammar of graphics
library(ggplot2)
```

p <-

functions for data ink

```
ggplot(data = <data>,
       mapping = aes(<aesthetic> = <variable>,
                       <aesthetic> = <variable>,
                       \langle \ldots \rangle = \langle \ldots \rangle +
geom_<type>(<...>) +
scale_<mapping>_<type>(<...>) +
coord_<type>(<...>) +
facet_<type>(<...>) +
<...>+
                                           element_blank()
# functions for non-data ink
                                           element_line(<...> = <...>)
                                           element_rect(<...> = <...>)
labs(<...>) +
theme(<...> = <...>) +
                                           element_text(<...> = <...>)
annotate(<...>) +
```


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Point. You cannot see or feel a point; it is a place without area. The point has a position that can be defined by coordinates (numbers on one, two, or three axes).

v

Line. A line can be understood as a number of points that are adjacent to one another. A line can be infinite or have two endpoints. The shortest distance between two points is a straight line.

Leborg

The shortest distance between two points.

Surface. A surface is defined by two lines that do not coincide or by a minimum of three points that are not located on a line. If the two lines have one coinciding point, the surface will be a plane.

Leborg

Volume. A volume is an lines, and points.

Leborg

Volume. A volume is an empty space defined by surfaces,

graphics, data-ink encodings

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graphics, options for *data-ink encodings*

Bertin

graphics, accuracy of *data-ink decodings*

Koponen & Hildén

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What data encodings do we find in the following named charts?

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VERTICAL BAR CHART

350 300 250 200 150 100 50 0 2013 2014 2015 2016 Source: Eurostat 2018. rd_e_gerdtot

Higher education spending in Iceland Euros per inhabitant

Koponen & Hildén

HORIZONTAL BAR CHART

Higher education spending (2016)

Euros per inhabitant

GROUPED BAR CHART

Tertiary education attainment in the Nordic-Baltic countries (2016)

ISCED education levels 5-8, population aged 25-64, %

STACKED BAR CHART

R&D spending by sector in the Nordic-Baltic countries (2016)

Euros per inhabitant

100% STACKED BAR CHART

Educational attainment (2016) Population aged 25-64, %

Source: Eurostat 2018. edat_lfse_04

Koponen & Hildén

Nordic R&D spending by sector (2016)

Euros per inhabitant

DOT PLOT

Nordic R&D spending by sector (2016)

Euros per inhabitant

Source: Eurostat 2018. rd_e_gerdtot

Koponen & Hildén

HISTOGRAM

Tertiary education attainment in Europe (2017) Percentage of population aged 25-64 with a university degree, NUTS2 regions (n = 318)

THE EFFECT OF BIN SIZE ON HISTOGRAM SHAPE

Percentage of population aged 25-64 with a university degree, NUTS2 regions 318 observations

BIN SIZE 5 • 14 BINS Count

BIN SIZE 2 • 32 BINS

Source: Eurostat 2018. edat_lfse_04

Koponen & Hildén

LINE CHART

Higher education spending in Sweden (2007–2016)

Euros per inhabitant

2016 Source: Eurostat 2018. rd_e_gerdtot

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Koponen & Hildén

AREA CHART

R&D spending by sector in Estonia (2007–2016) Euro per inhabitant

100% STACKED LINE CHART

R&D spending by sector in Estonia (2007–2016) Percentage of total spending, %

Source: Eurostat 2018. rd e aerdtot

Koponen & Hildén

Koponen & Hildén

STREAMGRAPH

R&D spending by sector in Estonia

Spending per inhabitant (euros)

Koponen & Hildén

CYCLE PLOT

Average monthly temperatures in Ivalo, Finland 1960-2017

Degrees in Celcius (C°), five-year moving average

Koponen & Hildén

SCATTERPLOT

European higher education spending and rate of tertiary education (2016)

DOT-DASH PLOT

European higher education spending and rate of upper secondary education (2016)

Upper secondary and post-secondary non-tertiary education

Euro spent per inhabitant 🛧

Percentage of population aged 25-64 ->

Source: Eurostat 2018. edat_lfse_04 and rd_e_gerdtot

Koponen & Hildén

STRIP PLOT

R&D spending by sector in the Nordic-Baltic countries (2016)

Euros per inhabitant

BEESWARM PLOT

ties (2016)

Euros per inhabitant, selected European countries

O O Source: Eurostat 2018. *rd_e_gerd*tot

Koponen & Hildén

BUBBLE CHART

Tertiary education attainment and higher education sector spending (2015)

Population aged 25-64 with a university degree, % ->

Source: Eurostat 2018 edat_lfse_04, rd_e_gerdtot, proj_15npms, and Statistics Iceland.

Koponen & Hildén

1-DIMENSIONAL BUBBLE CHART

European higher education sector spending (2015)

Selected European countries

Source: Eurostat 2018 rd_e_gerdtot, proj_15npms, and Statistics Iceland

SCATTERPLOT MATRIX

Selected European countries (2016) Source: Eurostat and World Bank 2018.

> **Higher education** spending (euros per inhabitant)

attainment

Tertiary education attainment (share of population aged 25-64 with a university degree)

Koponen & Hildén

HEXAGONAL BINNING

Employment in higher education and rate of tertiary education in Europe (2015) Selected NUTS2 regions, 349 observations

Percentage of people employed in higher education (active population) 🛧 3%

Sources: Eurostat 2018. edat_lfse_04 and rd_p_persreg

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Share of turnover in industrial activity by sector (2016)

Source: Eurostat 2018. tin00149

Koponen & Hildén

Studio work — exploratory data analysis

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