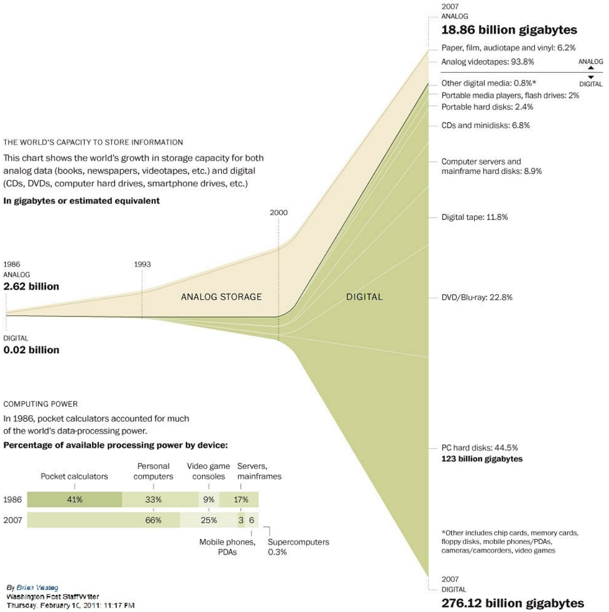
Methods for unstructured data

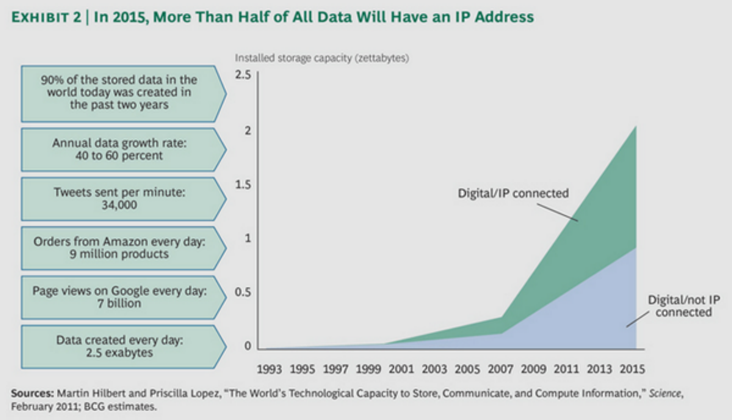
Introduction

Helge Liebert

Worldwide data storage capacity

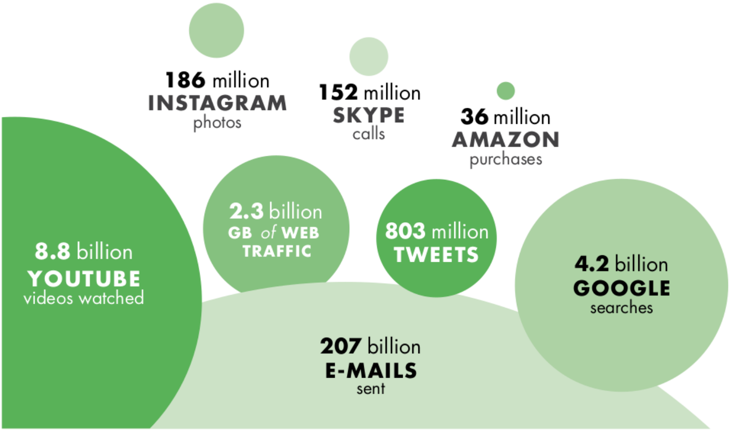


Data, then and now



Data, then and now

b. A typical day in the life of the internet



Sources: World Development Indicators (World Bank, various years); WDR 2016 team; http://www.internetlivestats.com/one-second/ (as compiled on April 4, 2015). Data at http://bit.do/WDR2016-FigO_4.

Note: In panel a, for some years data for electricity are interpolated from available data. GB = gigabytes.

Introduction

- 90% of data today has been created in the last two years.
- 235 million emails sent per day.
- 3.3 million Facebook posts created every minute.
- 3.8 million Google searches performed each minute.
- 1.7 megabytes of new information created every second, per person.

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➥ An immense amount of data, new and old, is recorded as text.

➥ More generally, much of this data is unstructured.

Structured vs. unstructured

Structured data

- Adheres to a defined data model.
- Examples: Tables, spreadsheets, relational databases, ...

Unstructured data

- Does *not* adhere to a defined data model.
- Typically text-heavy.
- Examples: Text feeds, speech transcripts, audio, images ...

Structured vs. unstructured

Structured data

- Adheres to a defined data model.
- Examples: Tables, spreadsheets, relational databases, ...

Semi-structured data

- Does *not* adhere to a formal data model,
- ... *but* contains tags or semantic mark-up.
- Examples: JSON, XML, emails, tagged text, ...

Unstructured data

- Does *not* adhere to a defined data model.
- Typically text-heavy.
- Examples: Text feeds, speech transcripts, audio, images ...

Text as data

- Text differs from other, traditional forms of data.
- Text is inherently *unstructured* and *high-dimensional*.
- One of the major fields of application of machine learning methods.
- Fast-growing field. Many new techniques developed in industry.
- Recent applications in economics and other social sciences.

This lecture

This lecture covers techniques for unstructured data.

- Methods for wrangling data.

➥ When unstructured $\approx$ dirty (or differently structured).

This lecture

This lecture covers techniques for unstructured data.

- Methods for wrangling data.

➥ When unstructured $\approx$ dirty (or differently structured).

- Methods for analyzing data which are naturally unstructured.

➥ No rectangular (or graph) structure, no well-defined relations between data elements.

Focus points

Focus on three main points.

1. Processing and transforming un-/semi-structured data.
2. Representing inherently unstructured text data.
3. Analyzing text data and using models to discover structure.
   (Supervised and unsupervised learning.)

Outline

1. Introduction

Data wrangling

2. Tools for scientific programming
3. Regular expressions and pattern recognition
4. Web scraping

Classical n-gram modeling approaches

5. Representing text as data
6. Supervised models for text data
7. Unsupervised models for text data

Information retrieval and distributional language models

8. Distributional models of meaning
9. Vector space representations

Assignment

Dates

Tuesday	15.09.2020	09.15-12.00	PC-Lab S18 HG.37
Wednesday	16.09.2020	14.15-18.00	PC-Lab S18 HG.37
Friday	18.09.2020	09.15-12.00	PC-Lab S18 HG.37
Tuesday	22.09.2020	09.15-12.00	PC-Lab S18 HG.37
Wednesday	23.09.2020	14.15-18.00	PC-Lab S18 HG.37
Friday	25.09.2020	09.15-12.00	PC-Lab S18 HG.37
Wednesday	30.09.2020	14.15-18.00	PC-Lab S18 HG.37

Technical requirements: Lab sessions

- All class material is available online:
  https://github.com/hliebert/course-unstructured-data.
- All material will run on the Windows computers in the lab.
- The lab materials can also be accessed online:
  Jupyter notebooks
  Rstudio server
- Alternatively, a linux virtual machine is available on the shared drive in the lab. Copy it to your computer and run it using VirtualBox. Has all course dependencies pre-installed. Extend the VM to your liking.
- Feel free to set up your own computer. Please ask if you need help.
- Clone/download the course repository to get started.

Required programs

- R.
- An editor or GUI (RStudio, VScode or Atom with R plugins, ...)
- If you want to use Jupyter notebooks or Python, install Anaconda (or its smaller miniconda version). On Linux, Anaconda is not necessary (but may be preferred to using pip and virtualenv).
- Run the R install script provided with the class material to install the R package dependencies and the R Kernel for Jupyter notebooks.
- A shell (bash or zsh) is pre-installed on Linux and MacOS. On MacOS, iterm2 is more convenient than Terminal. Use Windows Subsystem for Linux (WSL) on Windows, or Git Bash for a minimal set of features.
- To use Selenium from R, install Docker.
- To use Git (and minimal Bash on Windows), install Git.

How to install them

- Linux: Use your distribution's package manager.
- Mac: Use installer packages or set up and use homebrew as a package manager.
- Windows: Use installer packages or look into scoop or chocolatey as native package managers for Windows. WSL, Cygwin, Msys2 provide access to Unix functions on Windows.

Assignment

1. Web scraping assignment (20%)
2. Text analysis and research proposal (80%)

- Deadline: 25.10.2020.
- Grading is pass/fail.
- More details during the course of the lecture.

Primary references

- The course covers relatively broad and diverse topics, no single reference. Seminal references in the slides.
- Primary and secondary references below.
- Hastie et al. and Jurafsky & Martin books are available online (use newest 3rd edition draft of J & M).

Gentzkow, M., B. Kelly, and M. Taddy (2019). Text as Data. *Journal of Economic Literature* 57(3), 535–574. DOI: 10/gf7rd5.

Hastie, T., R. Tibshirani, and J. Friedman (2001). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Ed. by R. Tibshirani and J. H. (H. Friedman. New York.

Jurafsky, D. and J. H. Martin (2009). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. 2nd ed. Prentice Hall Series in Artificial Intelligence. Upper Saddle River, N.J: Pearson Prentice Hall.

Shotts, W. E. (2019). *The Linux Command Line: A Complete Introduction*. Second edition. San Francisco: No Starch Press.

Secondary references

- Reference material, applied or introductory text books.

Baumer, B., D. Kaplan, and N. Horton (2017). *Modern Data Science with R*. CRC.

Casella, G. and R. L. Berger (2001). *Statistical Inference*. Second. Duxbury Press.

Chacon, S. and B. Straub (2014). *Pro Git*. Apress.

James, G., D. Witten, T. Hastie, and R. Tibshirani (2015). *An Introduction to Statistical Learning with Applications in R*. Springer.

Matloff, N. (2011). *The Art of R Programming: A Tour of Statistical Software Design*. No Starch Press.

Mitchell, R. E. (2018). *Web Scraping with Python: Collecting More Data from the Modern Web*. Second edition. Sebastopol, CA: O'Reilly Media.

Munzert, S. (2014). *Automated Data Collection with R: A Practical Guide to Web Scraping and Text Mining*. Chichester, West Sussex, United Kingdom: Wiley.

Silge, J. and D. Robinson (2017). *Text Mining with R: A Tidy Approach*. First edition. Boston: O'Reilly.

Secondary references

Wasserman, L. (2006). *All of Nonparametric Statistics.* Springer.

Wasserman, L. (2010). *All of Statistics: A Concise Course in Statistical Inference.* Springer Texts in Statistics. New York, NY: Springer.