CSE 519: Data Science

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Lecture 6: Assembling Data Sets

Data Munging

Good data scientists spend most of their time cleaning and formatting data.

The rest spend most of their time complaining there is no data available.

Data munging or *data wrangling* is the art of acquiring data and preparing it for analysis.

Languages for Data Science

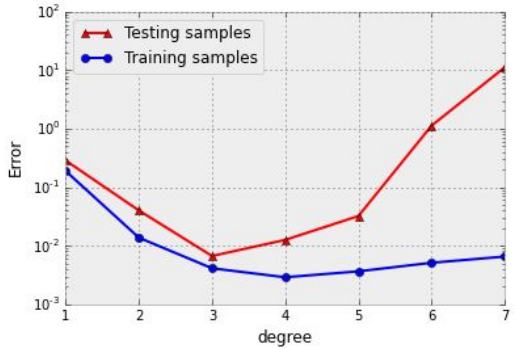
- *Python*: contains libraries and features (e.g regular expressions) for easier munging.
- *R*: programming language of statisticians.
- *Matlab*: fast and efficient matrix operations.
- *Java/C*: language for Big Data systems.
- *Mathematica/Wolfram Alpha*: symbolic math.
- *Excel*: bread and butter tool for exploration.

Notebook Environments

Mixing code, data, computational results, and text are essential for projects to be:

- reproducible
- tweakable
- documented.

```
In [40]: degrees = range(1, 8)
errors = np.array([regressor3(d) for d in degrees])
plt.plot(degrees, errors[:, 0], marker='^', c='r', label='Testing samples
plt.plot(degrees, errors[:, 1], marker='o', c='b', label='Training sample
plt.yscale('log')
plt.xlabel("degree"); plt.ylabel("Error")
  = plt.legend(loc='best')
```



By sweeping the degree we discover two regions of model performance:

- **Underfitting** (degree < 3): Characterized by the fact that the testing error will get lower if we increase the model capacity.
- **Overfitting** (degree > 3): Characterized by the fact the testing will get higher if we increase the model capacity. Note, that the training error is getting lower or just staying the same!.

Data Pipelines

Notebooks make it easier to maintain data pipelines, the sequence of processing steps from start to finish.

Expect to have to redo your analysis from scratch, so build your code to make it possible.

Standard Data Formats

Historically, computer scientists would rather share a toothbrush than a data format.

But accepted standards are now available:

- *CSV files*: for tables like spreadsheets
- *XML*: for structured but non-tabular data.
- *JSON*: Javascript Object Notation for APIs.
- *SQL databases*: for multiple related tables.

Where Does Data Come From?

The critical issue in any modelling project is finding the right data set.

This will certainly be the case for your projects!

Large data sets often come with valuable metadata: e.g. book titles, image captions, Wikipedia edit history...

Repurposing metadata requires imagination.

Sources of Data

- Proprietary data sources
- Government data sets
- Academic data sets
- Web search
- Sensor data
- Crowdsourcing
- Sweat equity

https://toolbox.google.com/datasetsearch

Proprietary Data Sources

Facebook, Google, Amazon, Blue Cross, etc. have exciting user/transaction/log data sets.

Most organizations have/should have internal data sets of interest to their business.

Getting outside access is usually impossible.

Companies sometimes release rate-limited APIs, including Twitter and Google.

Government Data Sources

- City, State, and Federal governments are increasingly committed to open data.
- Data.gov has over 100,000 open data sets!
- The Freedom of Information Act (FOI) enables you to ask if something is not open.
- Preserving privacy is often the big issue in whether a data set can be released.

Academic Data Sets

- Making data available is now a requirement for publication in many fields.
- Expect to be able to find economic, medical, demographic, and meteorological data if you look hard enough.
- Track down from relevant papers, and ask.
- Google topic and “Open Science” or “data”

Web Search/Scraping

Scraping is the fine art of stripping text/data from a webpage.

Libraries exist in Python to help parse/scrape the web, but first search:

- Are APIs available from the source?
- Did someone previously write a scraper?

Terms of service limit what you can legally do.

Available Data Sources

- Bulk Downloads: e.g. Wikipedia, IMDB, Million Song Database.
- API access: e.g. New York Times, Twitter, Facebook, Google.

Be aware of limits and terms of use.

Sensor Data Logging

The “Internet of Things” can do amazing things:

- Image/video data can do many things: e.g. measuring the weather using Flicker images.
- Measure earthquakes using accelerometers in cell phones.
- Identify traffic flows through GSP on taxis.

Build logging systems: storage is cheap!

Crowdsourcing

Many amazing open data resources have been built up by teams of contributors:

- Wikipedia/Freebase
- IMDB

Crowdsourcing platforms like Amazon Turk enable you to pay for armies of people to help you gather data, like human annotation.

Sweat Equity

But sometimes you must work for your data instead of stealing it.

Much historical data still exists only on paper or PDF, requiring manual entry/curation.

At one record per minute, you can enter 1,000 records in only two work days.

Often projects require sweat equity.

Project Data Sources

- Miss Universe?
- Movie gross?
- Baby weight?
- Art auction price?
- Snow on Christmas?
- Super Bowl / College Champion?
- Ghoul Pool?
- Future Gold / Oil Price?

Cleaning Data: Garbage In, Garbage Out

Many issues arise in ensuring the sensible analysis of data from the field, including:

- Distinguishing errors from artifacts.
- Data compatibility / unification.
- Imputation of missing values.
- Estimating unobserved (zero) counts.
- Outlier detection.

Errors vs. Artifacts

- Data errors represent information that is fundamentally lost in acquisition.
- Artifacts are systematic problems arising from processing done to data.

The key to detecting artifacts is the sniff test, examining the product closely enough to get a whiff of something bad.

First-time Scientific Authors by Year?

In a bibliographic study, we analyzed PubMed data to identify the year of first publication for the 100,000 most frequently cited authors.

What *should* the distribution of new top authors by year look like?

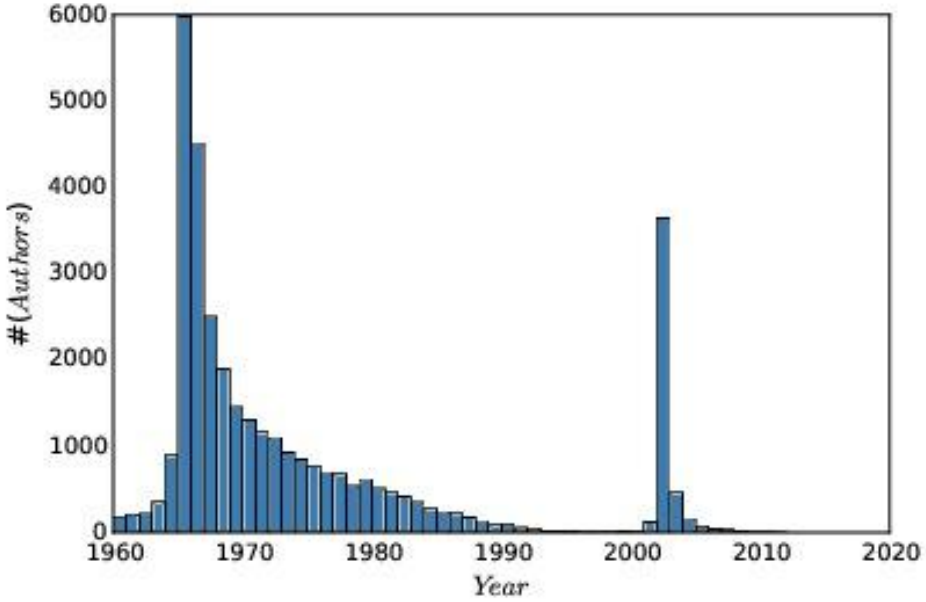
It is important to have a preconception of any result to help detect anomalies.

Might this be Right?

A student once tried to foist this off on me.

What artifacts do you see?

What possible explanations could cause them?



Mystery Solved!

Pubmed used author first names starting in 2002.

SS Skiena became

Steven S Skiena

Data cleaning gets rid of such artifacts.