Python for Data Scientists

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Goals for these two sessions

- For people who've never seen Python:

  Learn enough Python to want more

- For people who use a bit of Python:

  Learn new tricks useful in data science

- For people who know Python inside out:

  Showcase of data-science libraries

Overview (today)

- About me
- Quick history of Python
- Whirlwind tour of ecosystem & language
- Pros and cons for Python in data science

Overview (next Thursday)

- Showcase of key data science packages
  - NumPy
  - SciPy
  - Pandas
  - MatPlotLib & Seaborn
  - SciKit-Learn
- Efficient Python
- Where to learn more

About Me

- Previous life: trained as physicist, researcher in theoretical chemistry
- Started using Python in 2012 for research projects, contributed cKDTrees to SciPy.
- Changed careers in Sep 2013: online advertising / big data until Jan 2015, data scientist / engineer at Data Minded. Now freelancer in data engineering & data science.
- Used Python for data wrangling & exploration, data pipeline management and dynamic query generation.
- Organised MOOC coaches & corporate trainings on Python, Spark, Hadoop, …

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~~http://www.varilly-sciences.eu~~ (soon)

http://github.com/patvarilly

(Abridged) History of Python

Guido van Rossum
Python's Benevolent Dictator For Life (BDFL)

- Created in 1989 by Guido van Rossum at CWI in Amsterdam.
- Currently, two major, **incompatible** branches of Python: Python 2 and Python 3.
  - forked in 2008 to fix how strings & unicode are handled.
  - main development in Python 3 (now: 3.5.2)
  - Python 2 is frozen and supported until 2020. Good features from Python 3 are back-ported.
  - most scientific computing & data science written for Python 2 (but can use them in Python 3)
  - **we'll stick to Python 2 today**

Much more in depth: http://python-history.blogspot.com

(Abridged) History of Python

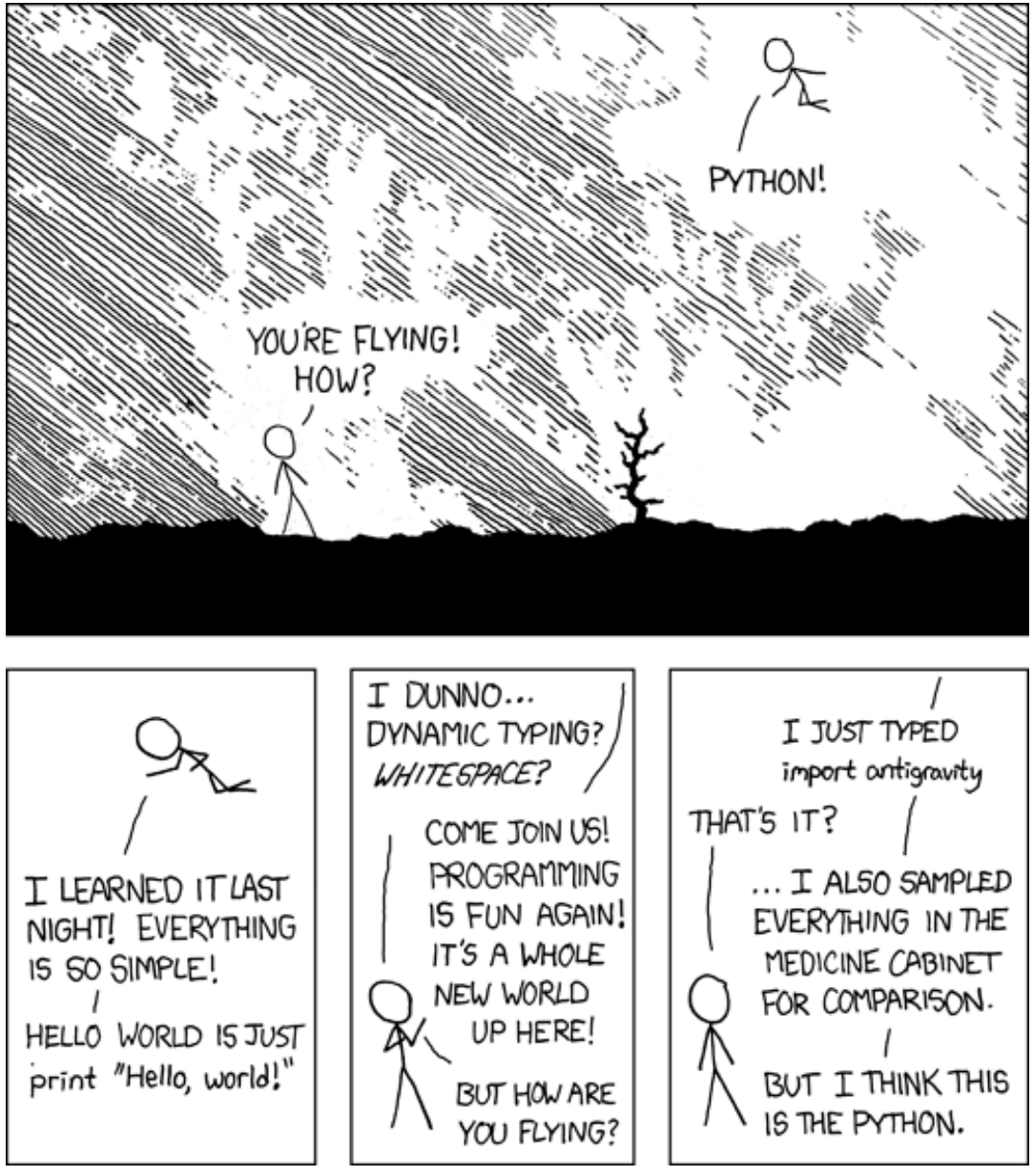
- Vast numbers of libraries & tools make Python **useful**:
  - 1995 – NumPy: fast vector and matrix algebra
  - 2001 – SciPy: optimization, integration, FFT, ODEs, …
  - 2007 – Matplotlib: MATLAB-style plotting
  - 2007 – Scikit-Learn: machine learning
  - 2007 – Cython: static typing for fast, compiled code
  - 2007 – IPython: much-improved REPL, notebooks for sharing & presenting (now Jupyter Notebook)
  - 2008 – Pandas: data frames for data wrangling
  - 2012 – Numba: near-transparent JIT compilation
  - 2012 – pySpark: big data / distributed computing
  - 2012 – seaboarn: easy and beautiful stats visualisations

Typical Python use cases

- Web development — Google's first crawler, youtube.com, bit.ly, SurveyMonkey, OpenERP, …
- System management — yum for packages, Ansible for infrastructure
- In-app scripting / glue code – Blender, Industrial Light & Magic
- Science – data analysis at LHC, astrophysics at ALMA
- Engineering — systems control at Siemens
- Finance — risk management at Swisscom
- Outreach – One Laptop Per Child, MIT's Intro to Programming

Sources: http://brochure.getpython.info, https://www.python.org/about/success, https://docs.python.org/3/faq/general.html

Atypical Python use cases



Zen of Python

Beautiful is better than ugly.

Explicit is better than implicit.

Simple is better than complex.

Complex is better than complicated.

Flat is better than nested.

Sparse is better than dense.

Readability counts.

Special cases aren't special enough to break the rules.

Although practicality beats purity.

Errors should never pass silently.

Unless explicitly silenced.

In the face of ambiguity, refuse the temptation to guess.

There should be one—and preferably only one—obvious way to do it.

Although that way may not be obvious at first unless you're Dutch.

Now is better than never.

Although never is often better than *right* now.

If the implementation is hard to explain, it's a bad idea.

If the implementation is easy to explain, it may be a good idea.

Namespaces are one honking great idea -- let's do more of those!

https://www.python.org/dev/peps/pep-0020/

Whirlwind tutorial of Python

- *Go to http://aa.bb.cc.dd:8888*
- *Make a folder for yourself*
- *Copy “Overview.ipynb” in your folder.*
- *Open it and follow along*

Pros of Python in data science

- Quick to write, interactive: encourages experimentation
- Huge library of packages: interact with any data source, lots of algorithm available with little effort
- Full & sensible programming language: not crippled, scales well (compare to SQL or Matlab)
- Emphasis on communication with others: “executable pseudo-code” (Zen of Python), IPython notebook

Cons of Python in data science

- Dynamic typing: errors show up mostly at runtime, not compile time
- Interpreted: naïve, pure Python can be very slow (300-500x slower than C)
- Data usually must fit in memory (with noteworthy exceptions, e.g., pySpark)
- R probably has more stats & machine learning libraries
- Python 2 vs Python 3 split still not fully resolved

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