

# Code is Big Data

Emmanuel Bengio - COMP 762

- ▶ D3, Data-Driven Documents
- ▶ Learning from Examples to Improve Code Completion Systems
- ▶ Method-Call Recommendations from Implicit Developer Feedback
- ▶ Milepost GCC: Machine Learning Enabled Self-tuning Compiler
- ▶ Learning to Execute

# D<sup>3</sup>, Data-Driven Documents

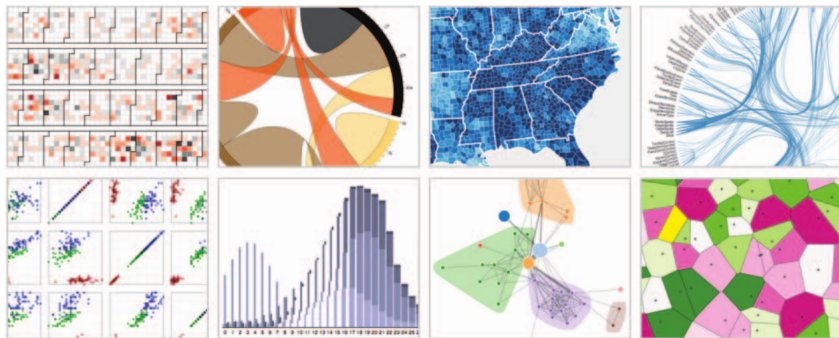
Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer

IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS, 2011

- ▶ Data visualization library
- ▶ Instead of creating a whole new hidden representation of the data, it operates directly on the DOM
- ▶ Bind data to some html/svg element, apply explicit transformations on it (e.g. position, color, thickness)
- ▶ Visualization is important in many ways to help us make sense of data (and we should do alot more of it)

# D<sup>3</sup>, Data-Driven Documents

- ▶ Also looks really nice



# Learning from Examples to Improve Code Completion Systems

Marcel Bruch, Martin Monperrus, and Mira Mezini  
ESEC 2009

- ▶ Comparison of 3 non-trivial code completion systems:
  - ▶ frequency based
  - ▶ association rule based
  - ▶ *Best Matching Neighbor* (kNN)
- ▶ Quantitative evaluation
- ▶ Evaluation by 10 experienced users
  - kNN-like approach performs best

# Learning from Examples to Improve Code Completion Systems

- ▶ There are gigabytes of code data (github, bitbucket, etc.)
- ▶ There are usage patterns, a basic algorithm like kNN does something good!
- ▶ (Imagine if we threw Deep Learning at this problem)

# Method-Call Recommendations from Implicit Developer Feedback

Sven Amann, Sebastian Proksch, and Mira Mezini  
ICSE 2014

- ▶ Use history of user's code completions as data
- ▶ Pose problem as Collaborative Filtering
- ▶ For new code completions, find best matches using CF
- ▶ The data is there, new CF algorithms are invented every year

# Milepost GCC: Machine Learning Enabled Self-tuning Compiler

Grigori Fursin, Yuriy Kashnikov, Abdul Wahid Memon, Zbigniew Chamski,  
Olivier Temam, Mircea Namolaru, Elad Yom-Tov, Bilha Mendelson, Ayal Zaks,  
Eric Courtois, Francois Bodin, Phil Barnard, Elton Ashton, Edwin Bonilla, John  
Thomson, Christopher K. I. Williams, Michael O'Boyle  
International journal of parallel programming, 2011

- ▶ Learn mapping from AST features to “-Ox -f[no]y -f...”
- ▶ Use machine learning to learn the mapping:
  - ▶ Predictive Search Distributions
  - ▶ Decision Trees
- ▶ Reduce execution time (~17%)
- ▶ Reduce compilation time (12%) and code size (7%)

# Learning To Execute

Wojciech Zaremba, and Ilya Sutskever

- Learn mapping from source code to output (at character level)

**Input:**

```
j=8584
for x in range(8):
    j+=920
b=(1500+j)
print((b+7567))
```

**Target:** 25011.

**Input:**

```
i=8827
c=(i-5347)
print((c+8704) if 2641<8500 else 5308)
```

**Target:** 12184.

- Learned model performs 9-digit addition with 99% accuracy



# Learning To Execute

- ▶ Why is this interesting?
  - ▶ Relatively simple RNN model can do this
  - ▶ Code is a viable domain for NN
- ▶ Using this kind of model for my last 3 papers could be beneficial:
  - ▶ Representation learning
  - ▶ Generative prediction (code completion)
  - ▶ Predictive supervised model