







My bio in 5 photos



MSc in applied maths and noise punk in South Africa



PhD in maths at Cambridge



Drove from Cambridge to Mongolia in a tiny car



Developer at a cybersecurity startup



Data Science strategy at ARM



Outline

About me

Why do we do data science?

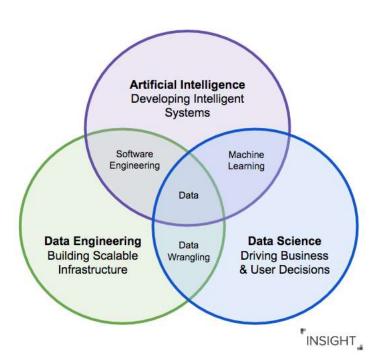
Making the promise of ML real: deployment (systems)

Demo: Clipper (RISE)

Best practices



What is Data Science?









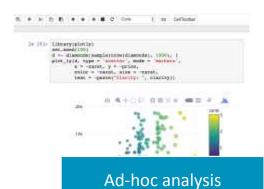








Optimising features



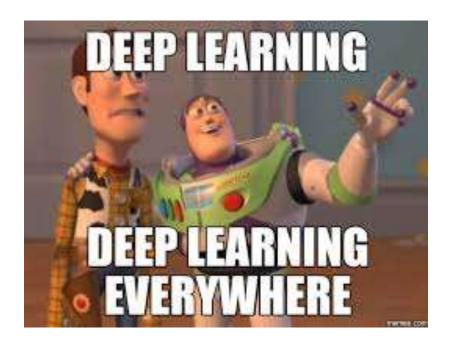




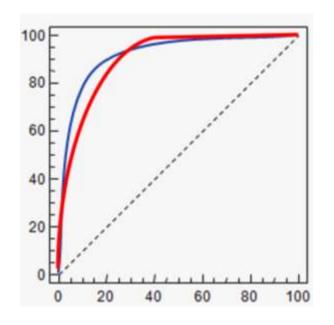


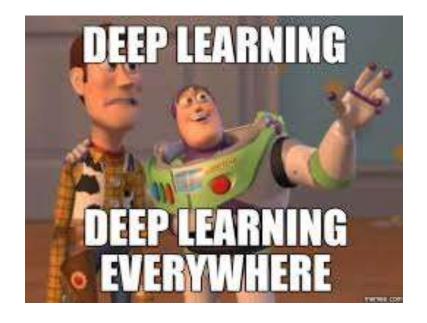




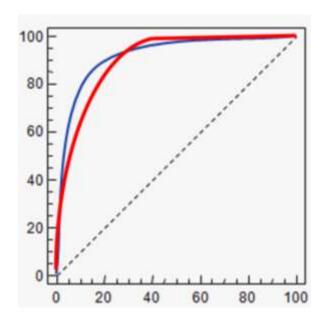






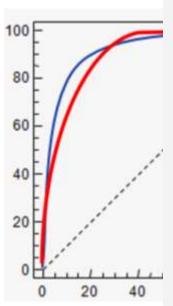


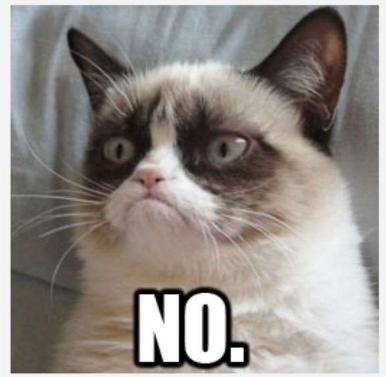












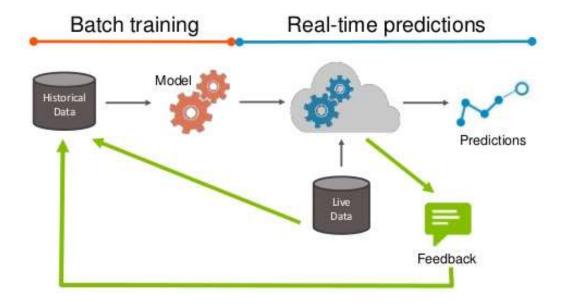




Deployment makes the promise of ML real

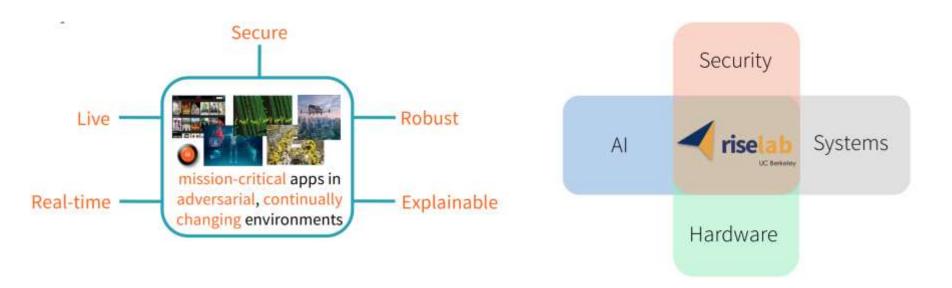


Deployment makes the promise of ML real













Simplifies integration of ML in apps Clipper makes product teams happy.

Simplifies model deployment Clipper makes data scientists happy.

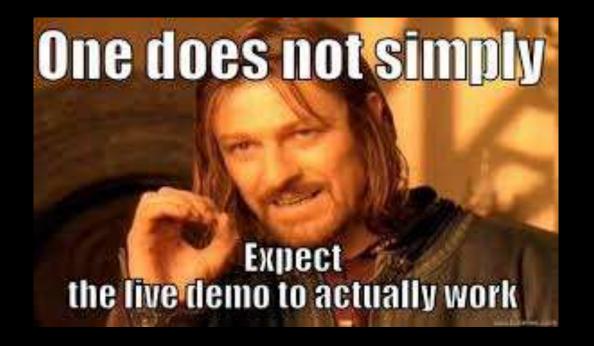
Throughput:

Clipper makes the infra-team less unhappy.

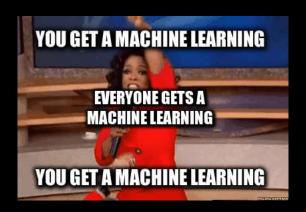
Accuracy: Clipper makes users happy.



Model deployment demo



Try it!

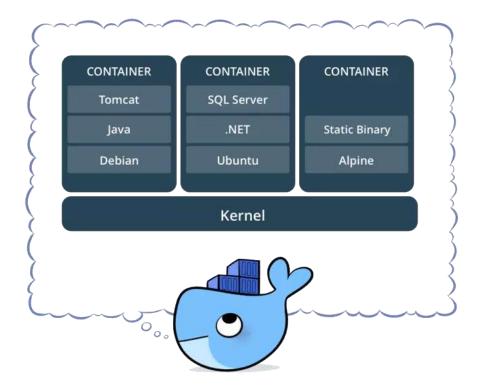


curl -X POST -d '{"input": [4.3, 2.0,1.0, 0.1]}' 172.16.34.147:1337/iris/predict





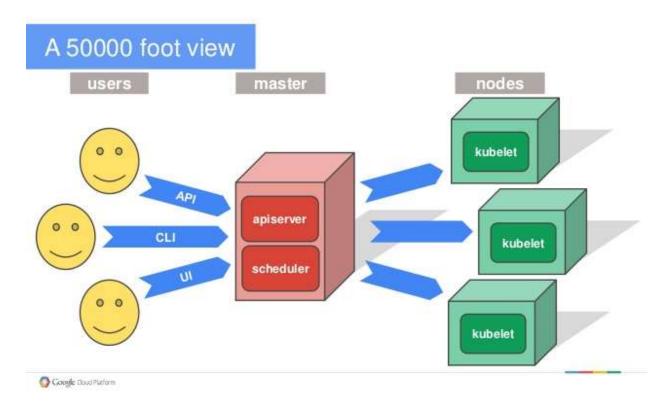
Containers & docker



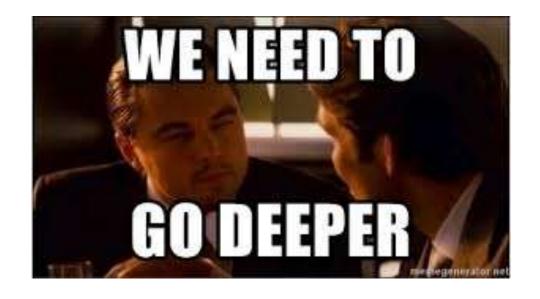
- Standardized packaging for software and dependencies
- Isolate apps from each other
- Share the same OS kernel
- Works with all major Linux and Windows Server



Scaling with Kubernetes







Clipper docs - http://clipper.ai/





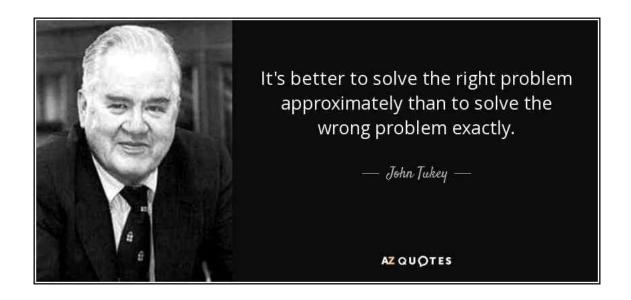
Best Practices Learn from the mistakes of others!



Best Practices
Learn from the mistakes of others!

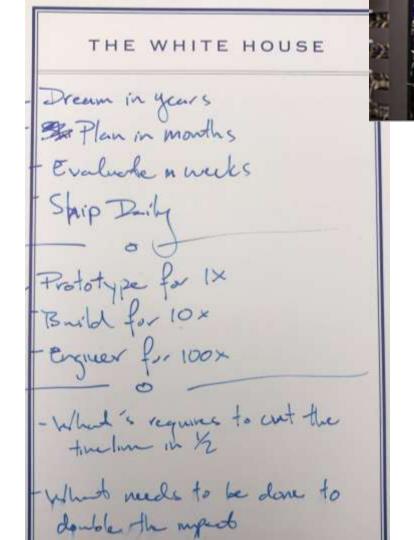
- 1. Solve the right problem
- 2. Fail better every day
- 3. Data quality matters
- 4. Simplicity is your friend
- 5. Debugging makes you a wizard
- 6. Fairness & privacy are not dirty words

What is your problem?





What is your problem?



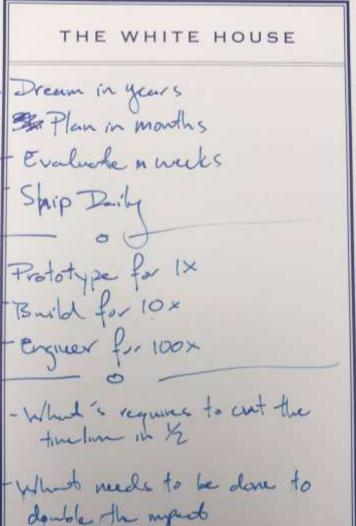
DJ Patil US Chief Data Scientist

arm

What is your problem?



Sheryl Sandberg COO Facebook









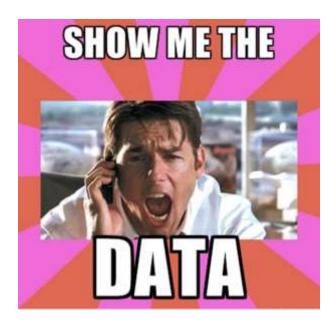












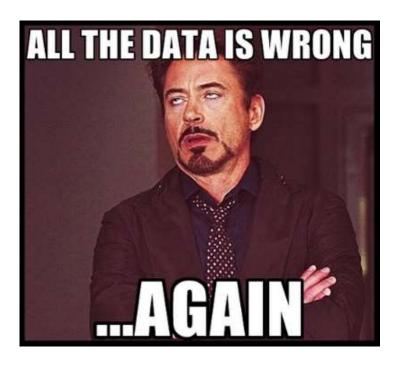


















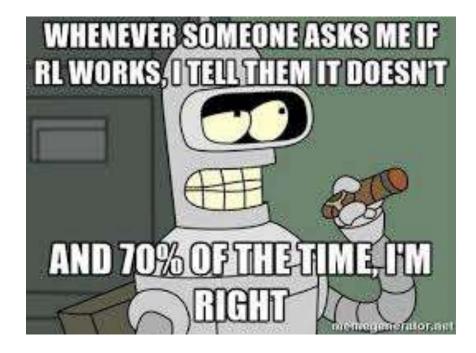




Data quality









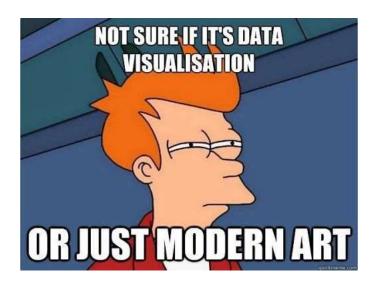
"There is a lot of value in combining many different datasets and computing simple stats"

-- John Quinn, DSA2017





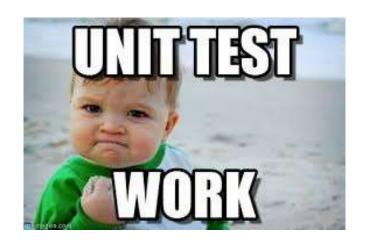
Visualisation
Linear models
Rules (gross!)





- Very soon, your simple prototype will become a complex system
- You are uncertain at the beginning of a project, so capture that!
- Simple models can be a baseline to measure complex models later





```
from unnecessary_math import multiply

def test_numbers_3_4():
    assert multiply(3,4) == 12

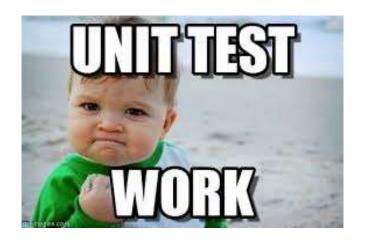
def test_strings_a_3():
    assert multiply('a',3) == 'aaa'

second import multiply

def test_numbers_3_4():
    assert multiply(3,4) == 12
```

http://pythontesting.net/framework/nose/nose-introduction/





http://pythontesting.net/framework/nose
/nose-introduction/

```
from unnecessary_math import multiply

def test_numbers_3_4():
    assert multiply(3,4) == 12

def test_strings_a_3():
    assert multiply('a',3) == 'aaa'
```

Ran 2 tests in 0.000s

> nosetests test_um_nose.py

OK

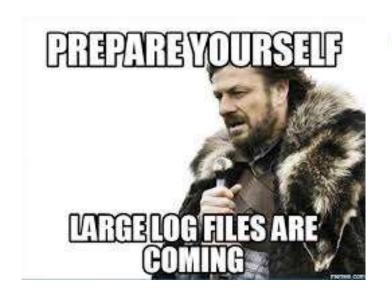


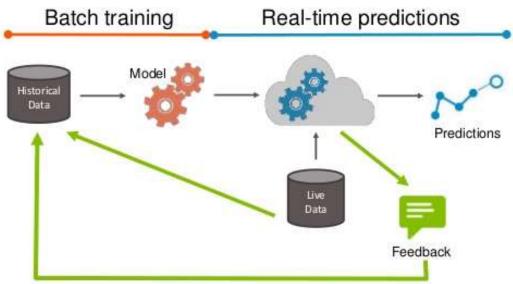
	COMMENT	DATE
Q	CREATED MAIN LOOP & TIMING CONTROL	14 HOURS AGO
Ó	ENABLED CONFIG FILE PARSING	9 HOURS AGO
o	MISC BUGFIXES	5 HOURS AGO
0	CODE ADDITIONS/EDITS	4 HOURS AGO
d	MORE CODE	4 HOURS AGO
9	HERE HAVE CODE	4 HOURS AGO
0	ARAAAAA	3 HOURS AGO
6	ADKFJ5LKDFJ5DKLFJ	3 HOURS AGO
0	MY HANDS ARE TYPING WORDS	2 HOURS AGO
þ	HAAAAAAAANDS	2 HOURS AGO

AS A PROJECT DRAGS ON, MY GIT COMMIT MESSAGES GET LESS AND LESS INFORMATIVE.



Deployment makes the promise of ML real







- how asking dumb questions is actually a superpower
- how you can read the source code to programs when all other avenues fail
- debugging tools that make you FEEL like a wizard
- Understanding what your _organization_ needs can make you amazing

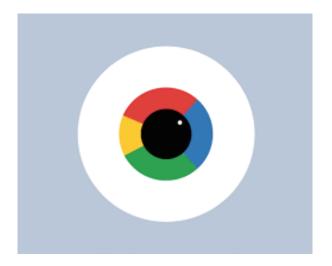
-- Julia Evans



https://jvns.ca/blog/so-you-want-to-be-a-wizard/



Fairness & Privacy



Surveillance or Assistance?



Fairness & Privacy





Can we use the tools above to build fair ML?

- 1. Solve the right problem
- 2. Fail better every day
- 3. Data quality matters
- 4. Simplicity is your friend
- 5. Debugging makes you a wizard

- 1. Thresholds the same for all groups?
- 2. Commit to fix fairness issues
- 3. Bias is in the data, not the algorithms
- 4. Easier to interpret at first
- 5. Unit test for fairness



Further reading

<u>Martin Zinkevitch – Rules of ML for Google</u> <u>engineers</u>

Andrew Ng -- ML systems at NIPS 2016

<u>Peter Warden – How and why to improve your training data</u>

<u>Michael Jordan – The AI revolution hasn't</u> <u>happened yet</u>

<u>Lydia Liu et al – delayed impact of fairness in ML</u>

My more detailed notes on data science projects

<u>Jason Brownlee – Concept Drift Info</u>

Katie Malone -- Picking data science projects



