Deep Learning Walkthrough - 08

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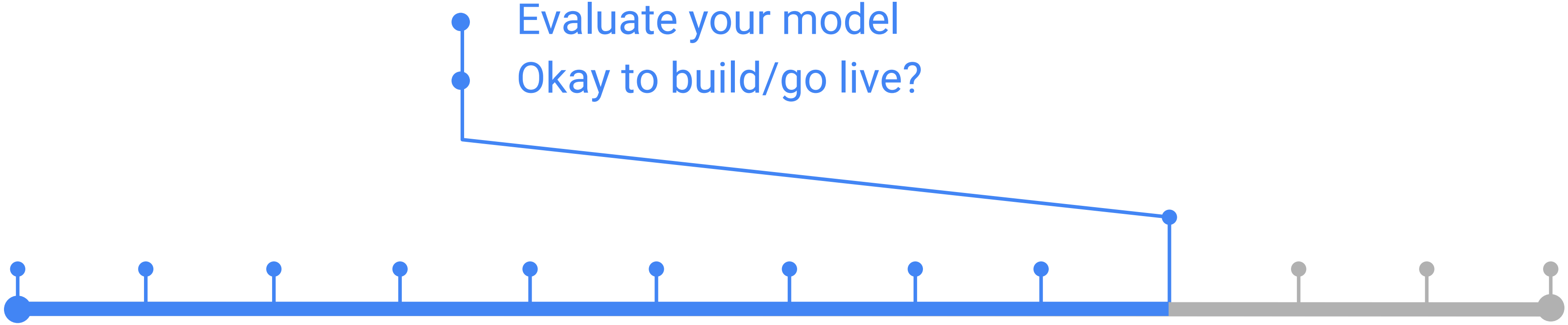
Google Cloud

Step 9 | Test your model

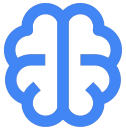
Evaluate your model

Okay to build/go live?



Chief actors:

Analyst



Decision maker

Google Cloud

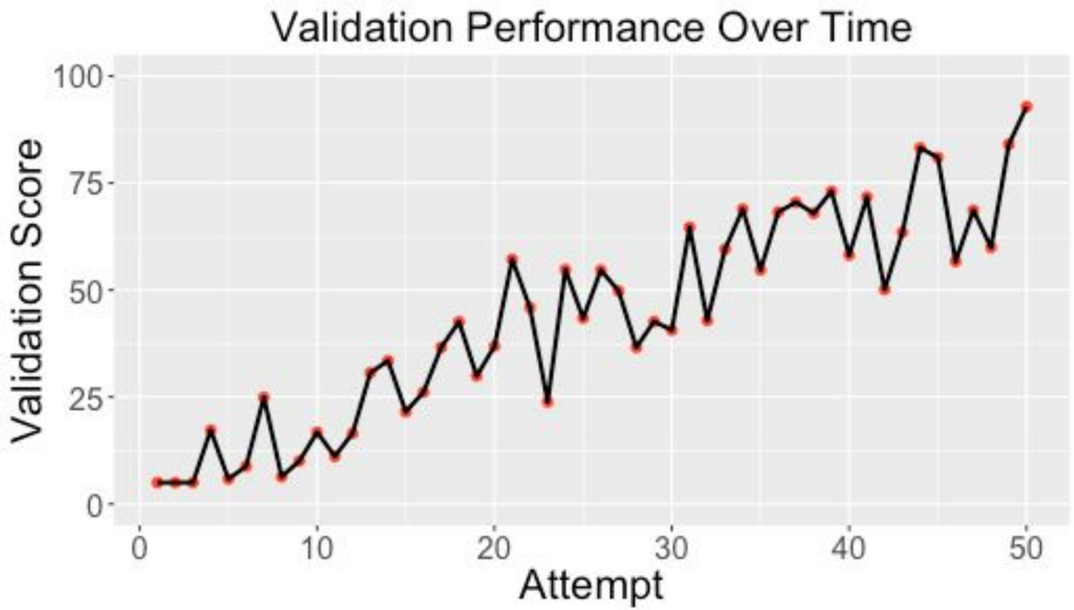
CAUTION: Entering Statistics Zone

Testing and validation
Why both?

You now have one best candidate model

Everything looked good in validation

Should we take it live?



Testing and validation
Why both?

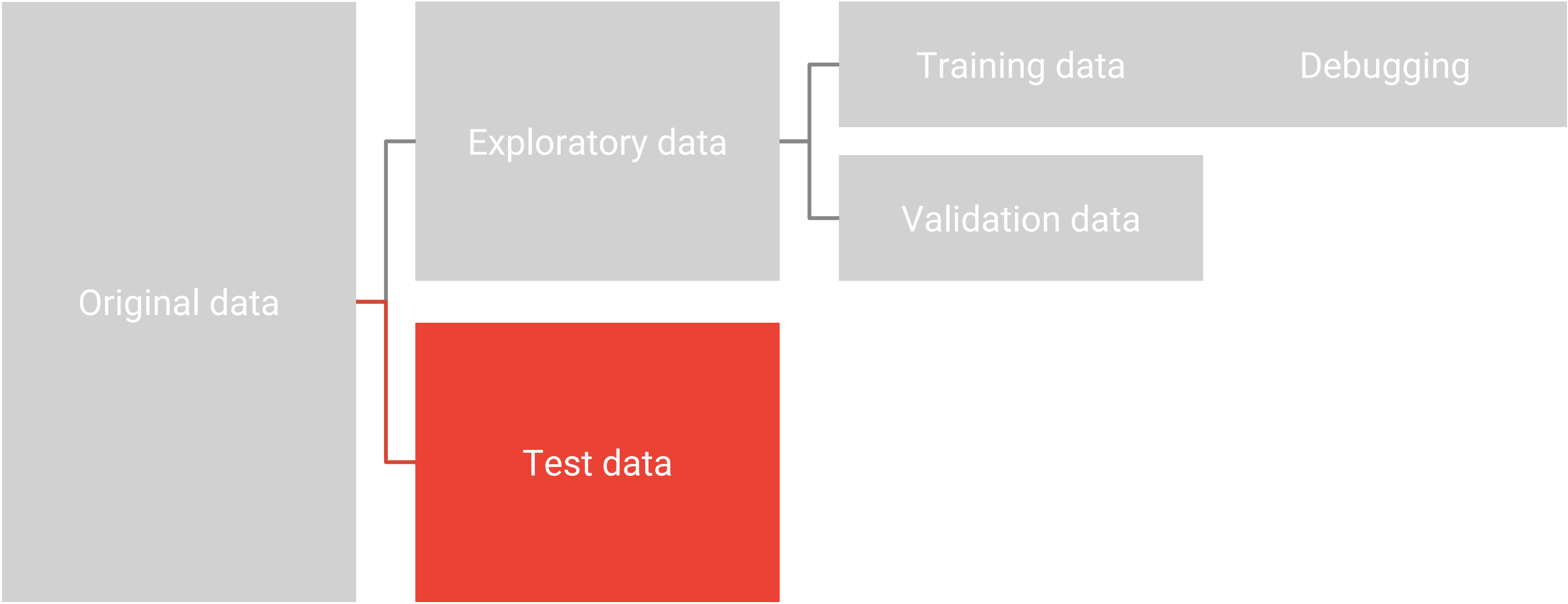
Your validation dataset gets polluted the more you use it, so it stops being an honest measure of performance

Only testing lets you know if your best is truly good enough

Testing, the final frontier

Now entering a cleanroom with precious, completely unpolluted (new) data and estimating the model's out-of-sample performance

Use this, not that



The decisions

Your mission: Make the most important decision

This model is the best you have
Should you kill it?

Welcome to **statistics!** This is what you need **hypothesis testing for.**

Key message

!

Testing is the final frontier before you take your model live

This is where statistical rigor enters the picture

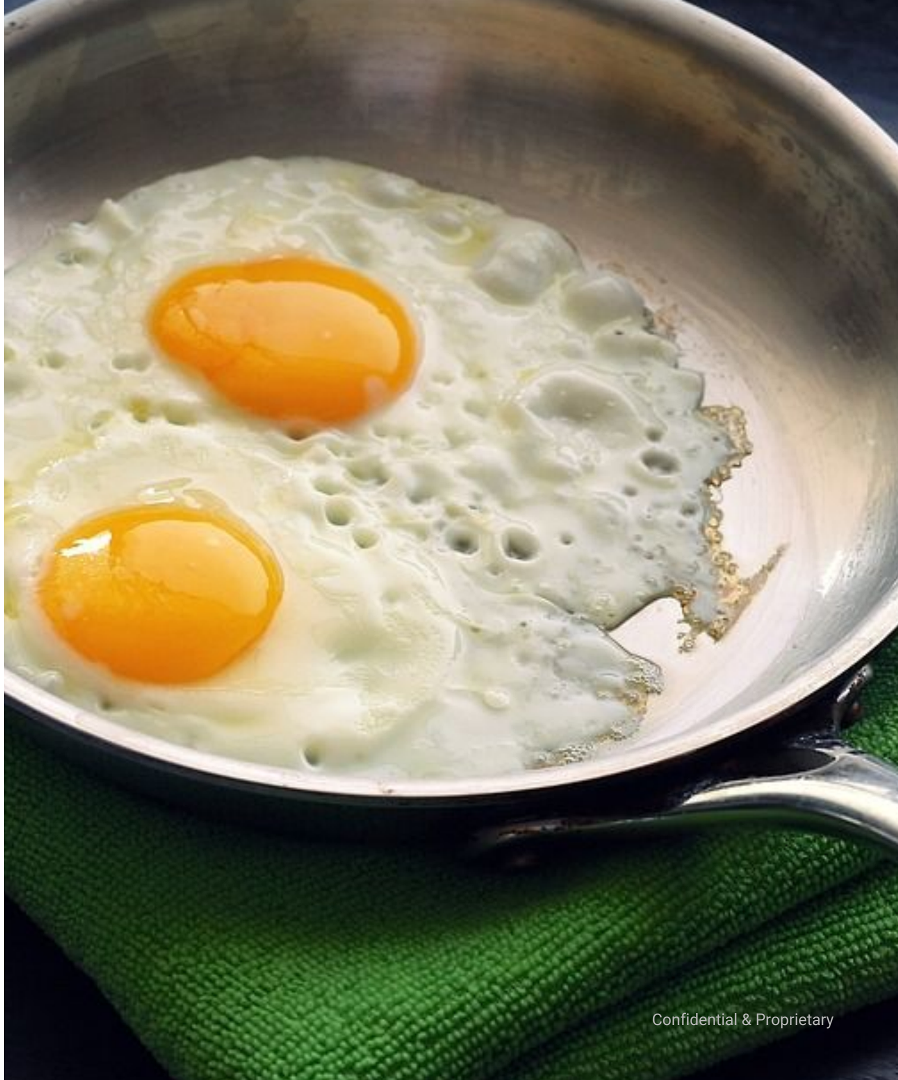
If testing fails, you can only start again if you can collect a new test dataset

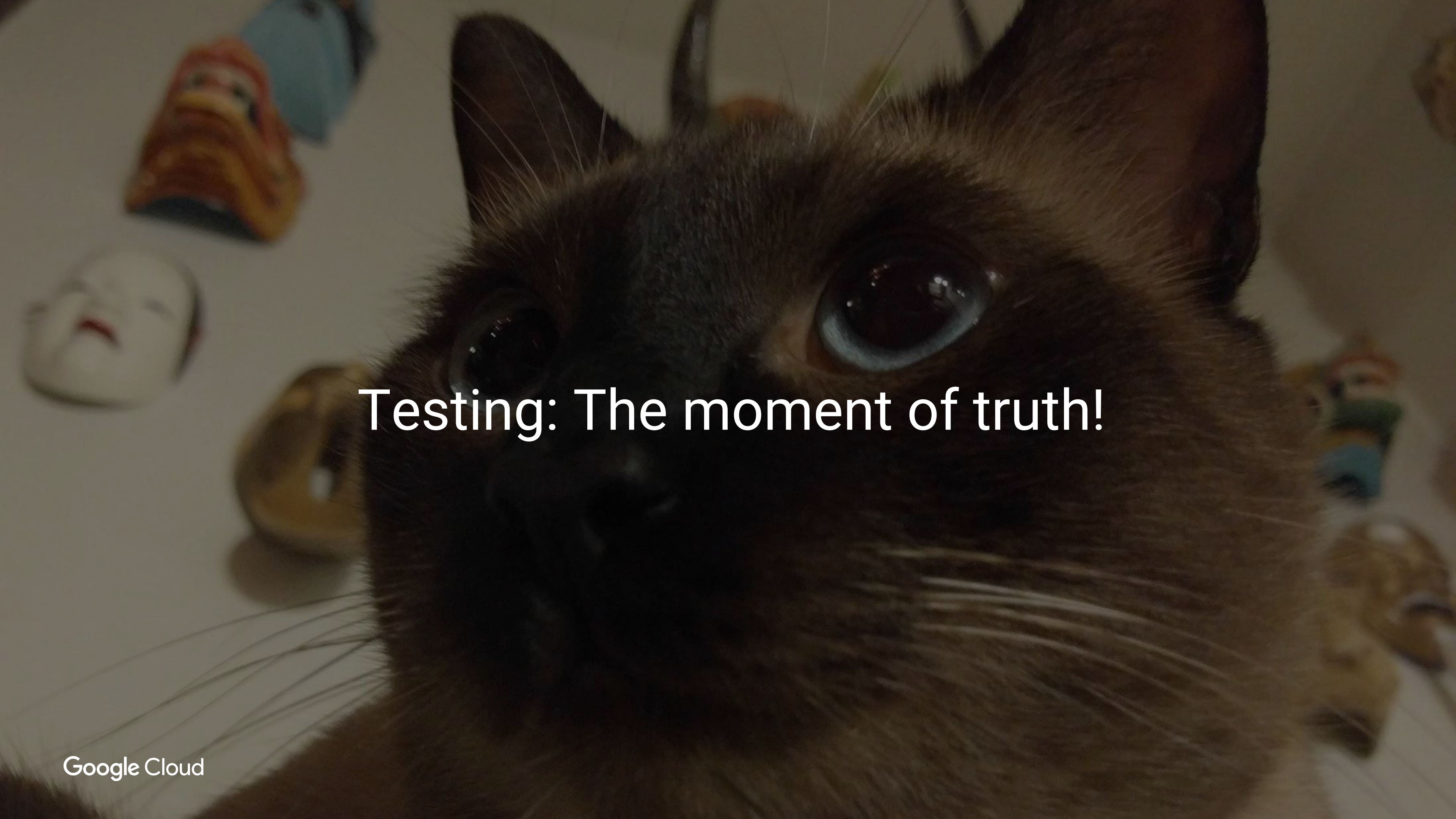
In practice

!

There is a way to try again.

Collect a new test dataset.





Testing: The moment of truth!

Step 9 - Statistical Testing

Apply cat_finder() to the test dataset ONE TIME ONLY. Since this is testing, we'll only look at the final performance metric (accuracy) and the results of the statistical hypothesis test.

In [24]:
```
# Hypothesis test we'll use:
from statsmodels.stats.proportion import proportions_ztest

# Testing setup:
SIGNIFICANCE_LEVEL = 0.05
TARGET_ACCURACY = 0.80
```

In [25]:
```
files = os.listdir(TEST_DIR)
predicted = cat_finder(TEST_DIR, model_version)
observed = get_labels(TEST_DIR)
print('\nTest accuracy is ' + str(get_accuracy(observed, predicted, roundoff=4)))
```

```
INFO:tensorflow:Restoring parameters from ../../ user /data/output_cnn_big/model.ckpt-3000
1000 predictions completed (out of 15748)...
2000 predictions completed (out of 15748)...
3000 predictions completed (out of 15748)...
4000 predictions completed (out of 15748)...
5000 predictions completed (out of 15748)...
6000 predictions completed (out of 15748)...
7000 predictions completed (out of 15748)...
8000 predictions completed (out of 15748)...
9000 predictions completed (out of 15748)...
10000 predictions completed (out of 15748)...
11000 predictions completed (out of 15748)...
12000 predictions completed (out of 15748)...
```

```
5000 predictions completed (out of 15748)...
6000 predictions completed (out of 15748)...
7000 predictions completed (out of 15748)...
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11000 predictions completed (out of 15748)...
12000 predictions completed (out of 15748)...
13000 predictions completed (out of 15748)...
14000 predictions completed (out of 15748)...
15000 predictions completed (out of 15748)...
15748 predictions completed (out of 15748)...

Test accuracy is 0.8416
```

In [26]:

```
# Using standard notation for a one-sided test of one population proportion:
n = len(predicted)
x = round(get_accuracy(observed, predicted, roundoff=4) * n)
p_value = proportions_ztest(count=x, nobs=n, value=TARGET_ACCURACY, alternative='larger')[1]
if p_value < SIGNIFICANCE_LEVEL:
    print('Congratulations! Your model is good enough to build. It passes testing. Awesome!')
else:
    print('Too bad.  Better luck next project.  To try again, you need a pristine test dataset.')
```

```
Congratulations! Your model is good enough to build. It passes testing. Awesome!
```

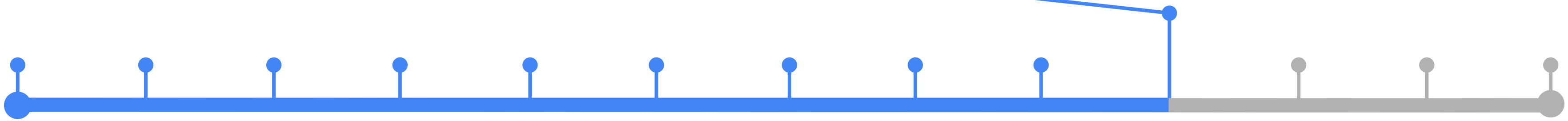
Danger! Pitfall alert

Never test on data that was involved in any way in training or validation

You will fool yourself into launching something horrible

Step 9 is finished | You have a document clearly detailing:

- Decision process
- Whether to go live
- Performance estimate



Chief actors:

Analyst

Decision maker

Step 9 is finished | You have a document clearly detailing:

- Notebook for Steps 1 and 9
- Yes!
- 84% accuracy

Chief actors:

Analyst

Decision maker

Google Cloud

End of demo!

If you found it useful, share the love and say hi on twitter.com/quaesita.

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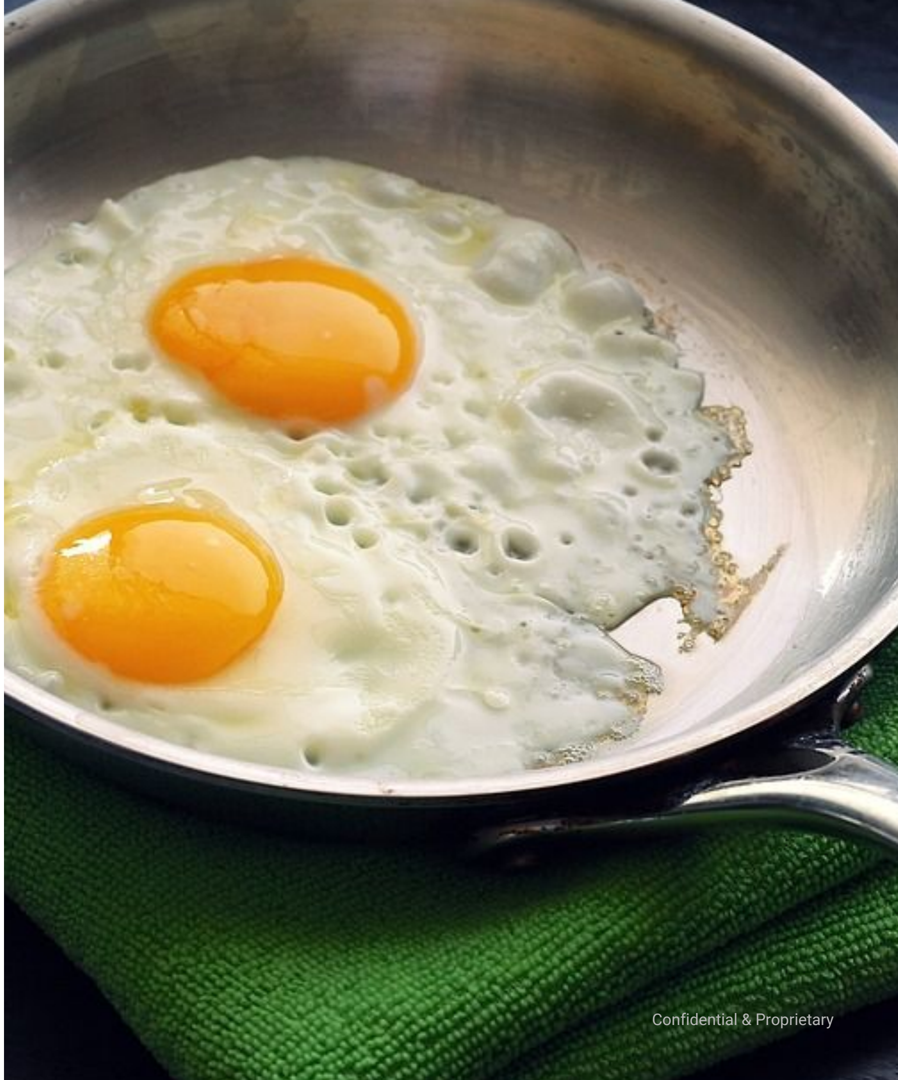
Google Cloud

In practice

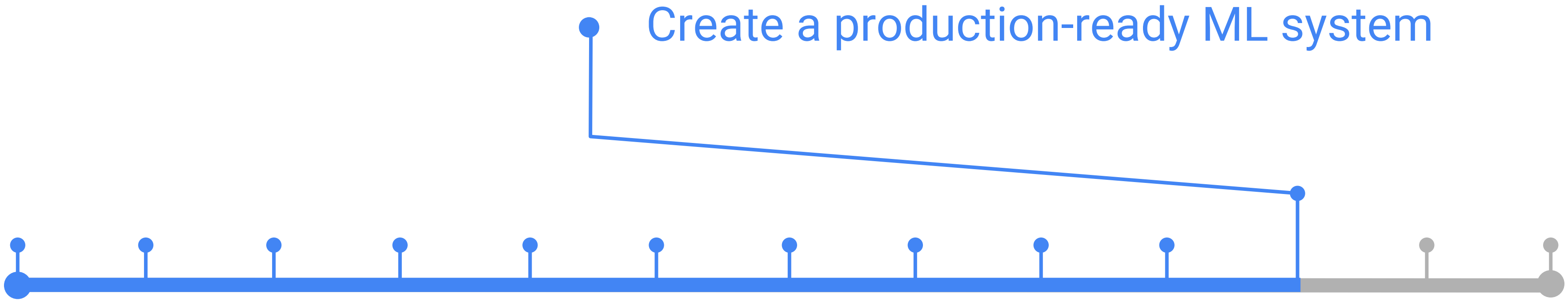
!

ML doesn't only have to involve big launches in industry production systems. Use it at home too.

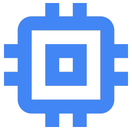
For you, a "launch" might refer to a decision to rely on some model from now on.



Step 10 | Build your ML system



Chief actors:



You can find a tutorial on Step 10 at:

github.com/google-aai/tf-serving-k8s-tutorial

Authors: Brian Foo and Ron Bodkin

Brian
Foo

Ron
Bodkin

Google Cloud

Danger! Pitfall alert

Your system might learn all kinds of things you would be embarrassed to show users, e.g. use of profanity in speech.

Don’t forget to use a **policy layer** on top of your model’s output to check the output and keep undesirable things from surfacing.

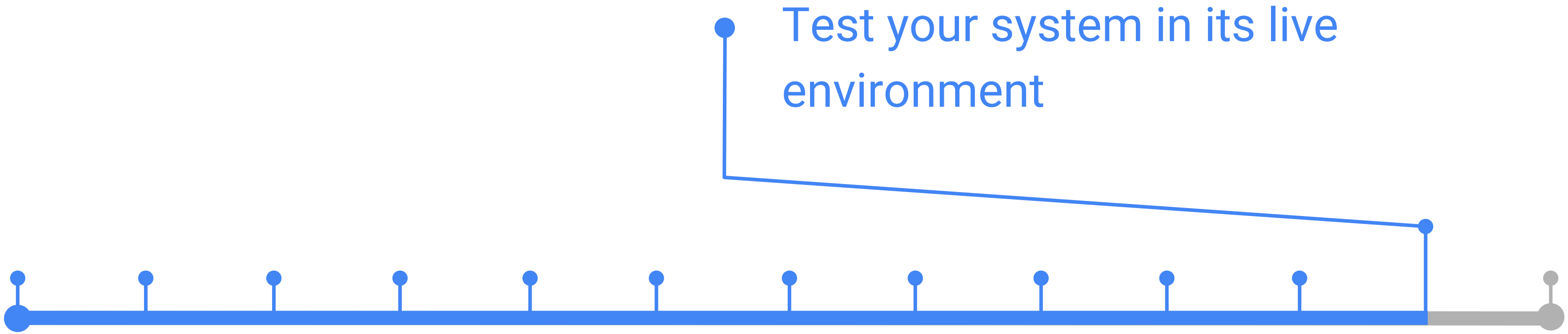
Step 10 is finished | Your engineering effort got you:

- Production-ready system
- Automated retraining
- Safety nets

Chief actors:

Engineer

Step 11 | Make launch decision



Chief actors:

Analyst

Decision maker

Danger! Pitfall alert

Don't launch all at once.

It's better to look before you leap.

Plan a gradual ramp-up where you start serving the model to a small fraction of traffic.

Live-traffic experiments are a great idea!

Training-serving skew

Beware the training-serving skew

To ensure your model works where you'll be serving it, test again in **production**!

Live traffic experiments

Second time we'll need **statistics** for decision: Launch it or don't launch it?

Don't be sloppy on this one. Make this choice rigorously by running an experiment

Live traffic experiments

Components of a real experiment:

1. Hypothesis
2. Different treatments
3. Randomization to treatments

Live traffic experiments

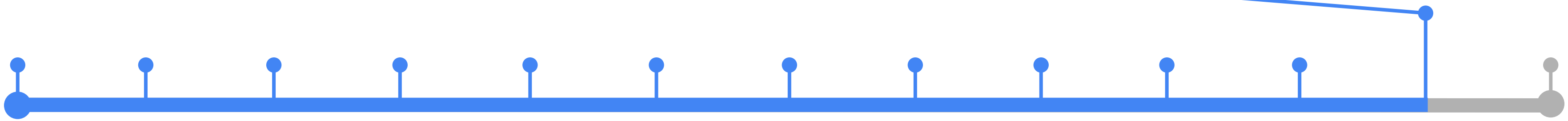
You can do real experiments here

1. Performance good enough?
2. ML system vs no ML system
3. Live traffic sent at random to ML system or old system*

*When you’re dealing with massive scale, a good idea is to do a 1% live traffic experiment. (1% your ML system, 99% unchanged)

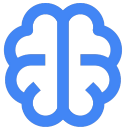
Step 11 is finished | You’ve ramped up and gradually you’re:

- Serving model to users
- Using a policy layer
- Staying cautious



Chief actors:

Analyst



Decision maker

Step 12 | Monitor and maintain

Does your model stand the test of time?

Chief actors:

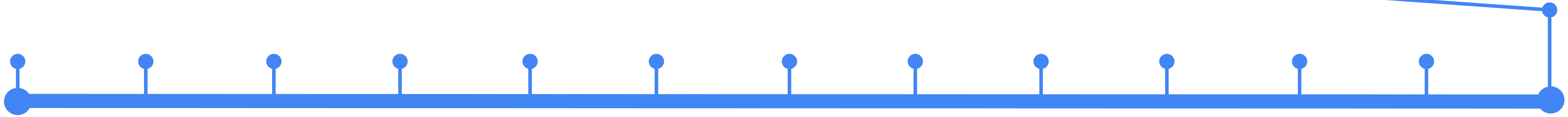
Reliability engineer

Analyst

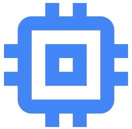
But it worked when I bought it

Step 12 is never finished | But a good start is having:

- Monitoring plan
- Maintenance plan
- Tracking dashboards
- Good documentation



Chief actors:



Reliability engineer

Analyst

Classic learning resources

- More things from Cassie announced here: http://twitter.com/quaesita
- ML course on YouTube: work.caltech.edu/lectures.html#lectures
- ML course on Coursera: coursera.org/learn/machine-learning
- Intro ML textbook (clear math, R code): bcf.usc.edu/~gareth/ISL/
- Intro ML guide (sense of humor, Python code): guidetodatamining.com/
- Intro ML book (older classic, WEKA examples): Data Mining by Ian Witten
- Online intro to neural networks: neuralnetworksanddeeplearning.com/
- Read more about neural networks: colah.github.io/
- Tinker with neural networks: playground.tensorflow.org/
- Bayesian ML intro with Python code: Bayesian Methods for Hackers
- Reference book PDFs (can give beginners indigestion): Bishop, Elements of SL

Thank you for learning!

If you found this useful, share the love and say hi on twitter.com/quaesita.

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