# Online Evaluation of Machine Learning Models

MAPR®

**Ted Dunning**
CTO

***What you'll learn***

Monitoring machine learning-based systems is different from monitoring conventional systems. Attendees will come away with an understanding of the difference as well as some practical methods for monitoring real-world systems.

***Description***

Academic machine learning involves almost exclusively off-line evaluation of machine learning models. In the real-world this is, somewhat surprisingly, often only good enough for a rough cut that eliminates the real dogs. For production work, online evaluation is often the only option to determine which of several final round candidates might be chosen for further use. As Einstein is rumored to have said, theory and practice are the same, in theory. In practice, they are different. So it is with models. Part of the problem is interaction with other models and systems. Part of the problem has to do with variability of the real world. Often, there are adversaries at work. It may even be sunspots. One particular problem arises when models choose their own training data and thus couple back onto themselves.

In addition to these difficulties, production models almost always have service level agreements that have to do with how quickly they must produce results and how often they are allowed to fail. These operational considerations can be as important as the accuracy of the model … right results returned late are worse than slightly wrong results returned in time.

I will provide a survey of useful ways to evaluate models in real world use. This will include the use of decoy and canary models, non-linear latency histogramming, model-delta diagrams and more. These techniques may sound arcane, but each has a simple heart and should not require any advanced mathematics to understand.

## Contact Information

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# Agenda

Why this is much harder than it looks

- Reference to cows

Why cross validation and offline evaluation often don't work

- Explore versus exploit

Decoys and canaries

- Quick rendezvous

Comparing models

Keeping an eye on the basics

Recap and Q&A

# Assume a cow is a radially symmetrical sphere

Assume a cow is a radially symmetrical sphere

Modeling the cow is now simpler

Assume a cow is a radially symmetrical sphere

Modeling the cow is now simpler but it can’t walk or eat

Assume a cow is a radially symmetrical sphere

Modeling the cow is now simpler fine for modeling cows in orbit

# Assume we can do offline evaluation of models

Assume we can do offline evaluation of models

(Academic) life is now much easier

Assume we can do offline evaluation of models

(Academic) life is now much easier but we ignore important realities

# Let’s talk about why

Let’s talk about why

Examine this artistic work


YouTube
SIGN IN
0:09 / 1:54
Cat Wearing A Shark Costume Cleans The Kitchen On A Roomba. Shark Week. #SharkCat cleaning Kitchen!
12,689,042 views
43K
1.5K
SHARE
SAVE


**Cats Being Jerks Compilation NEW**
ThenewLim
2.5M views


**People Who Had One Job And Still Failed**
mystery shack
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**ANIMALS and POWER OF MUSIC**
VideoMaster
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**Epic laugh : Funniest Scared Cat Home 2018 Compilation - Funny cat Videos #2**
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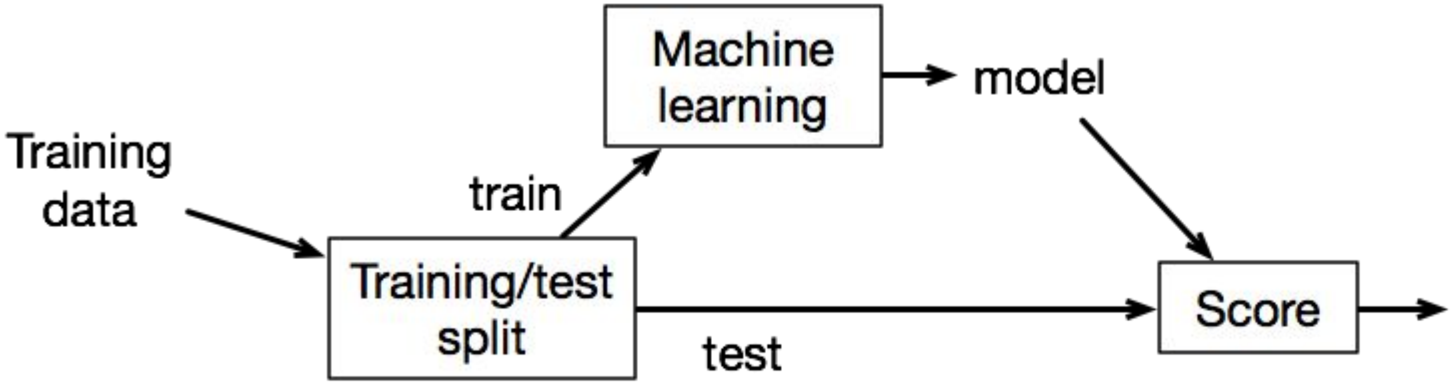
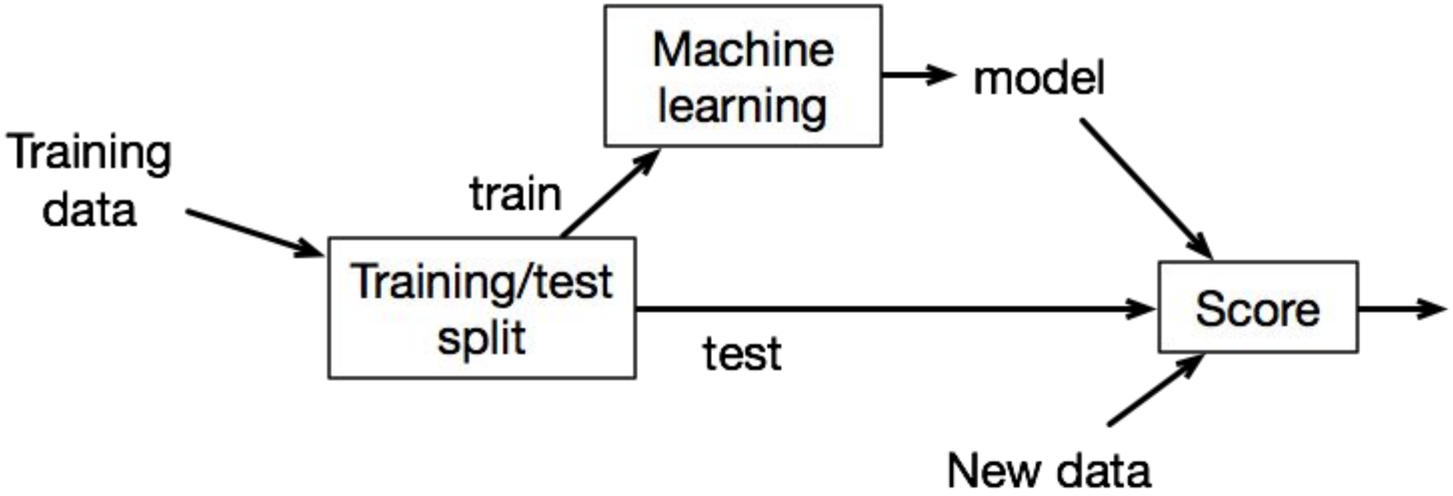
**24 MAGICAL FOOD TRICKS YOU HAVE TO TRY**
5-Minute Crafts
Recommended for you

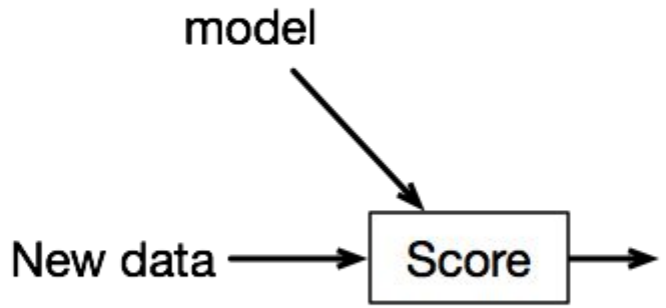

**Cat meeting the puppies for the first time.**
Stefan Atkinson
12M views

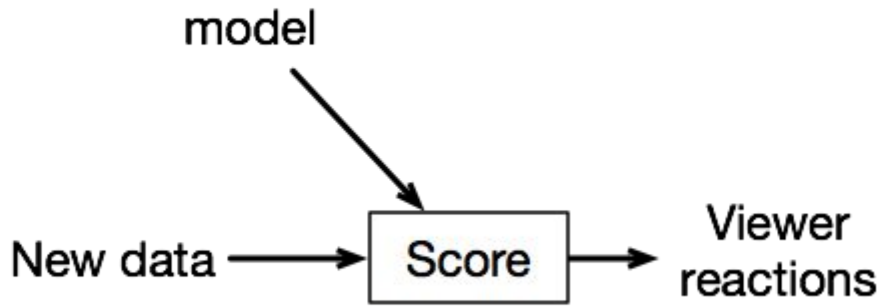

**Raven's personality compared to Human Narcissist**
Peter Caine Dog Training
466K views

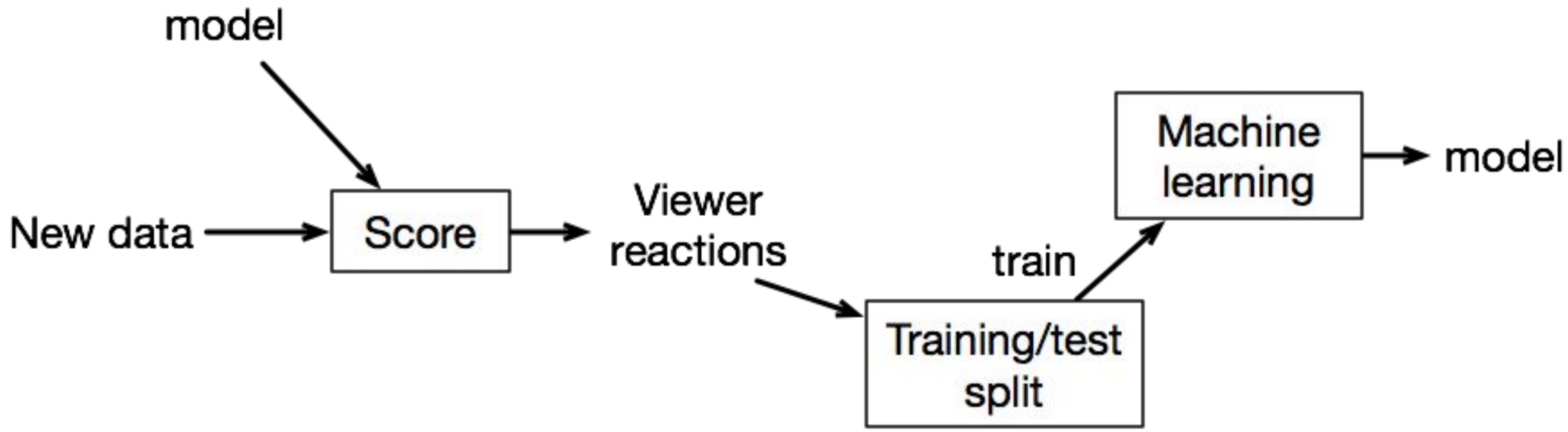

**Silver man secret revealed from start to finish, floating and levitating trick**
Education
Recommended for you

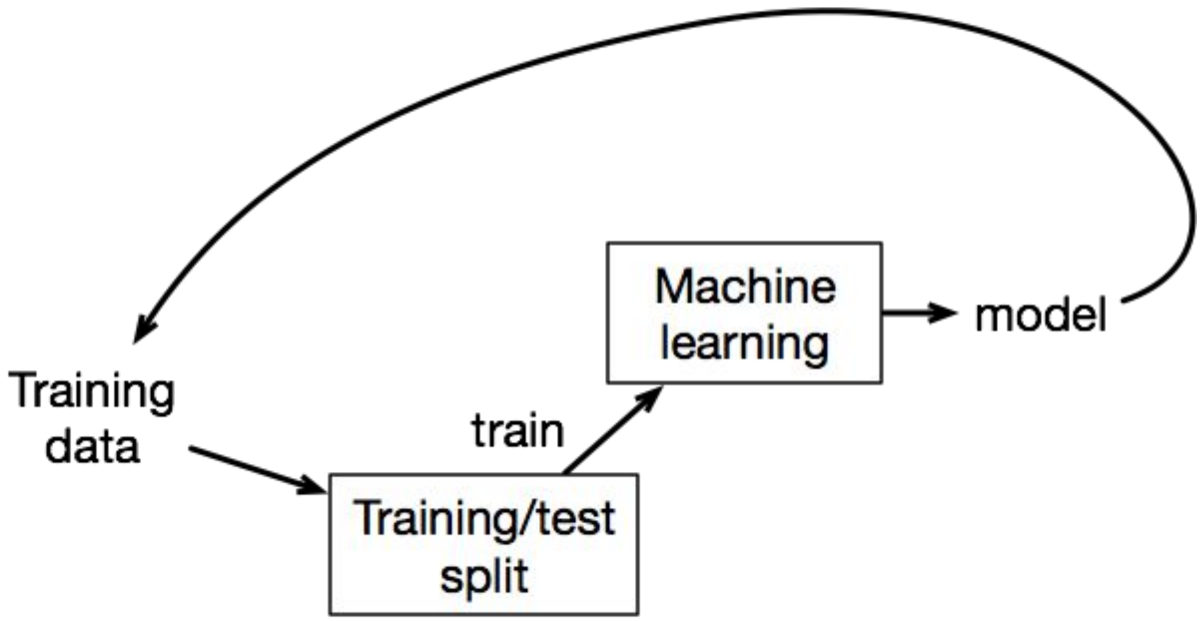

Training
data
Training/test
split
train
Machine
learning
model
test
Score


Machine learning
model
Training data
train
Training/test split
Score
test
New data


model
New data
Score


model
New data
Score
Viewer
reactions


model
New data
Score
Viewer
reactions
Training/test
split
train
Machine
learning
model


Machine
learning
model
Training
data
train
Training/test
split

# Many models choose their own training data

Many models choose their own training data

What they do today
is what they learn from tomorrow

The crux is a choice between

*exploiting* current knowledge
and
*exploring* for new knowledge

# Quick thought:

Quick thought:

Worse can be better

# Result Dithering

Dithering is used to re-order recommendation results

- Re-ordering is done randomly

Dithering is *guaranteed* to make off-line performance worse

Dithering also has a near perfect record of making actual performance much better

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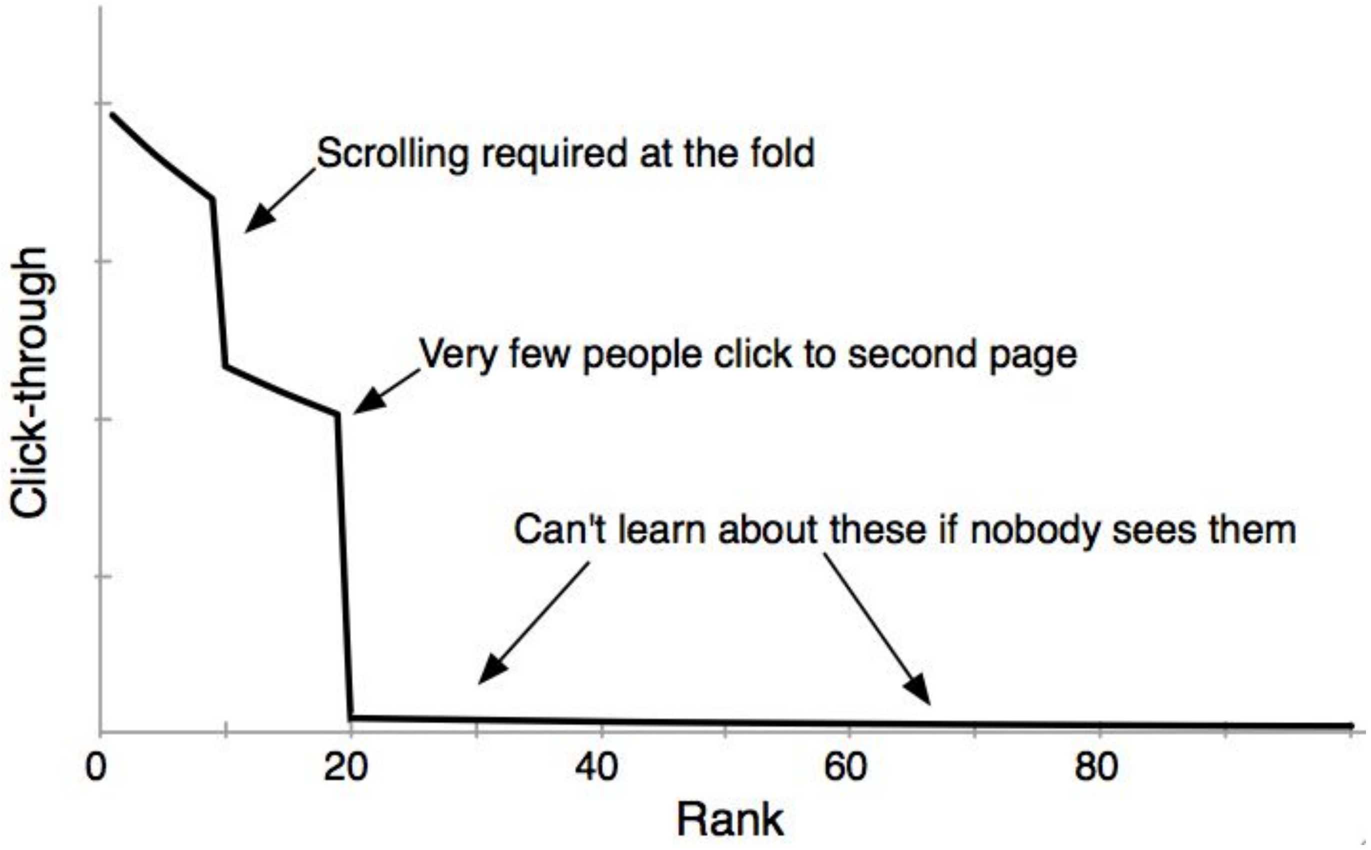
“***Made more difference than any other change***”

# Why Use Dithering?



# Simple Dithering Algorithm

Synthetic score from log rank plus Gaussian

$$s = \log r + \mathcal{N}(0, \log \epsilon)$$

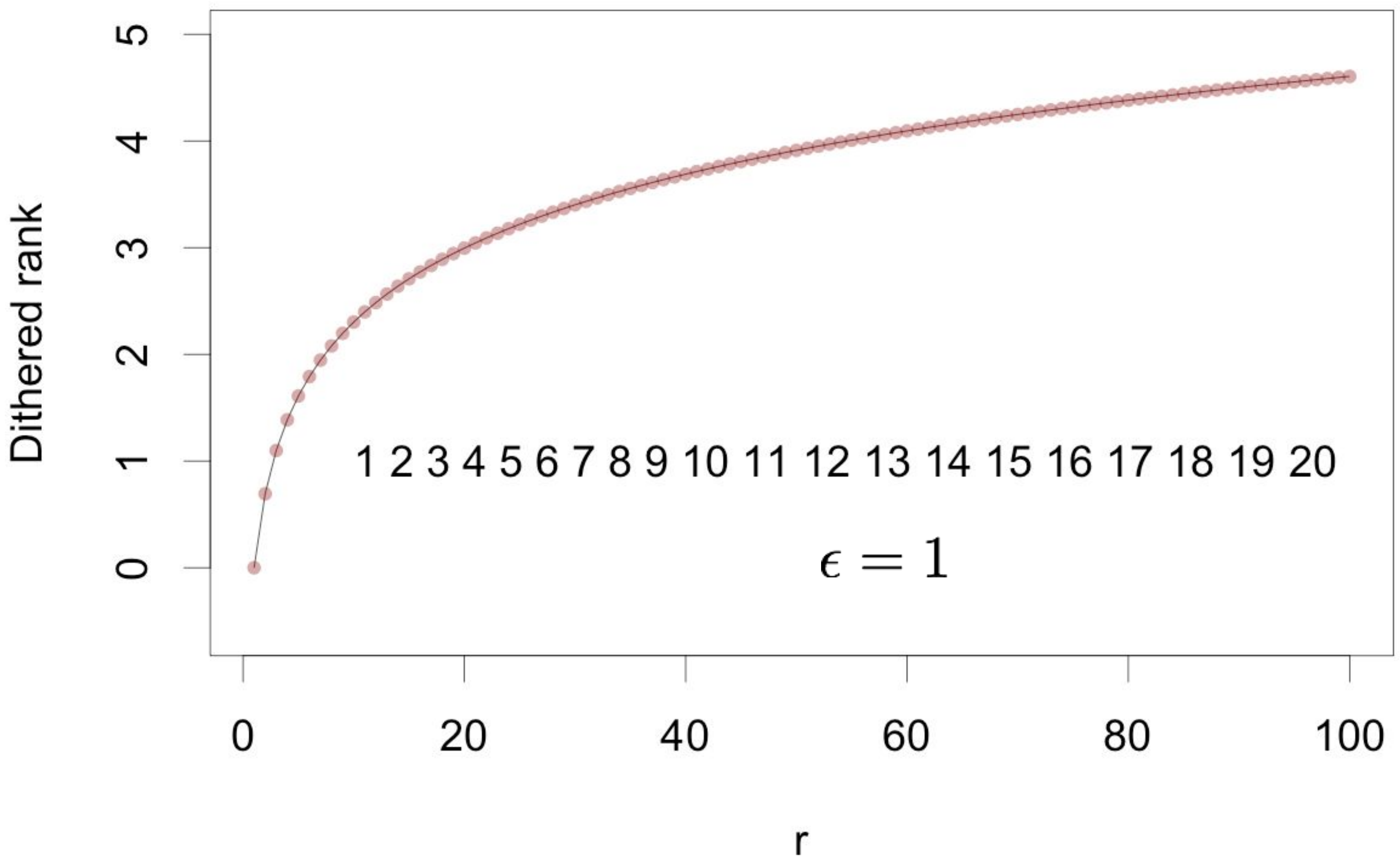
Pick noise scale to provide desired level of mixing

$$\frac{\Delta r}{r} \propto \epsilon$$

Typically

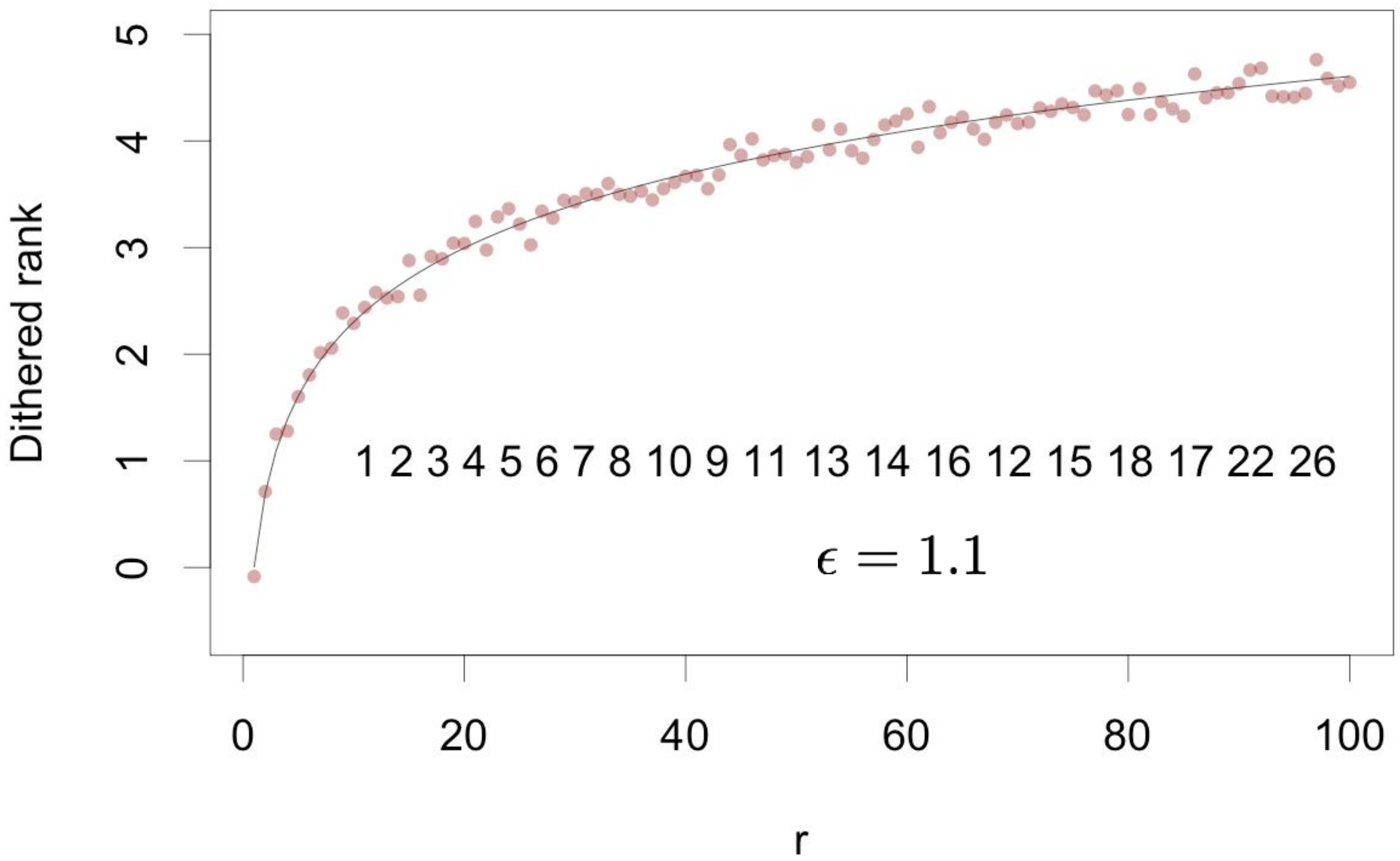
$$\epsilon \in [1.5, 3]$$

Also… use $\lfloor t/T \rfloor$ as seed

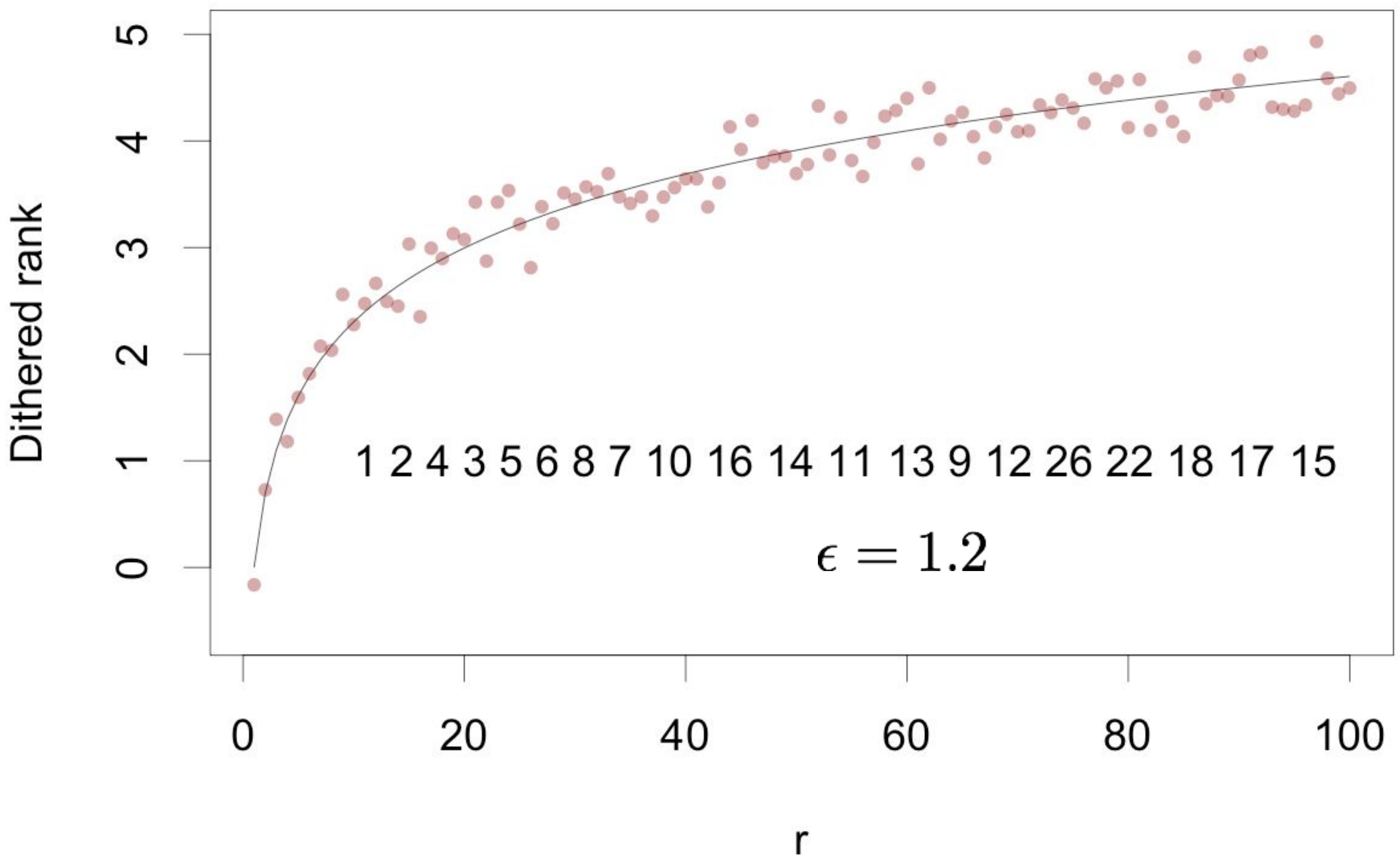

Dithered rank
0
1
2
3
4
5
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
$\epsilon = 1$
0
20
40
60
80
100
r

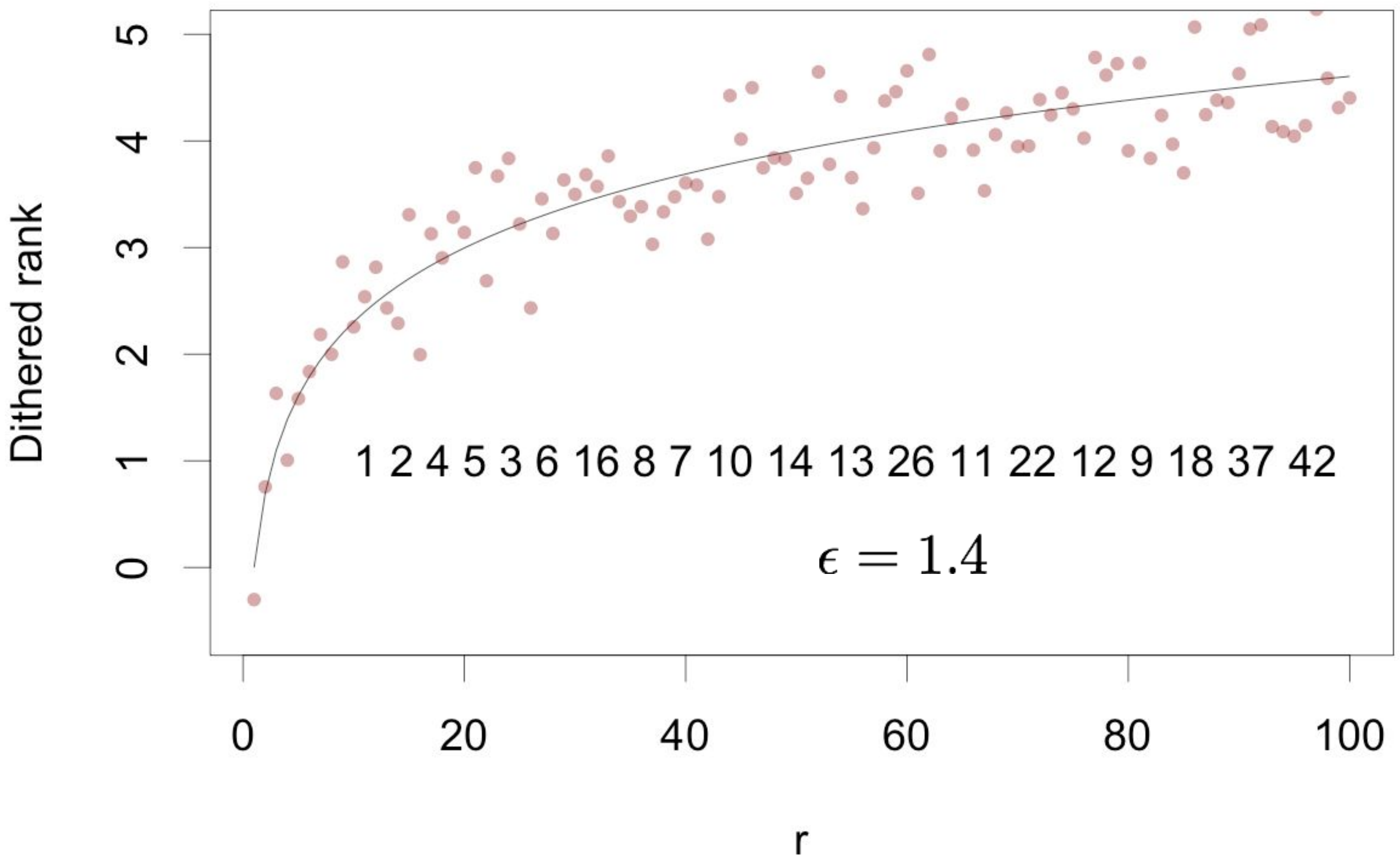


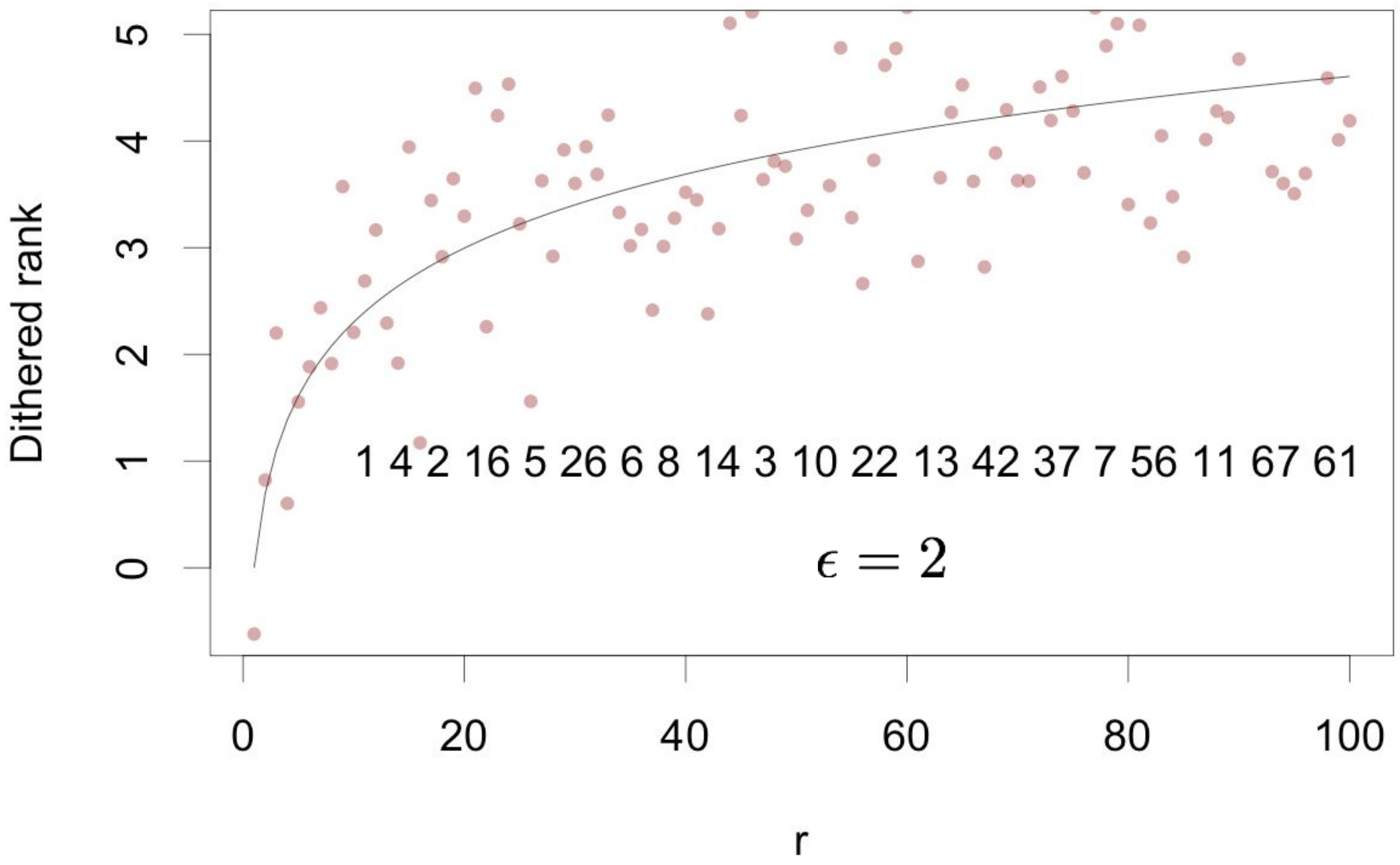
MAPR



Dithered rank
0
1
2
3
4
5
1 2 3 4 5 6 7 8 10 9 11 13 14 16 12 15 18 17 22 26
$\epsilon = 1.1$
0
20
40
60
80
100
r


Dithered rank
0
1
2
3
4
5
0
20
40
60
80
100
r
1 2 4 3 5 6 8 7 10 16 14 11 13 9 12 26 22 18 17 15
$\epsilon = 1.2$


Dithered rank
5
4
3
2
1
0
1 2 4 5 3 6 16 8 7 10 14 13 26 11 22 12 9 18 37 42
$\epsilon = 1.4$
0
20
40
60
80
100
r


Dithered rank
5
4
3
2
1
0
1 4 2 16 5 26 6 8 14 3 10 22 13 42 37 7 56 11 67 61
$\epsilon = 2$
0
20
40
60
80
100
r

The good news is that we can make a model better (long term) by adding noise (making it worse in the short term)

The bad news is off-line testing is the ultimate short-term test

It can’t distinguish useful exploration from bad results

This is
profoundly depressing

We need some help

# But first,

But first,

some bad news

# Evaluating models is even harder than it looks

Why not try testing on live data?

Why not use A/B testing to find out which of A or B is better?

Because it doesn't work like that

Take a good exploiter (A) and a wild explorer (B) and run a test with 95% A and 5% B

- Result is likely to be that A will perform better by learning from B's exploration
- Killing B will make A get worse (no exploration)
- Killing A will give us a lousy model (no exploitation)

# Watchfulness is key

This doesn't mean we can't test models

we just need more care than you might think at first

Steps for testing

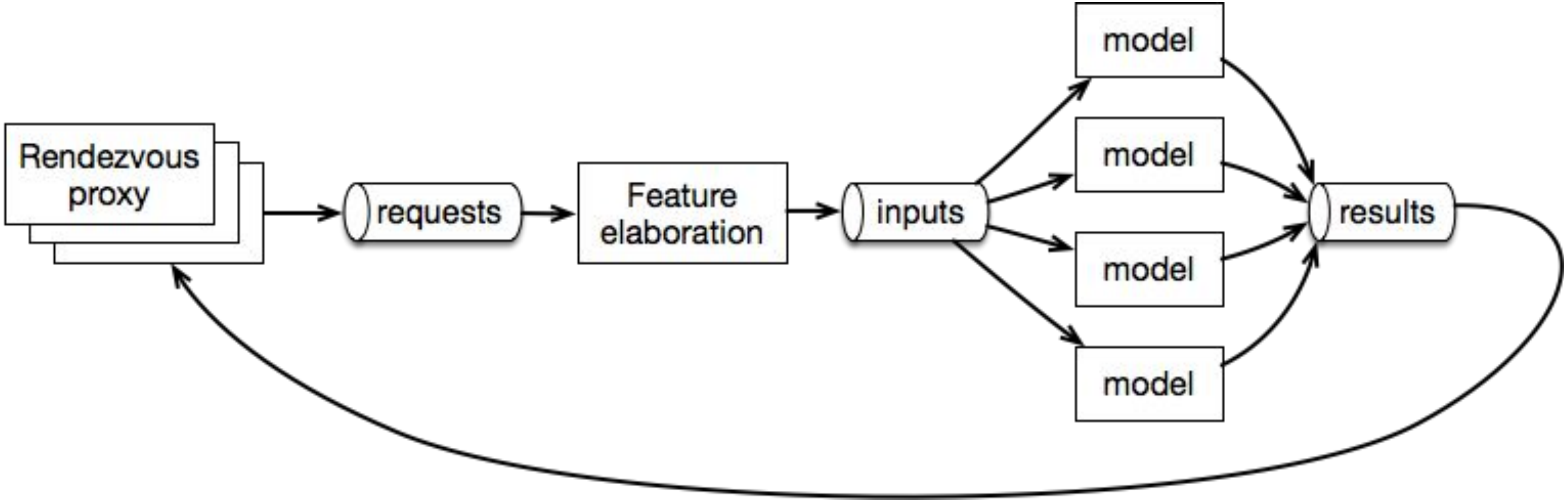
1. Offline testing is still useful. Look for gross failures, look at differences
2. Online difference testing is still useful. Look for large differences
3. Cautious changes in A/B volumes can work well
   a. Look for changes versus historic performance dependent on bandwidth change
   b. Consider isolating and comparing

      A trains A1,   A+B trains A2,   A+B trains B

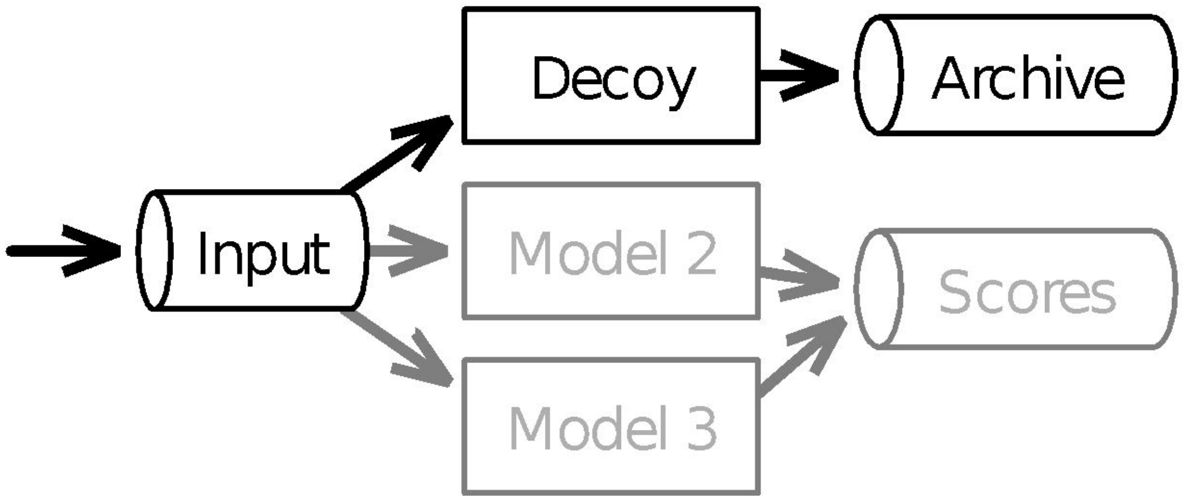
4. Key is to detect changes

# So how can we simul-cast multiple models?

# Rendezvous architecture



# Recording Raw Data (as it really was)



# Quality & Reproducibility of Input Data is Important!

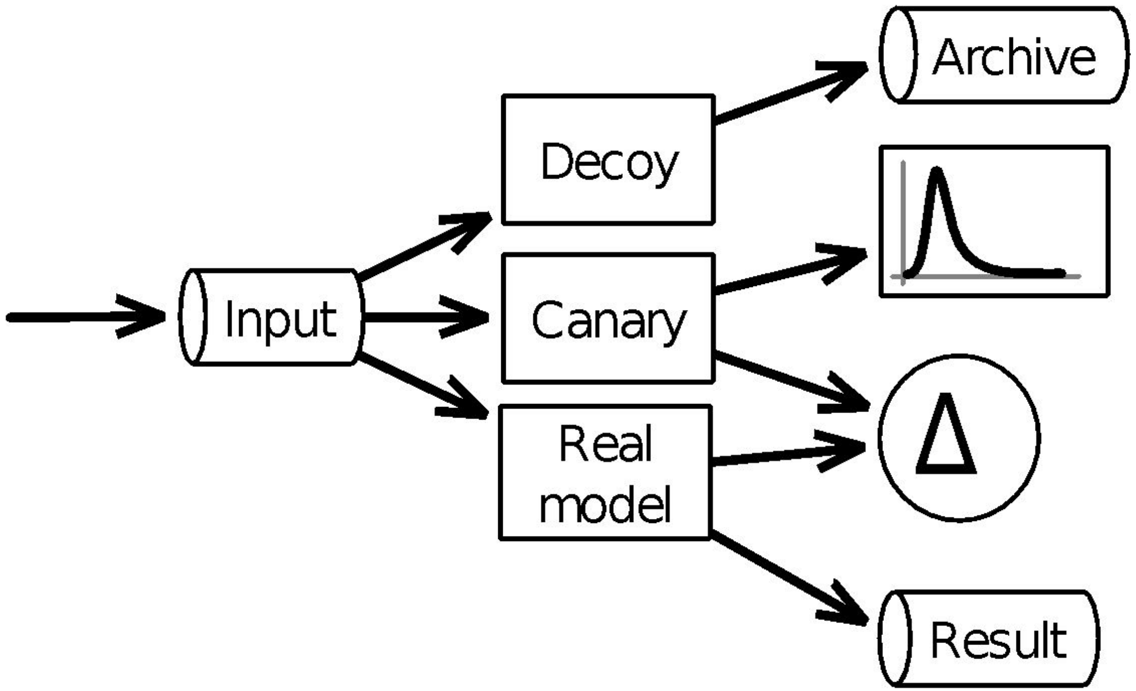
Recording raw-ish data is really a big deal

- Data as seen by a model is worth gold
- Data reconstructed later often has time-machine leaks
- Databases were made for updates, streams are safer

Raw data is useful for non-ML cases as well (think flexibility)

Decoy model records training data as seen by models under development & evaluation

# Canary for Comparison



# What Does the Canary Do?

The canary is a real model, but is very rarely updated

The canary results are almost never used for decisioning

The virtue of the canary is stability

Comparing to the canary results gives insight into new models

Key point:
stream-first architecture allows multiple live models

# Key point:
# rendezvous architecture allows exact recording of inputs and outputs

Key point:
rendezvous architecture
allows live comparison
versus the canary model

# How to find change

Basic idea is that histograms let us get counts

change in distribution will result in different count proportions

Implementation via t-digest or LogHistogram

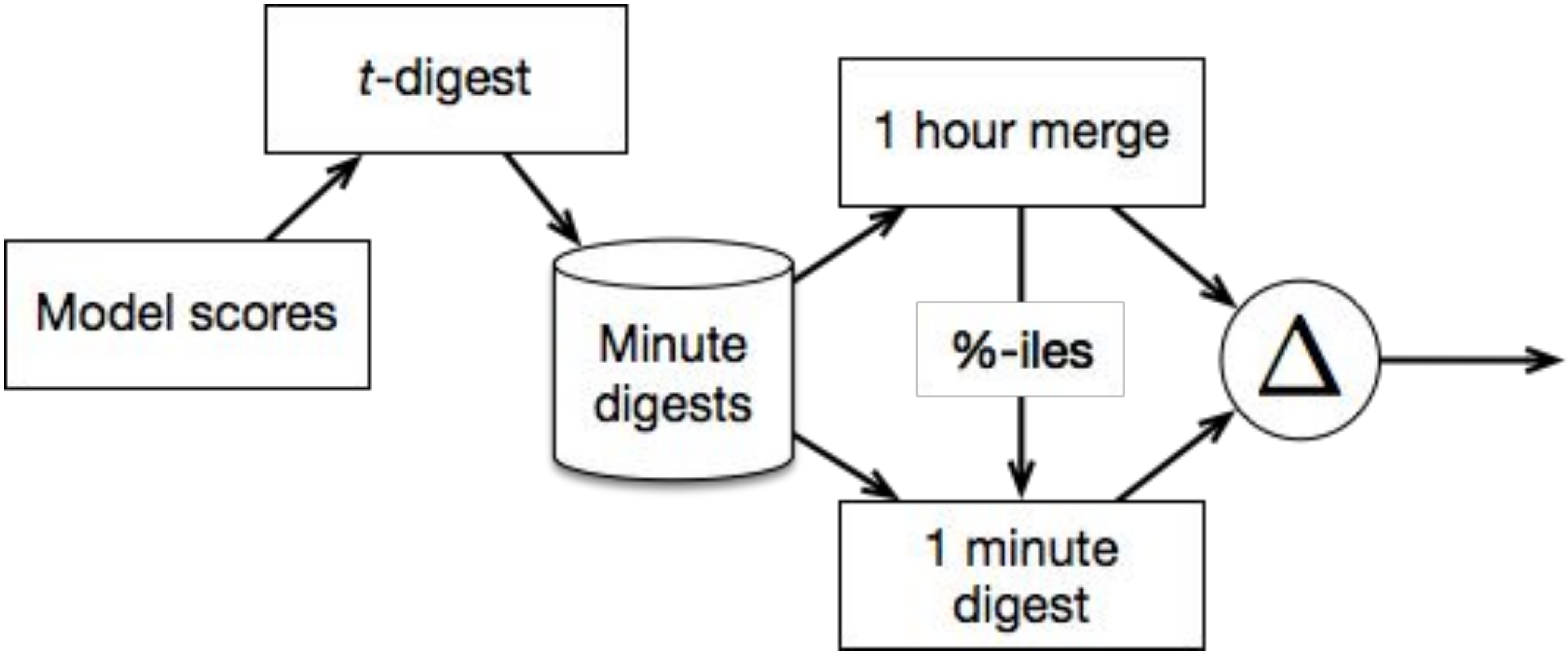
we can find reference quantiles at (say) 0.9, 0.99, 0.999, 0.9999

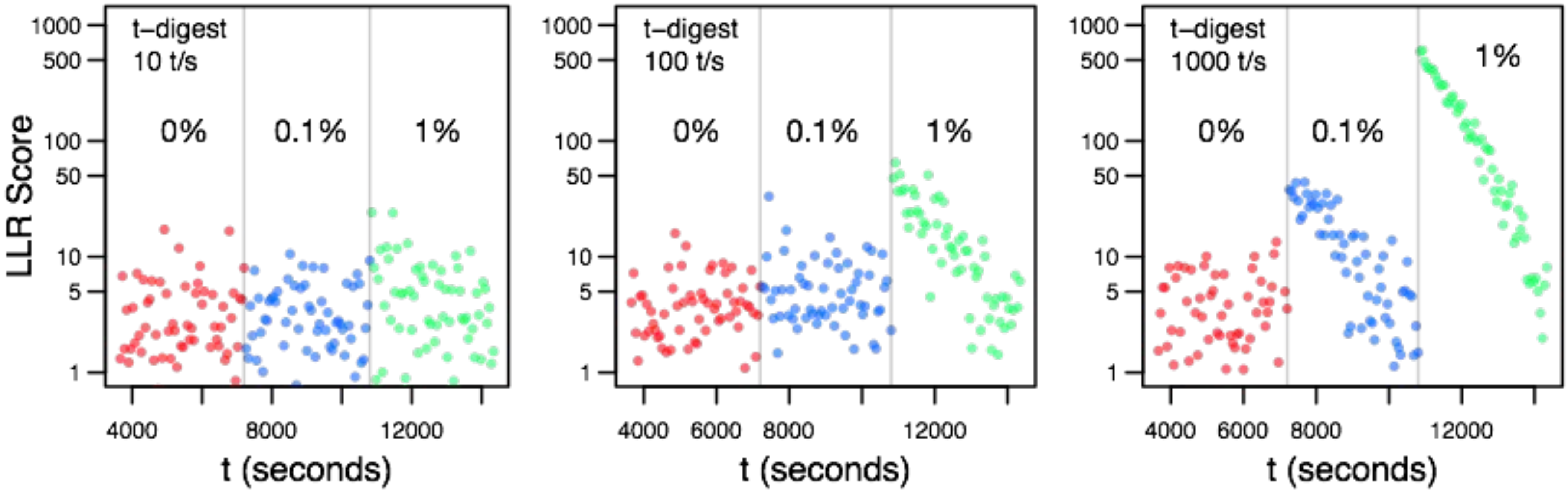
then use those quantiles to probe counts from test data

Compare counts using g-test

2 x n array of counts => score

# Score distribution monitoring




LLR Score
t–digest
10 t/s
0%
0.1%
1%
t–digest
100 t/s
0%
0.1%
1%
t–digest
1000 t/s
0%
0.1%
1%
1000
500
100
50
10
5
1
4000
6000
8000
12000
t (seconds)

# More change monitoring

We can repeatably train models

    if we can version control all training code and parameters (yes, we can)

    if we can version control all training data (yes, with platform help)

With those repeatable model builds

    we can build A1 = learn(A), A2 = learn(A + B), B1 = learn(A+B)

    if A1 and A2 produce essentially identical scores, B is not aiding A

        and A2 versus B1 is probably a fair comparison

With no synergy, direct comparison makes sense

# More with rendezvous

Score quality is only part of the game

The other part is system reliability

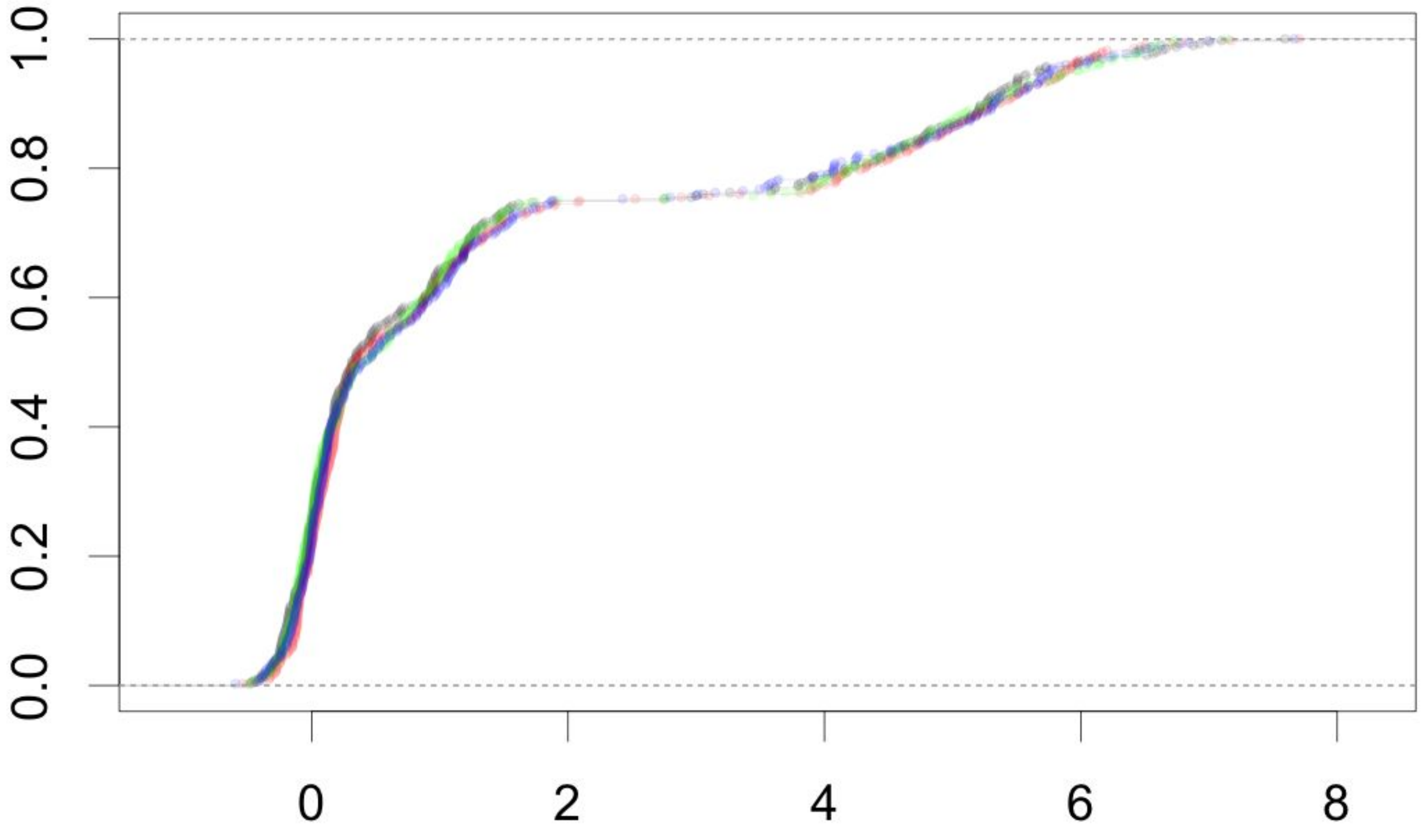
Same monitoring techniques can be used

Monitor latency, monitor rendezvous branch proportions

Score/latency/whatever distribution is the primary unit of monitoring

Let's talk about how to do that

# Cumulative distribution is key



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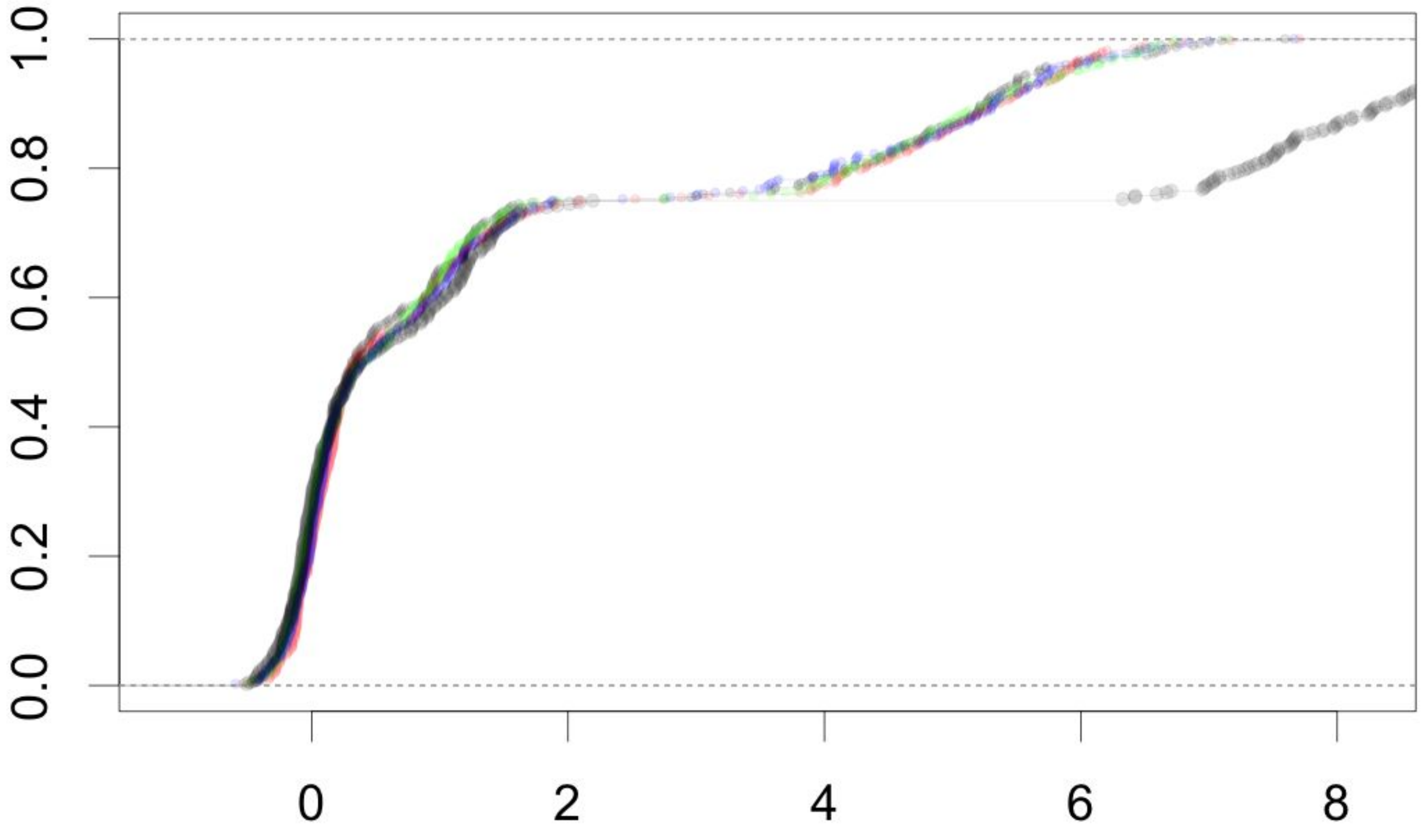

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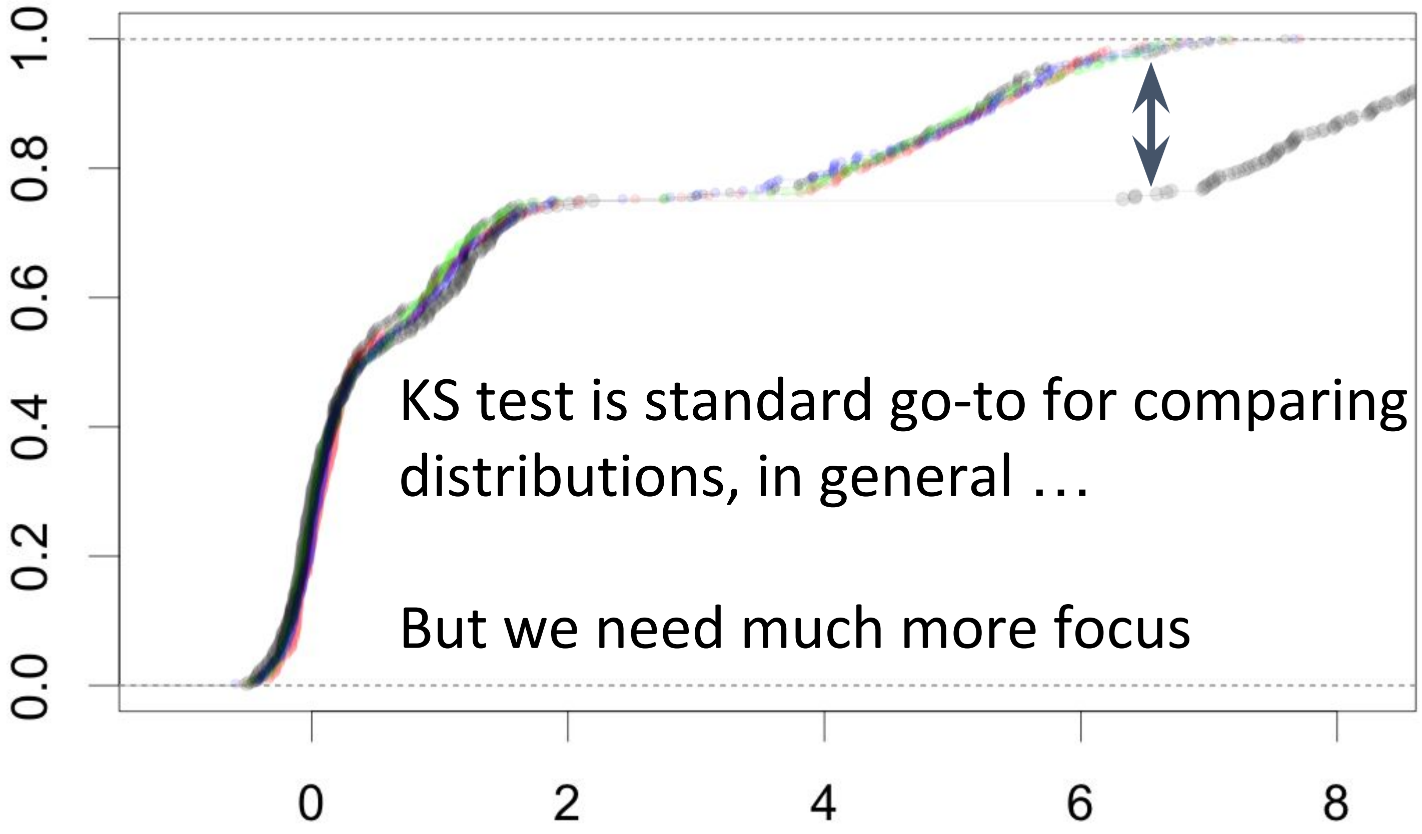
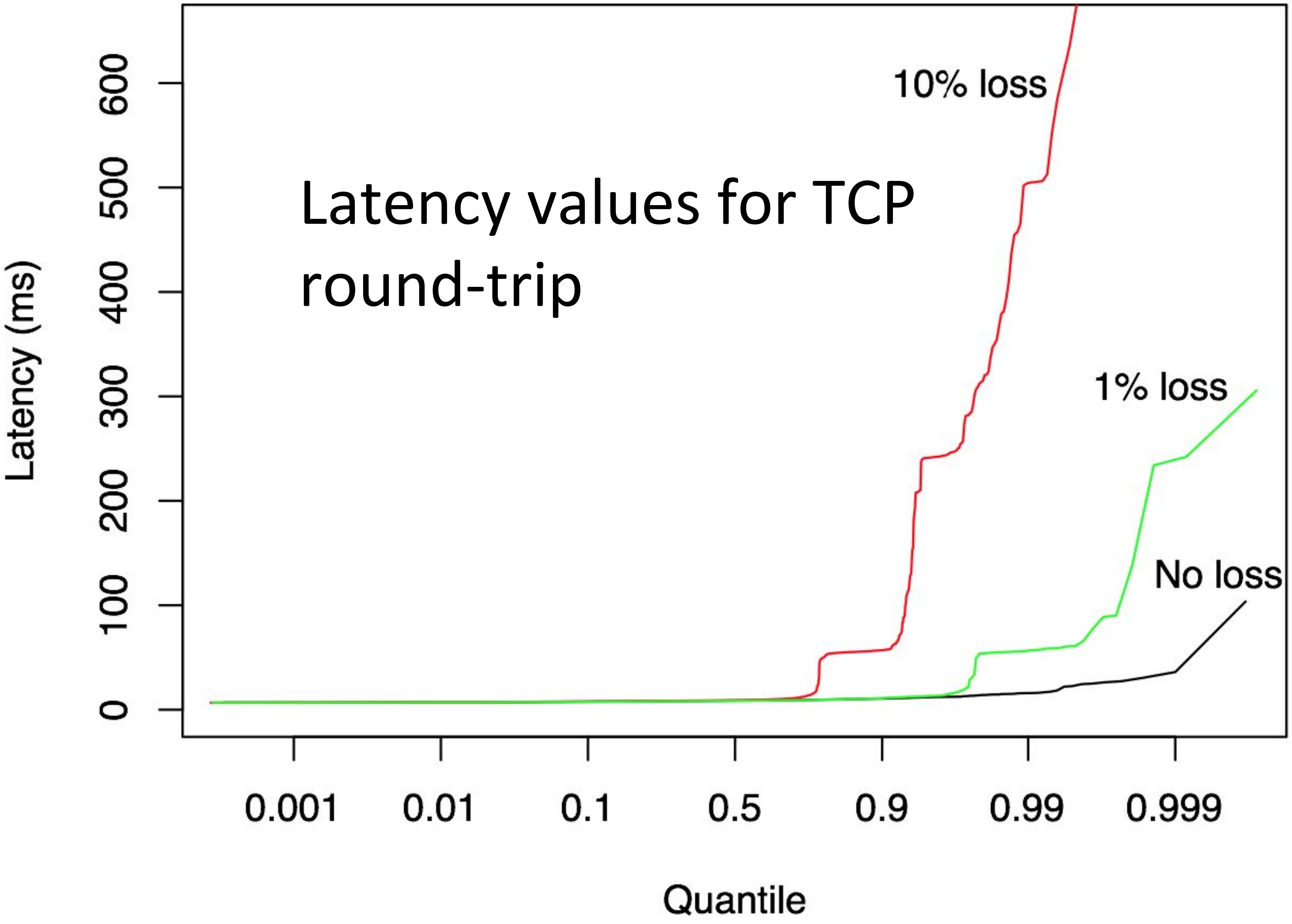
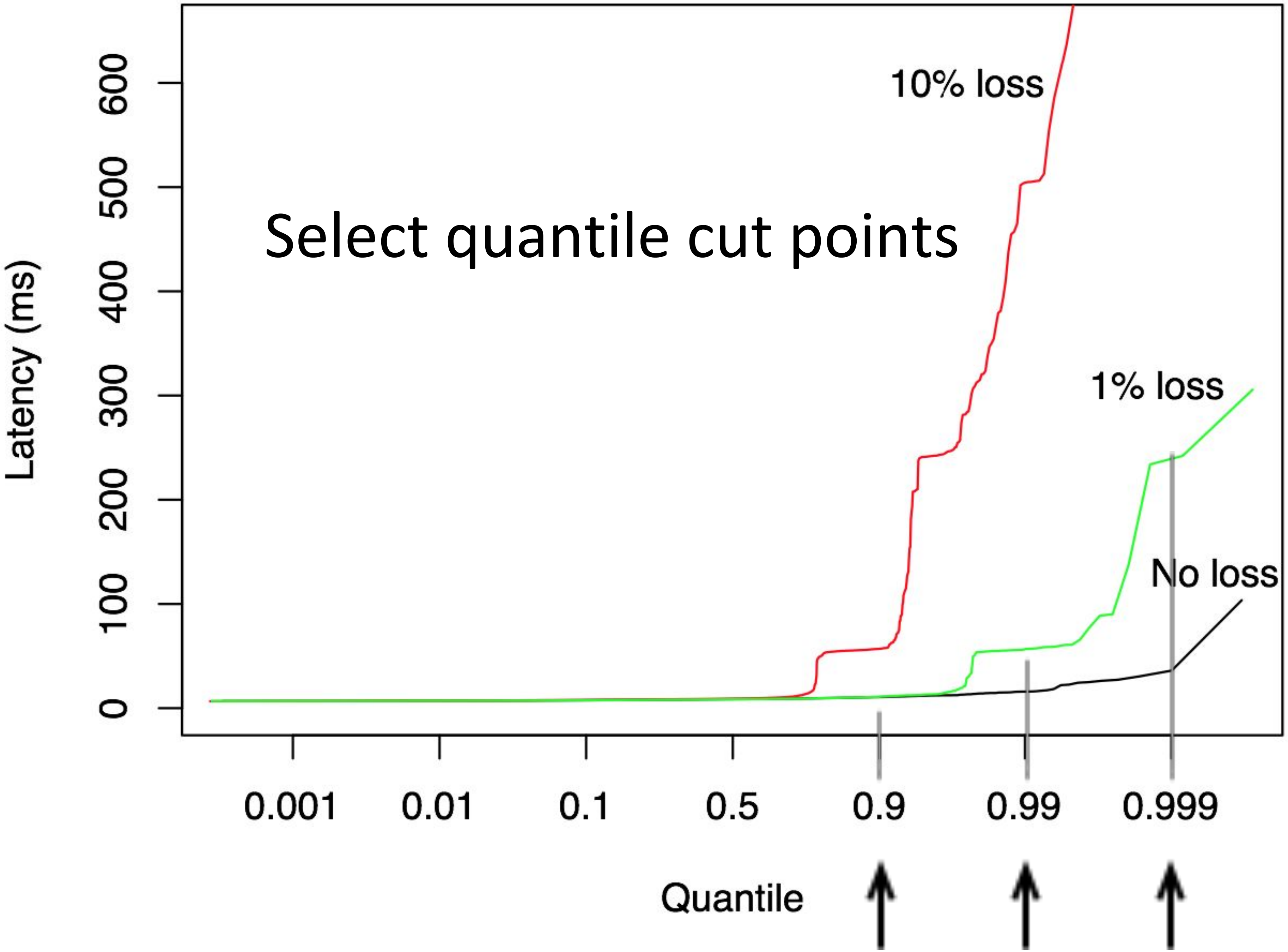


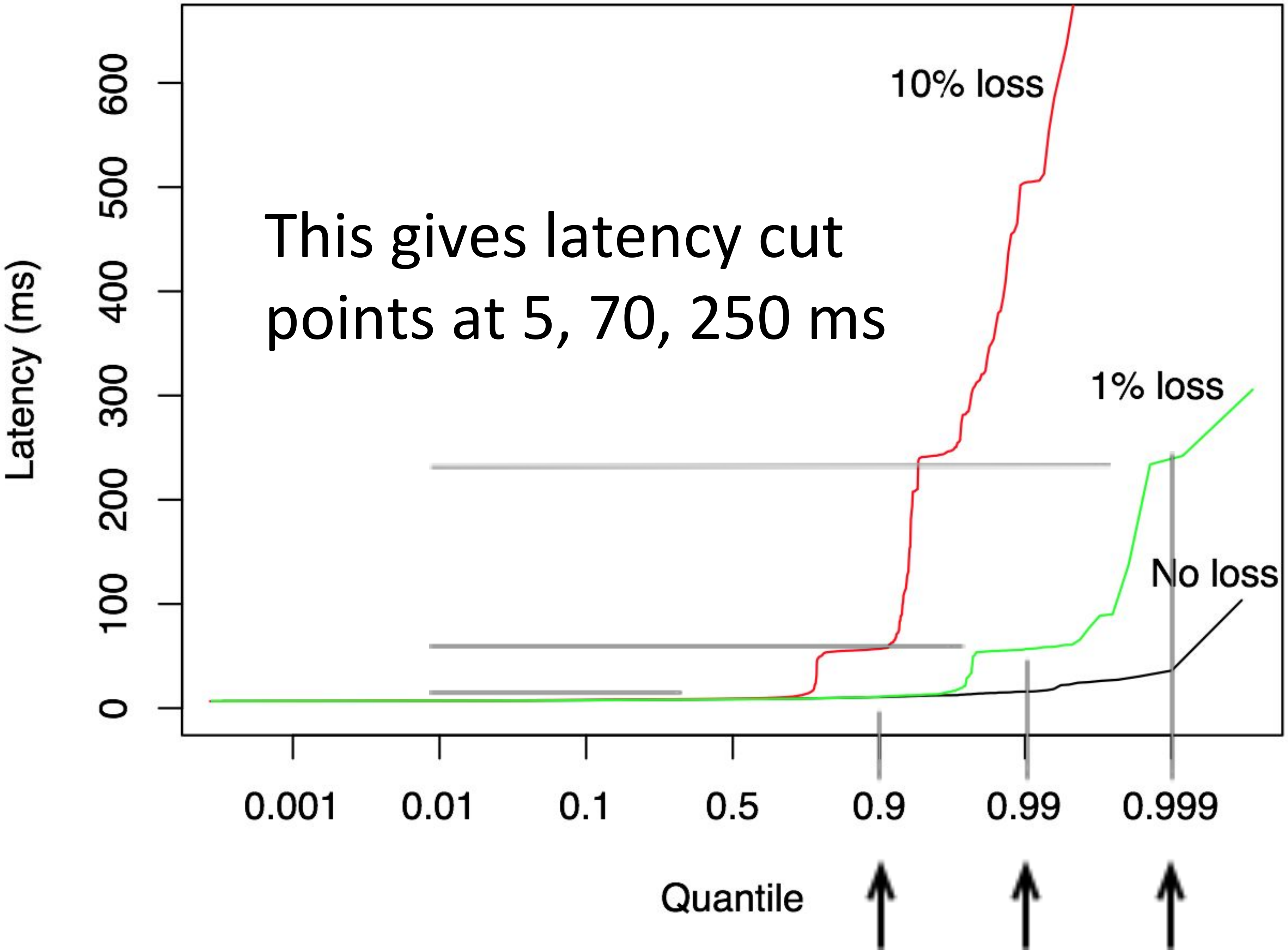
Transpose that graph and look again at just the top end

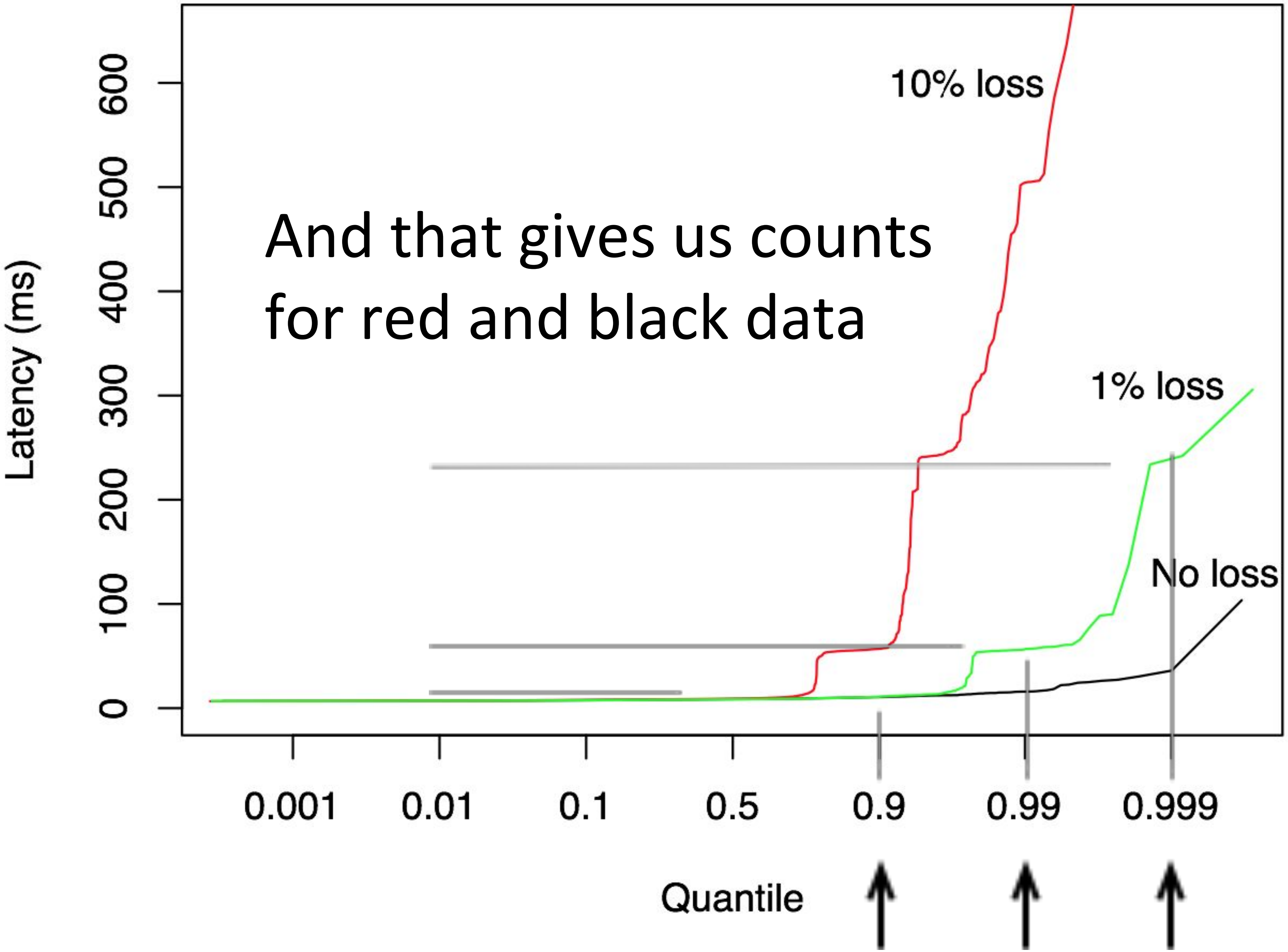
(because that’s what Gil did)


Latency values for TCP round-trip
10% loss
1% loss
No loss
Latency (ms)
0
100
200
300
400
500
600
0.001
0.01
0.1
0.5
0.9
0.99
0.999
Quantile

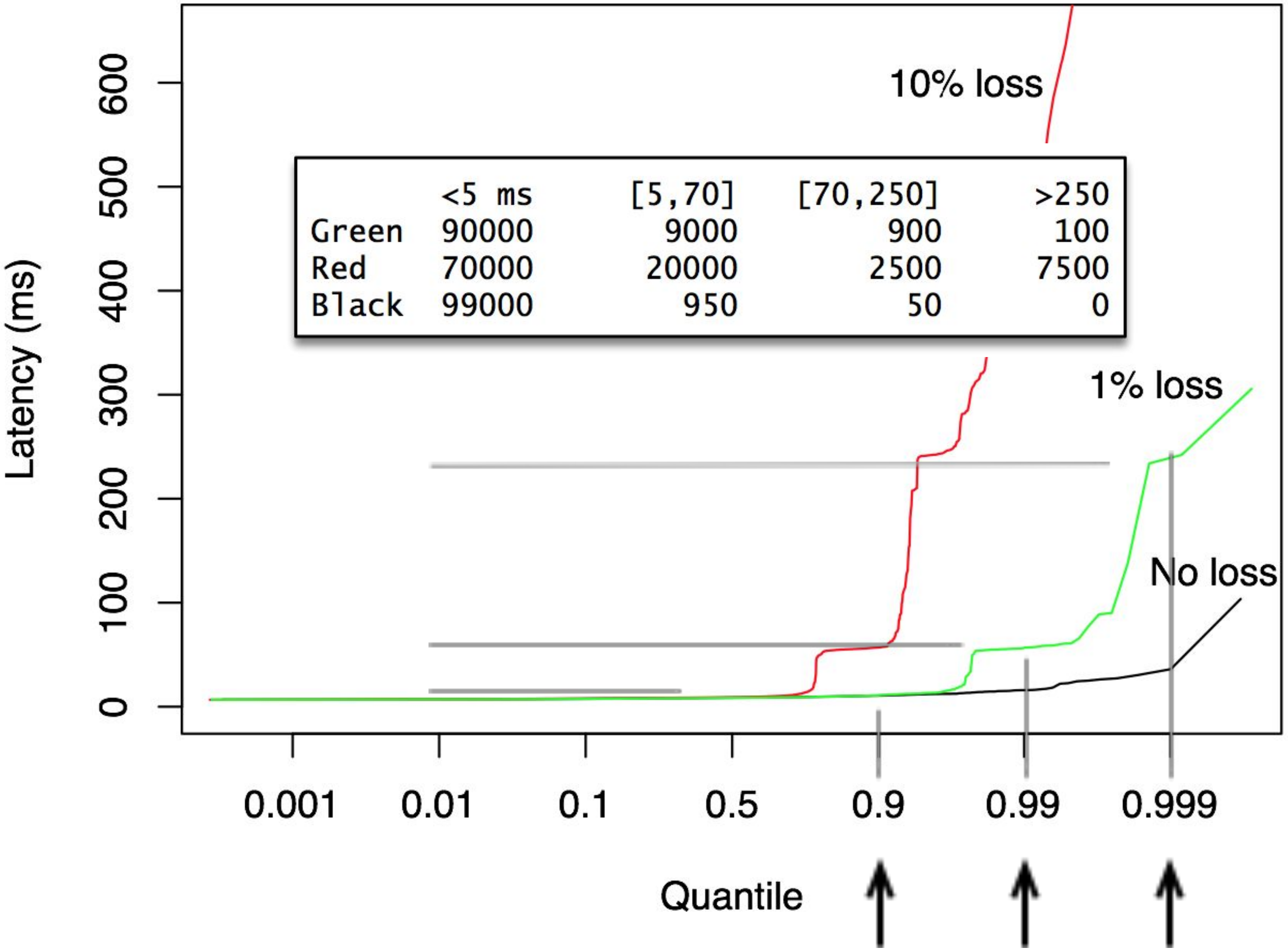
Select quantile cut points




This gives latency cut points at 5, 70, 250 ms
10% loss
1% loss
No loss
Latency (ms)
0
100
200
300
400
500
600
0.001
0.01
0.1
0.5
0.9
0.99
0.999
Quantile




And that gives us counts for red and black data



Latency (ms)
0
100
200
300
400
500
600
10% loss
1% loss
No loss
| | <5 ms | [5,70] | [70,250] | >250 |
|---|---|---|---|---|
| Green | 90000 | 9000 | 900 | 100 |
| Red | 70000 | 20000 | 2500 | 7500 |
| Black | 99000 | 950 | 50 | 0 |
0.001
0.01
0.1
0.5
0.9
0.99
0.999
Quantile

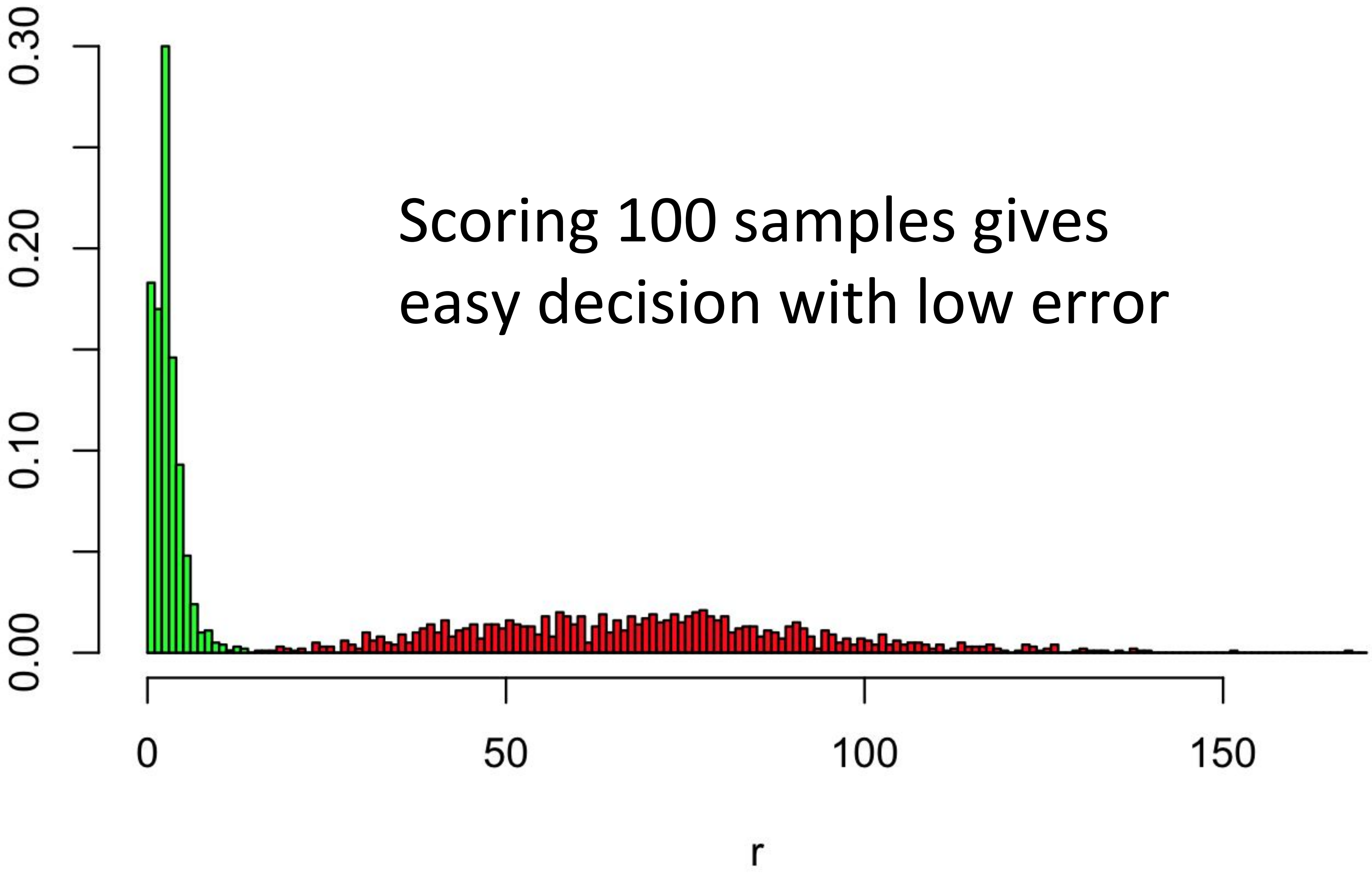
# Quick results of method

For these conditions,

Comparing 100 samples of red/green versus 100,000 green samples

- Average score of roughly 70 for red versus 2.7 for green
- Probably of detecting red with 100 samples is near 100%
- Probability of false positive is near 0

Even with 10 samples, probability of detecting difference is 80%




Scoring 100 samples gives easy decision with low error

# Summary

Model evaluation ***can*** be much harder than it seemed due to training data loop

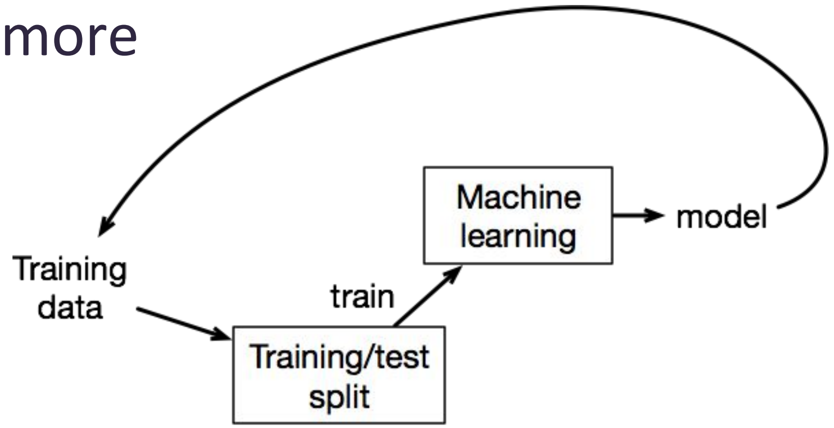
- Offline evaluation is a fine rough cut, but not much more
- A/B testing is subject to crossfeed

Rendezvous helps with monitoring

Proper answers come from careful score monitoring

- Current versus past
- Current versus canary
- With and without challenger data

You have to monitor to ensure you meet site reliability guarantees as well



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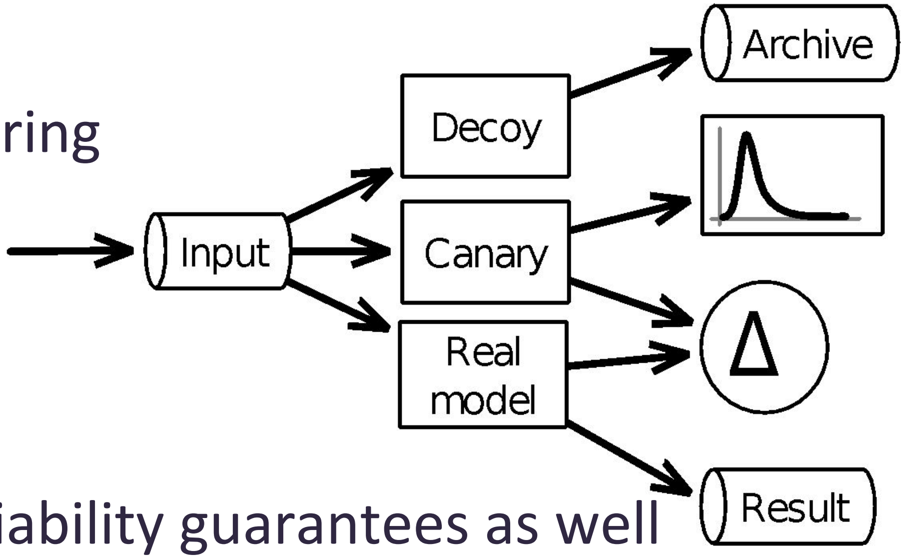

# Summary of methods

You need quantile sketching

- *t*-digest is a fine quantile sketch and very general
- non-linear histogram (LogHistogram, HdrHistogram) is useful for latencies

And you need test of distribution

- g-test compares counts very well
- KS-test focuses on the wrong thing

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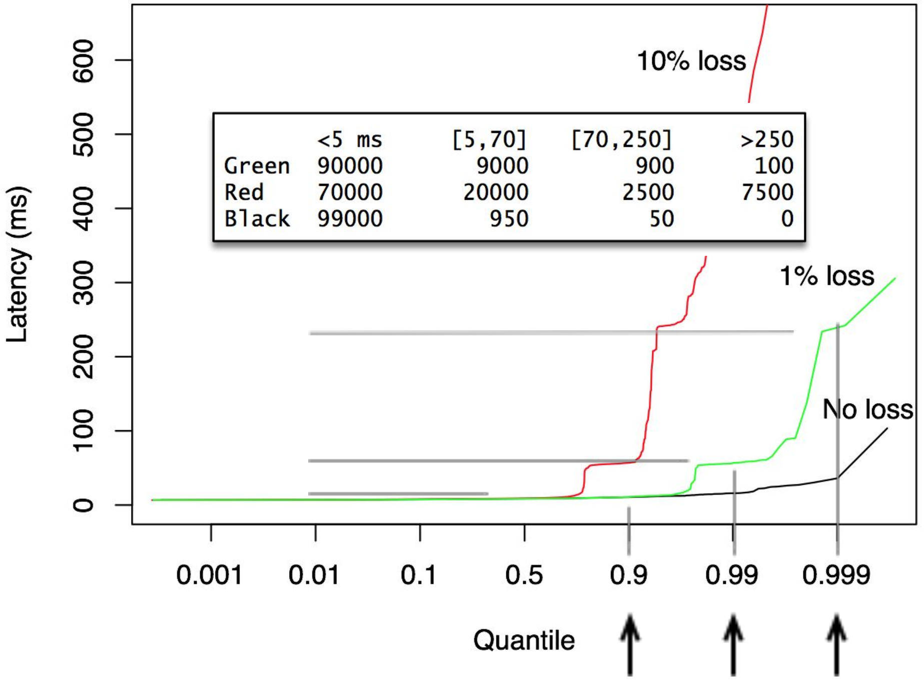
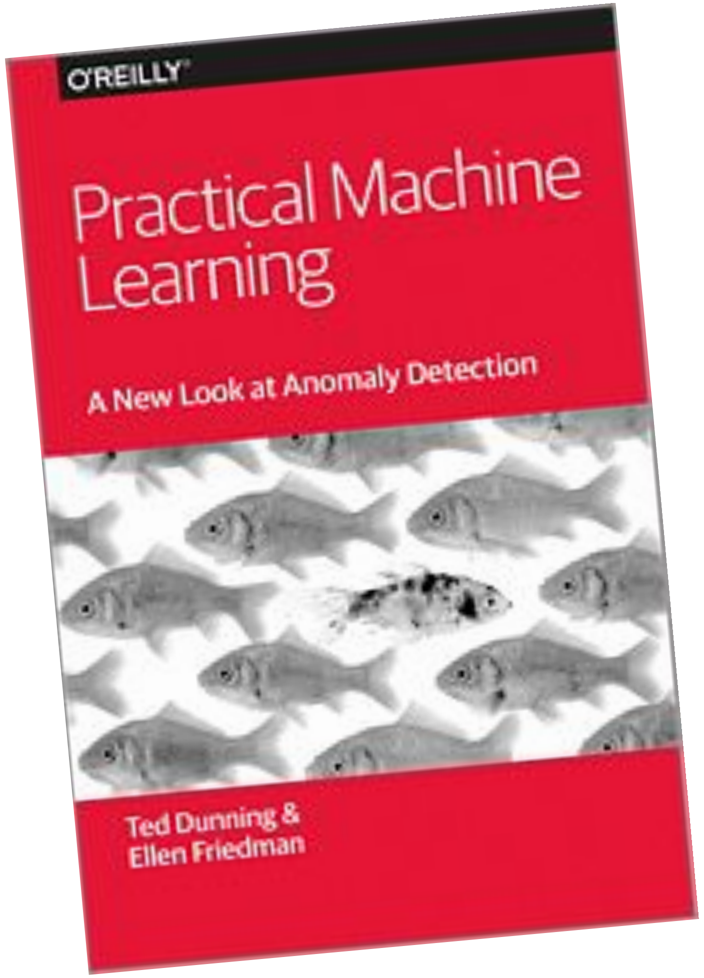



| | <5 ms | [5,70] | [70,250] | >250 |
|---|---|---|---|---|
| Green | 90000 | 9000 | 900 | 100 |
| Red | 70000 | 20000 | 2500 | 7500 |
| Black | 99000 | 950 | 50 | 0 |

# Additional Resources: Available Now

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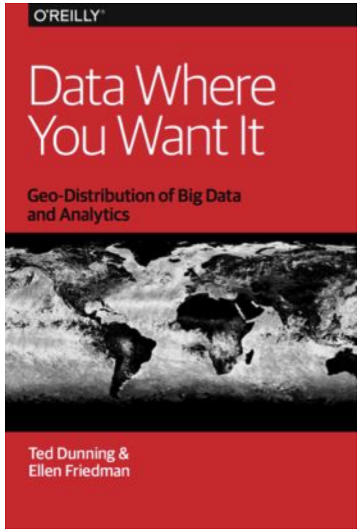


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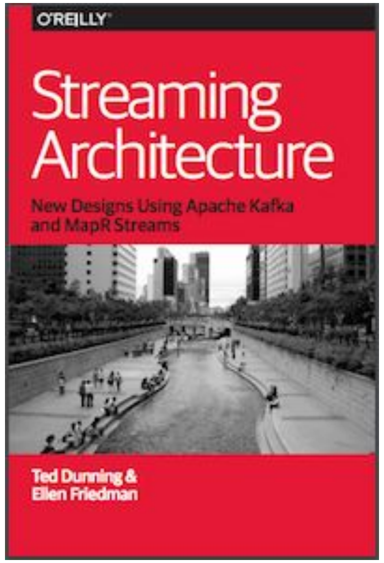


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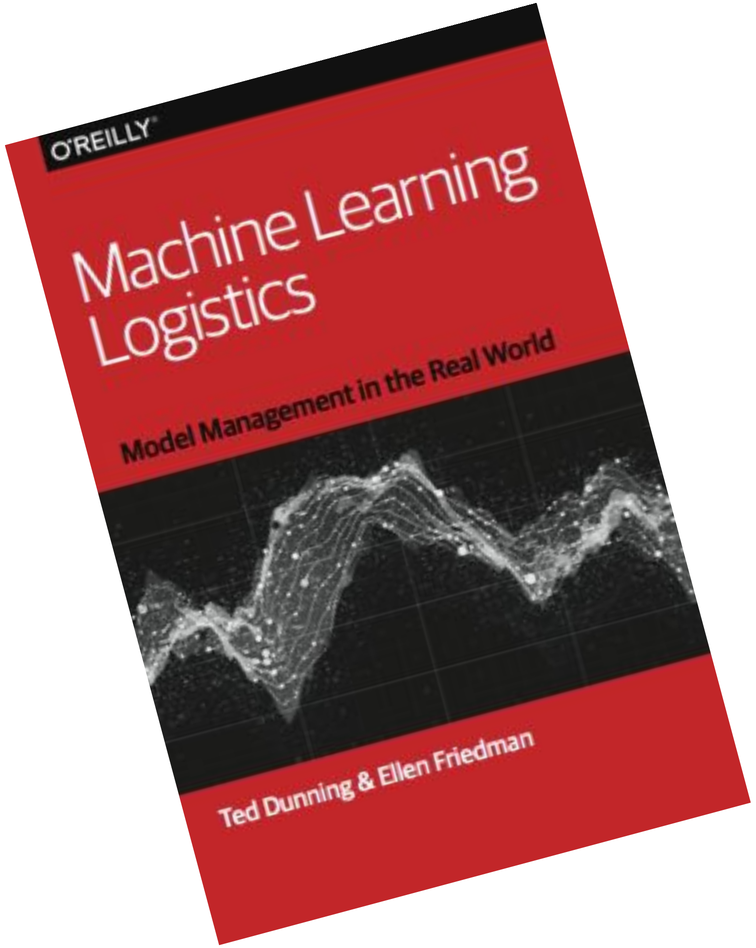
https://mapr.com/streaming-architecture-using-apache-kafka-mapr-streams/

# Previous book: how to manage machine learning models




Machine learning deserves special techniques

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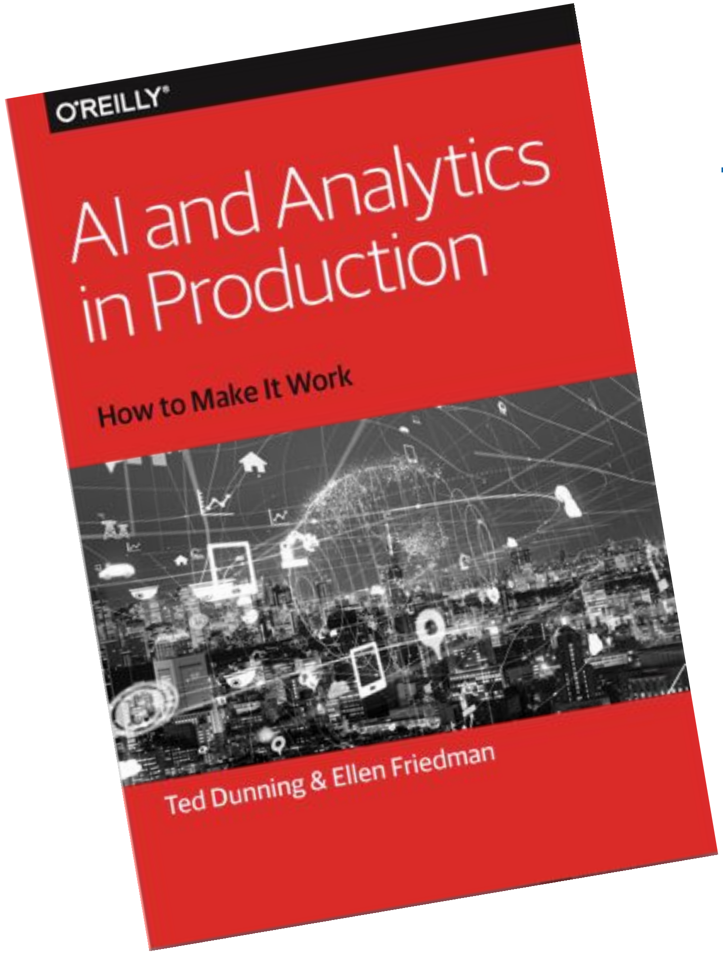
# *AI & Analytics in Production: How to Make It Work*

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