Scientific Software: Art, Engineering, or Science?

Robert Lupton, Princeton University
LSST Pipeline Scientist

2nd ASTERICS-OBELICS School
2018-06-08

La deuxième école d'Astérics et Obélics

The Good Old Days

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- Small data volumes

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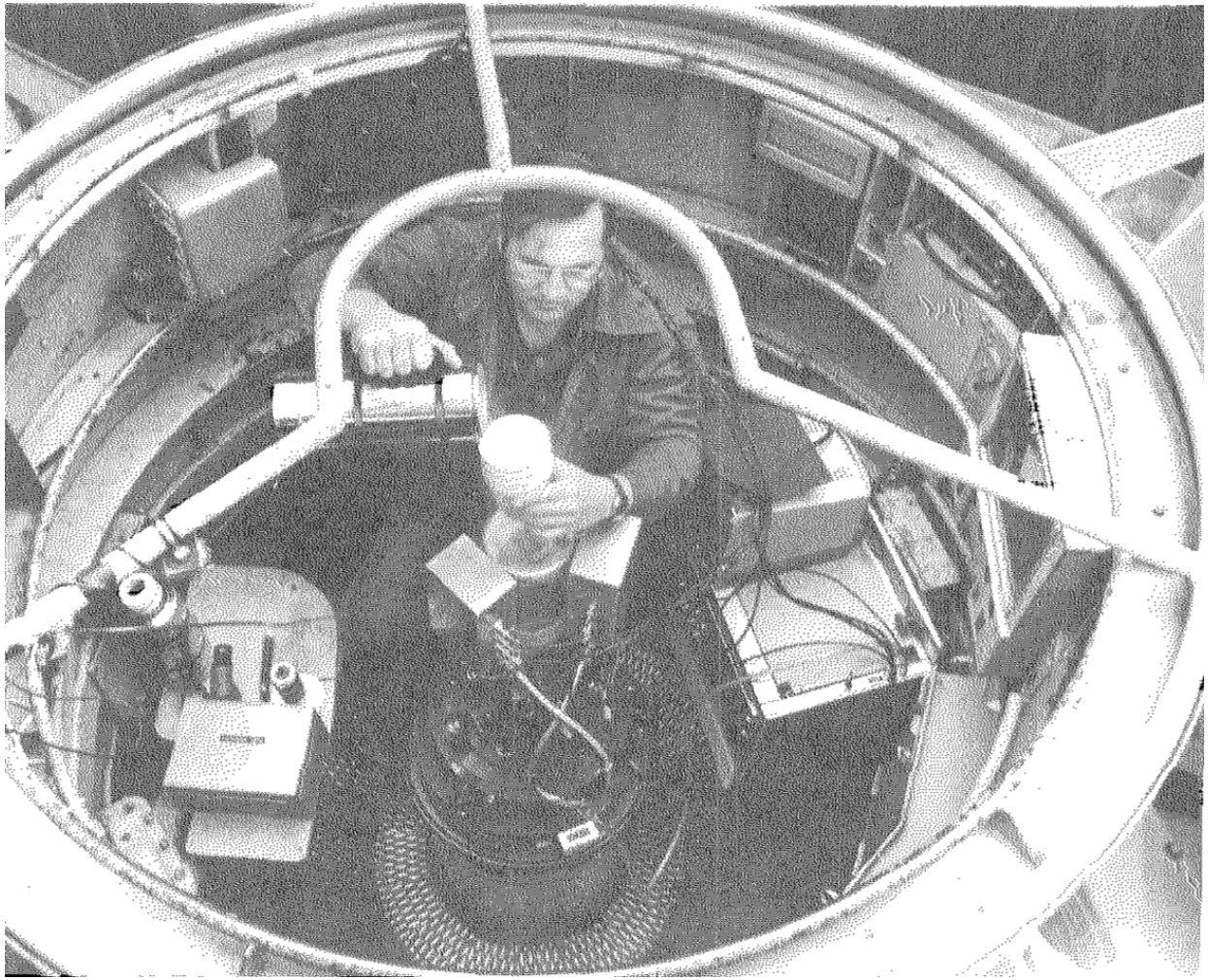
  - Small cameras and small teams



Ed Danielson with Gunn and Westphal's PFUEI (Gustafson, 1983)

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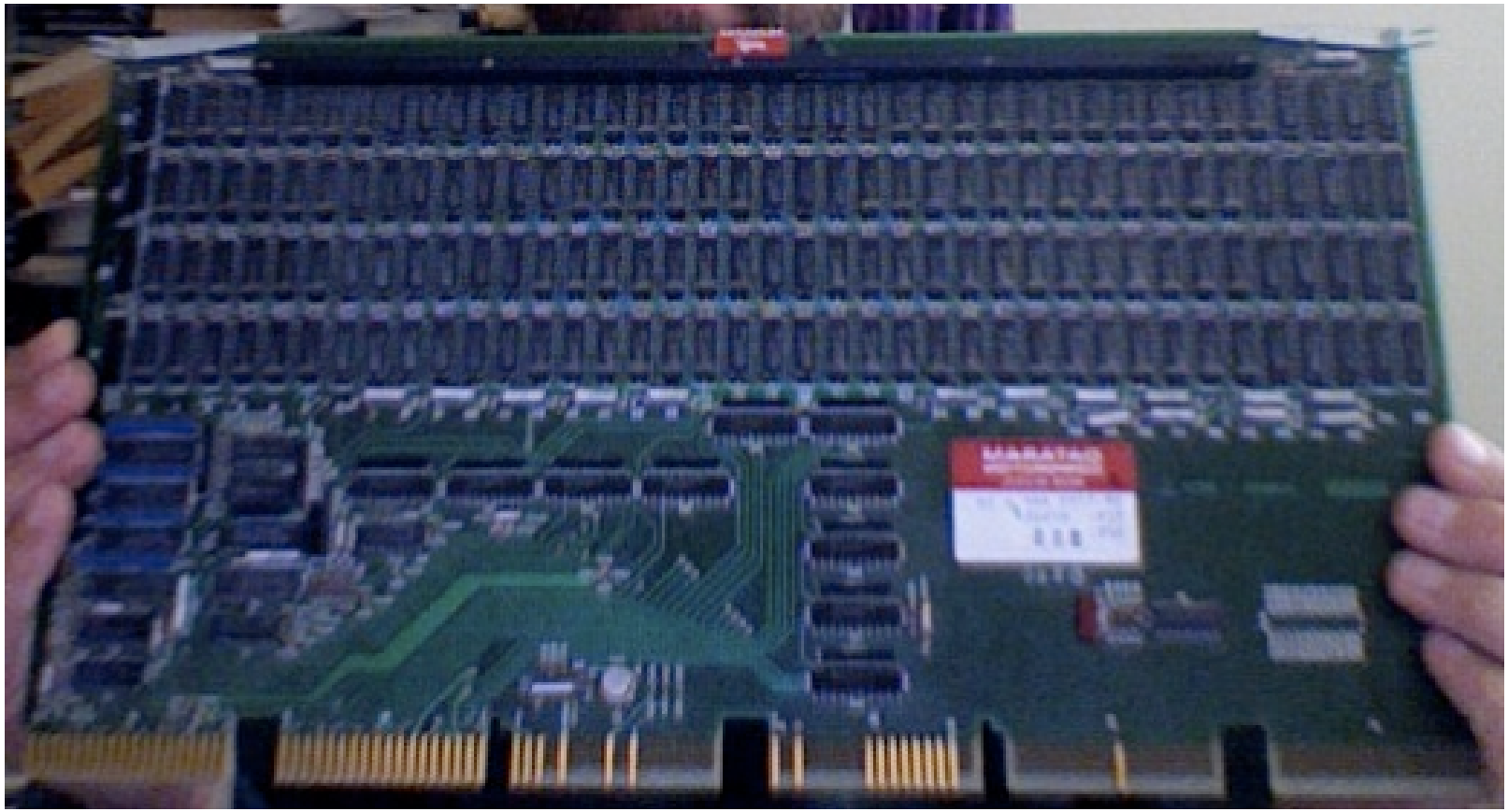

4*(32 + 7) 16 kbi chips; 256 kB

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Swæ clæne [lar] wæs oðfeallenu on Angelcynne ðæt swiðe feawa wæron behionan Humbre ðe hiora ðeninga cuðen understondan on Englisc, oððe furðum an ærendgewrit of Lædene on Englisc areccean; ond ic wene ðætte noht monige begiondan Humbre næren.
Ælfred se Cyning, c. 895 CE

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So general was [learning's] decay in England that there were very few on this side of the Humber who could understand their rituals in English, or translate a letter from Latin into English; and I believe that there were not many beyond the Humber.

Alfred the Great, c. 895 CE

The Problem

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Let’s take a look at some of these issues.

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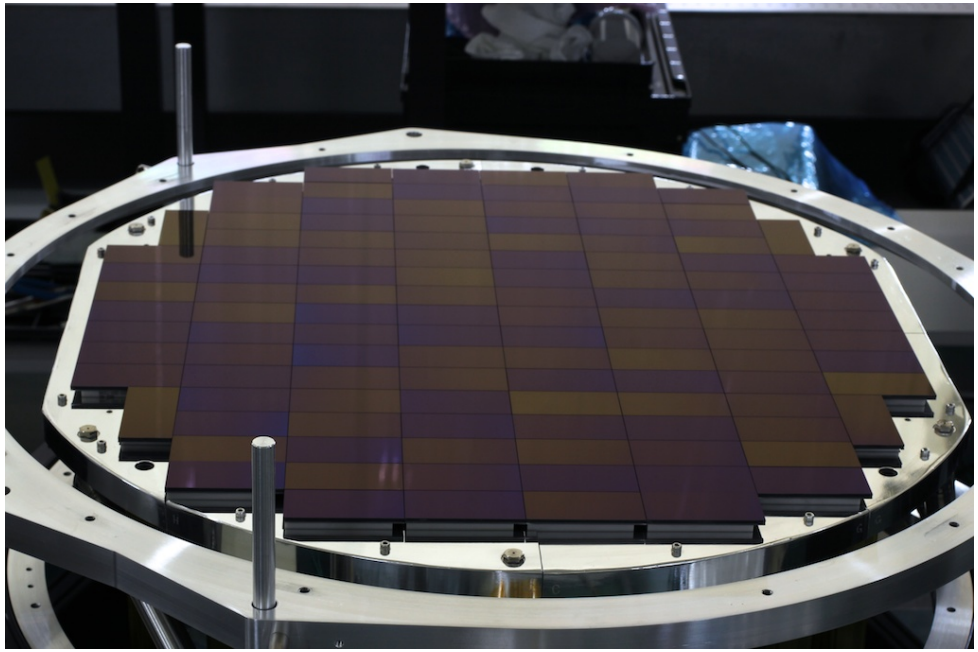

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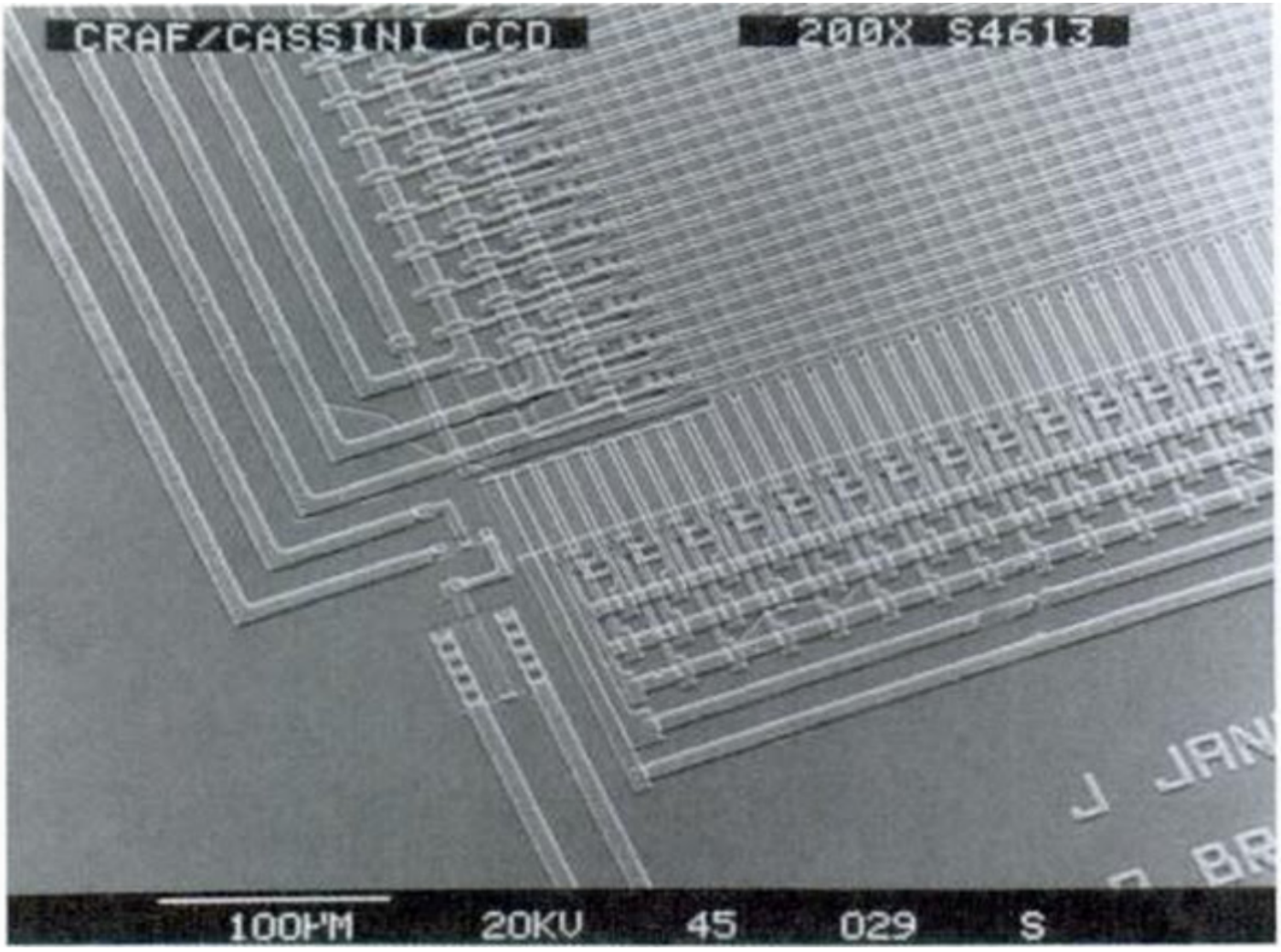

Corner of active area, parallel gates, serial register, and output capacitor

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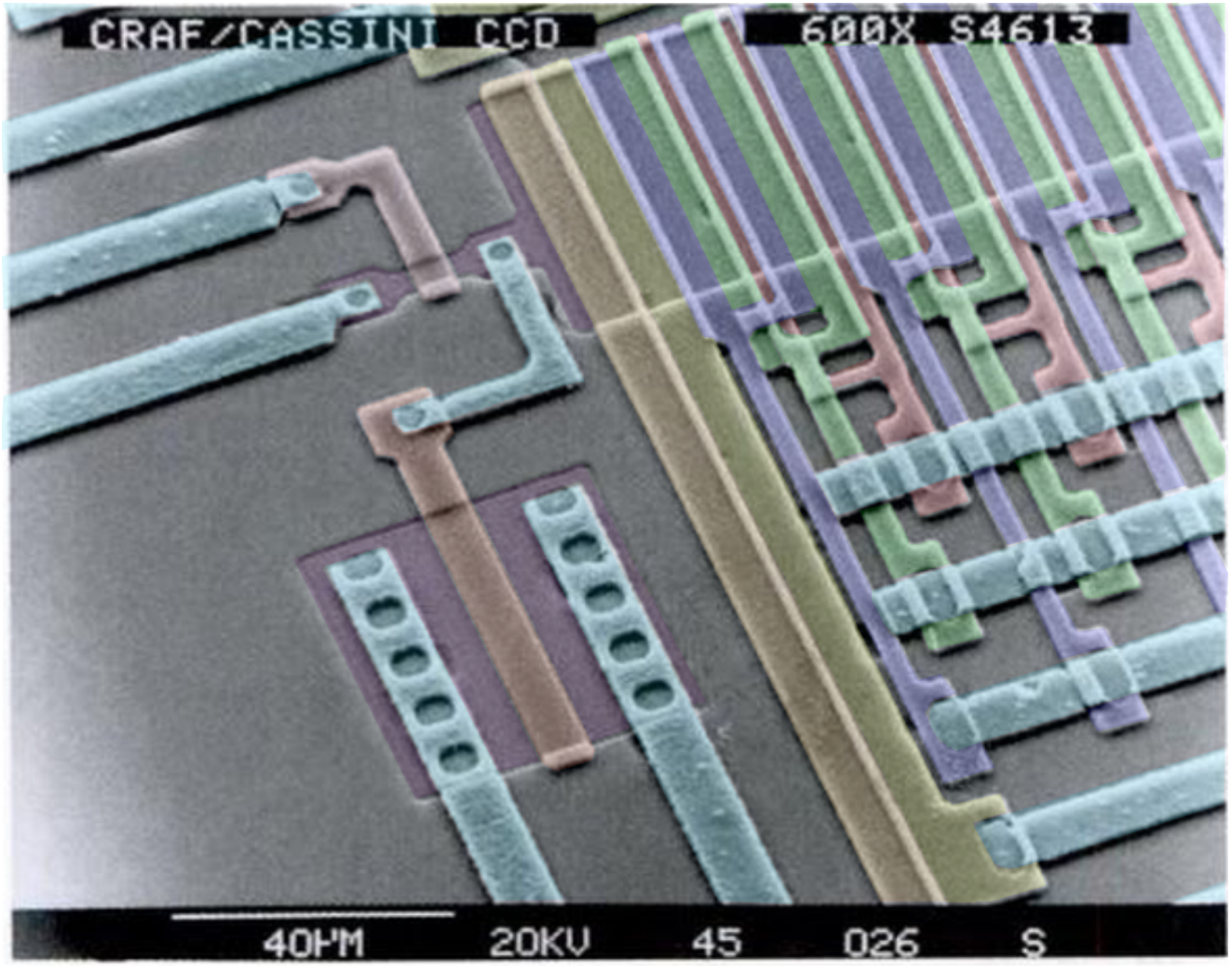

Serial register, reset gate, and output capacitor

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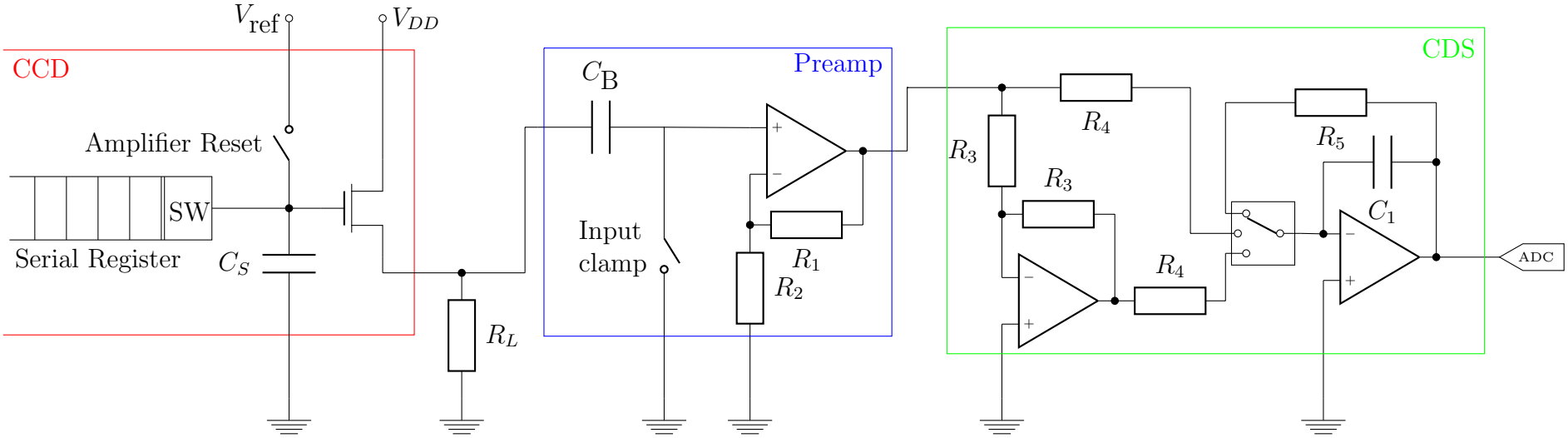
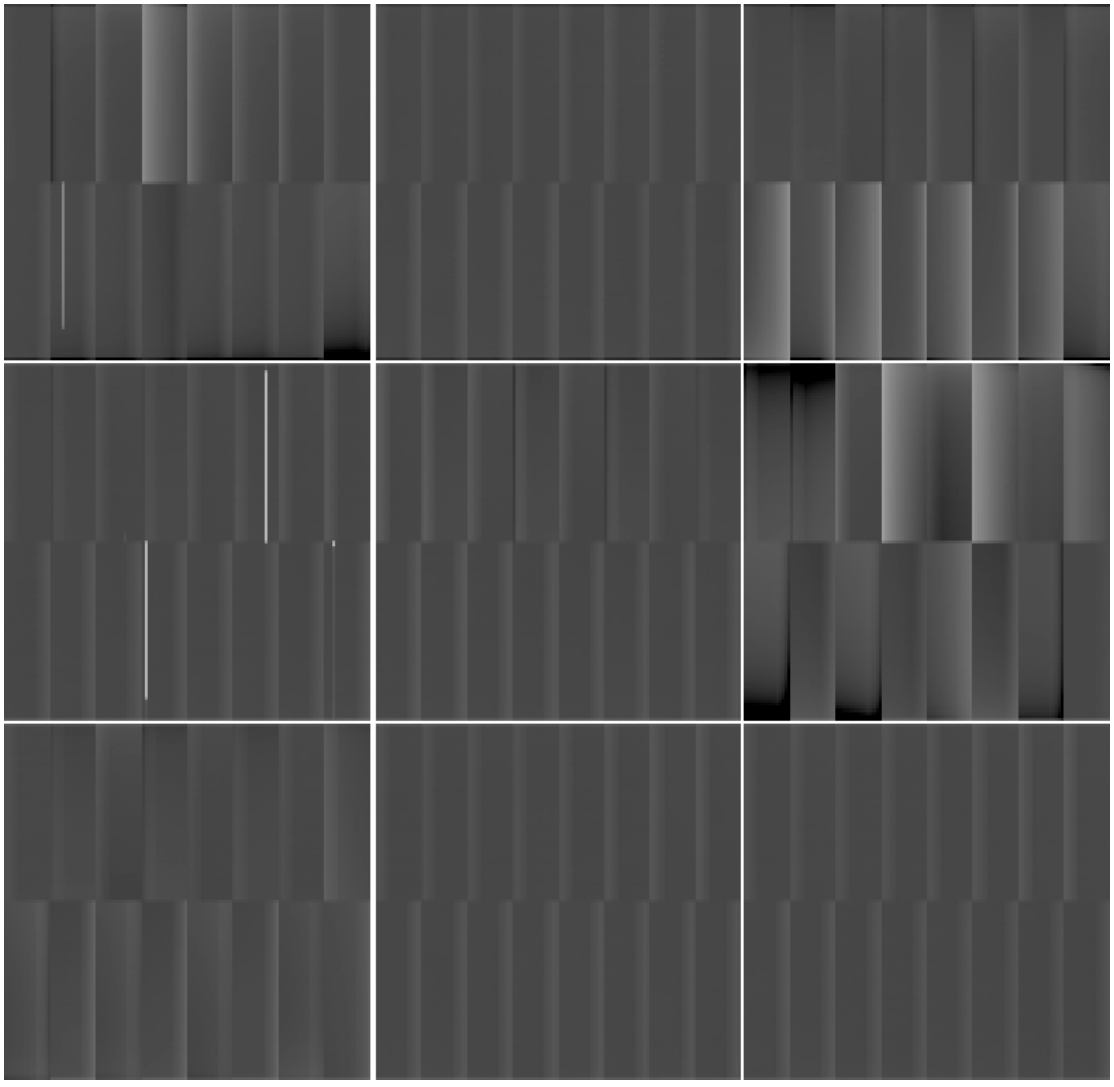


Video chain

Why does my data look like this?



LSST Raft RTM5

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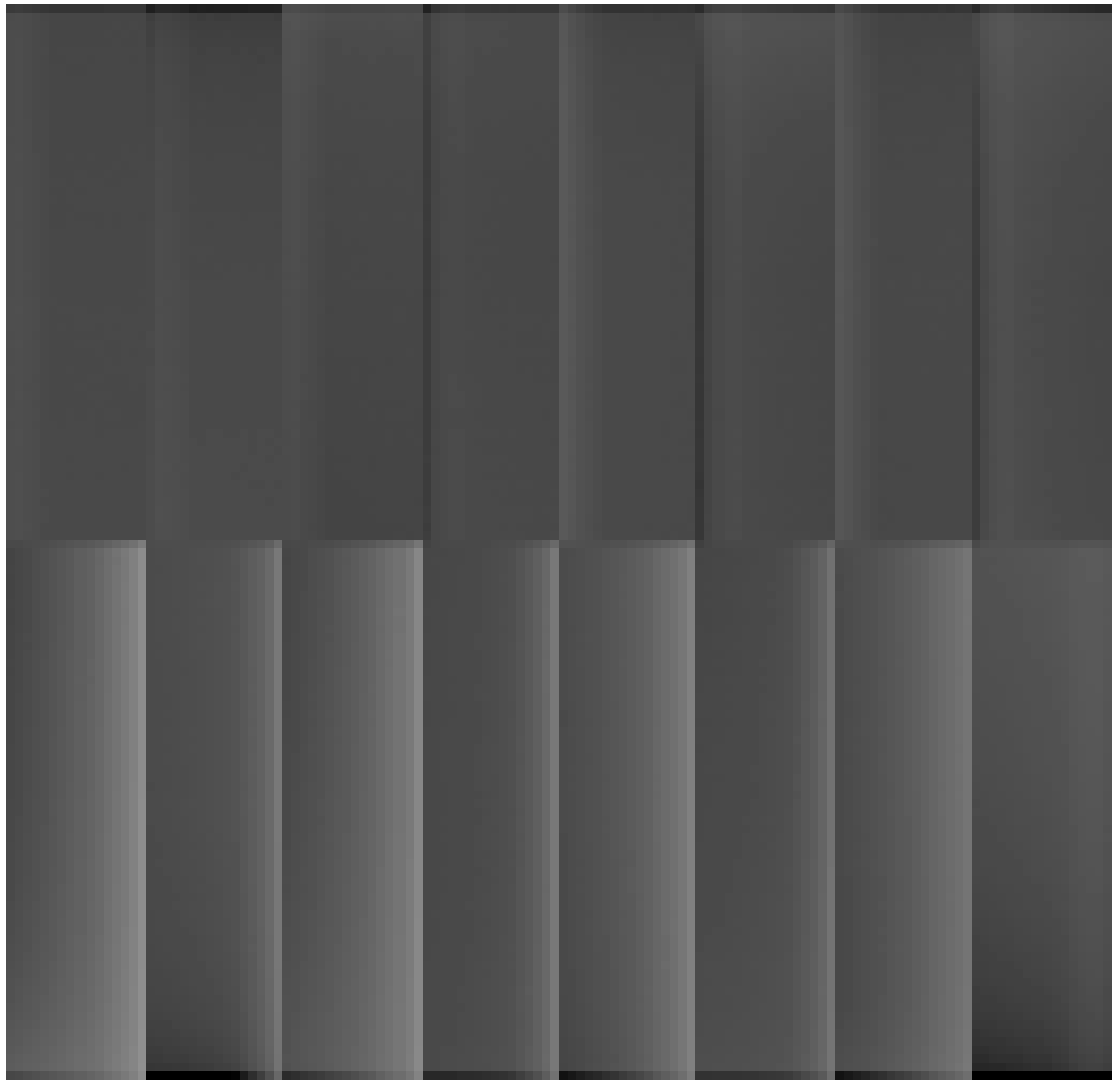

LSST Raft RTM5 S22

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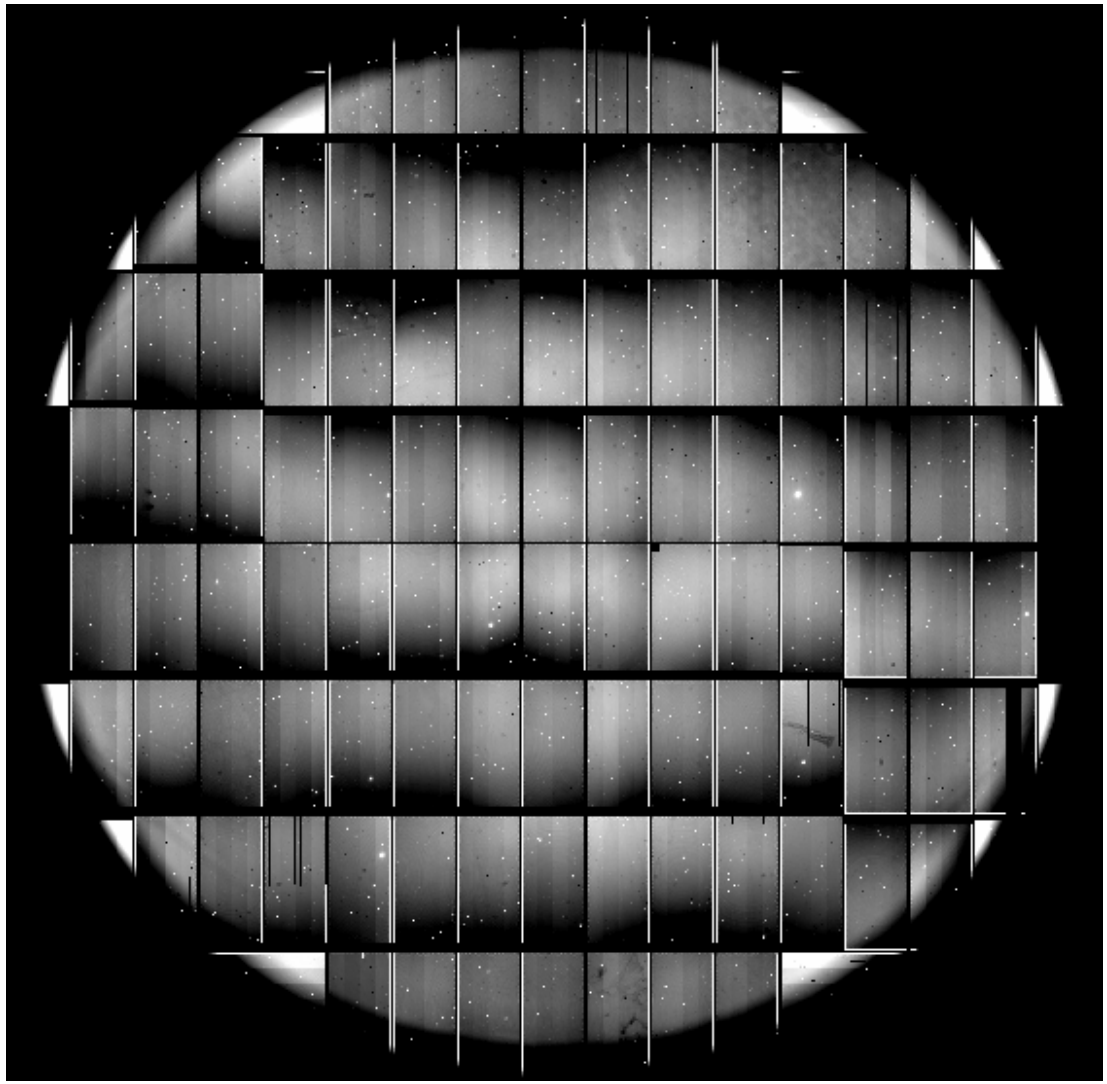

HSC g-band

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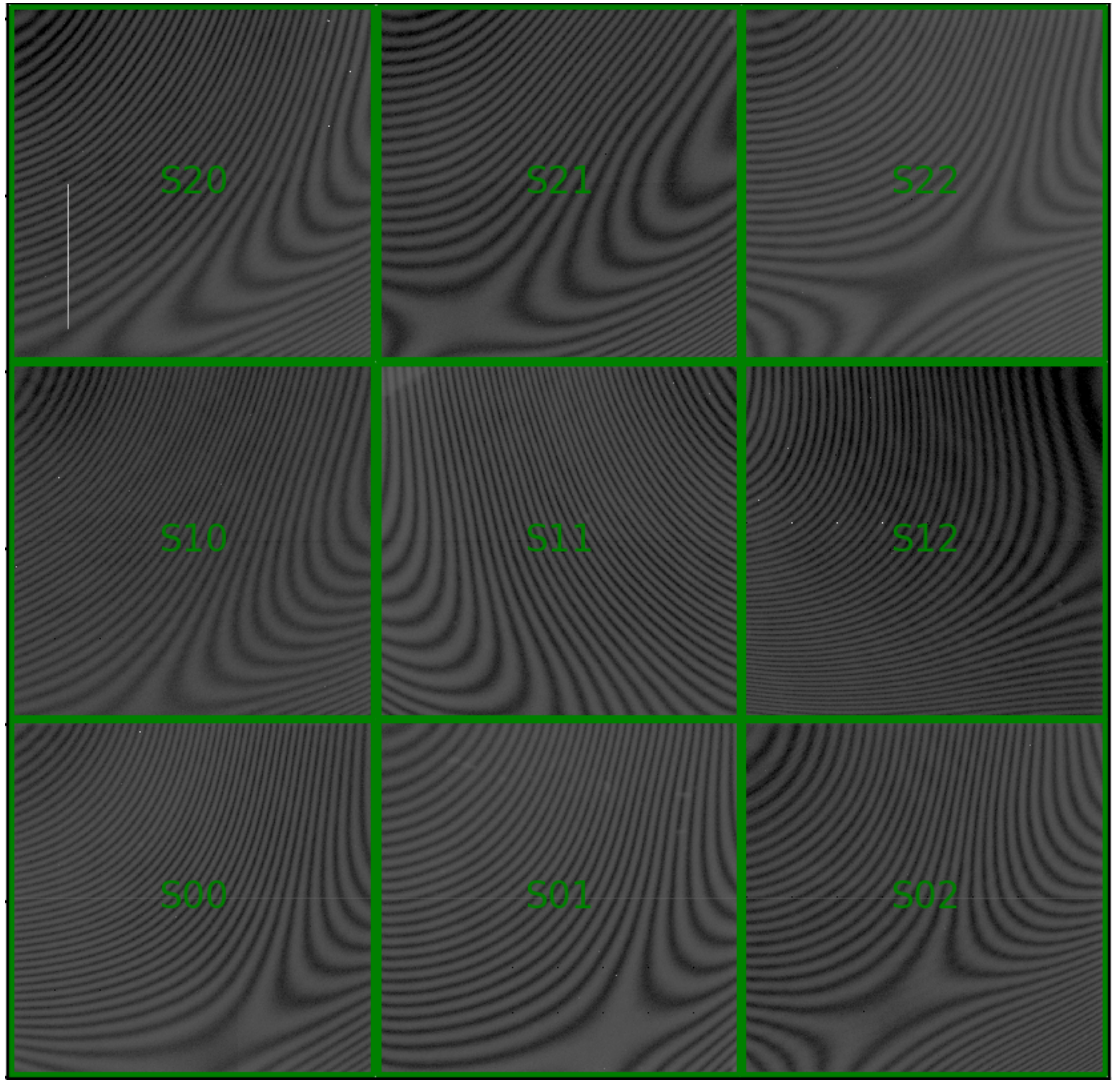
LSST Raft RTM5 post-ISR



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I am not convinced that this is true, even if we could compete financially with Google and Microsoft.

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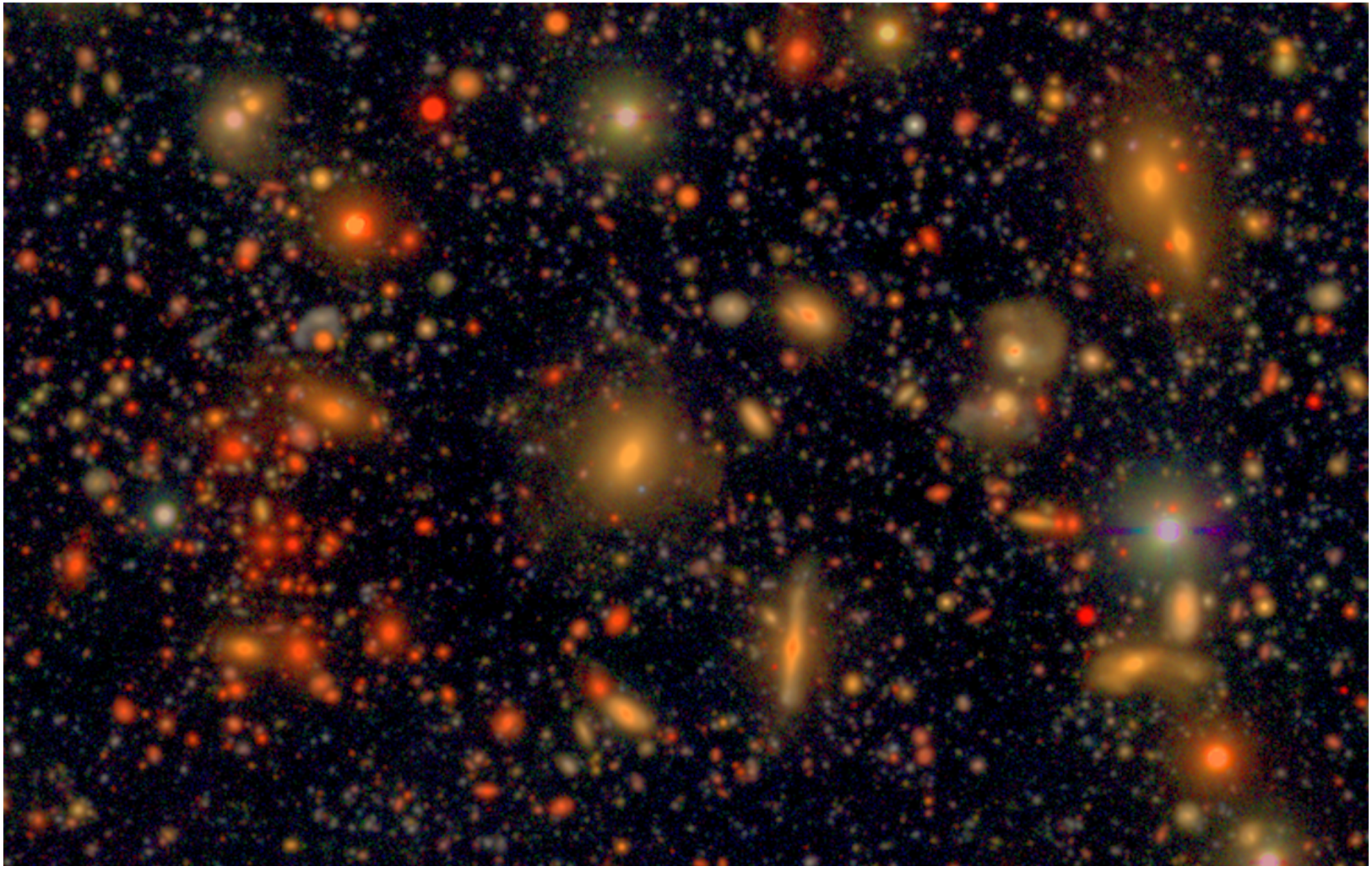

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> *If you were plowing a field, which would you rather use: Two strong oxen or 1024 chickens?*
> *Seymour Cray*

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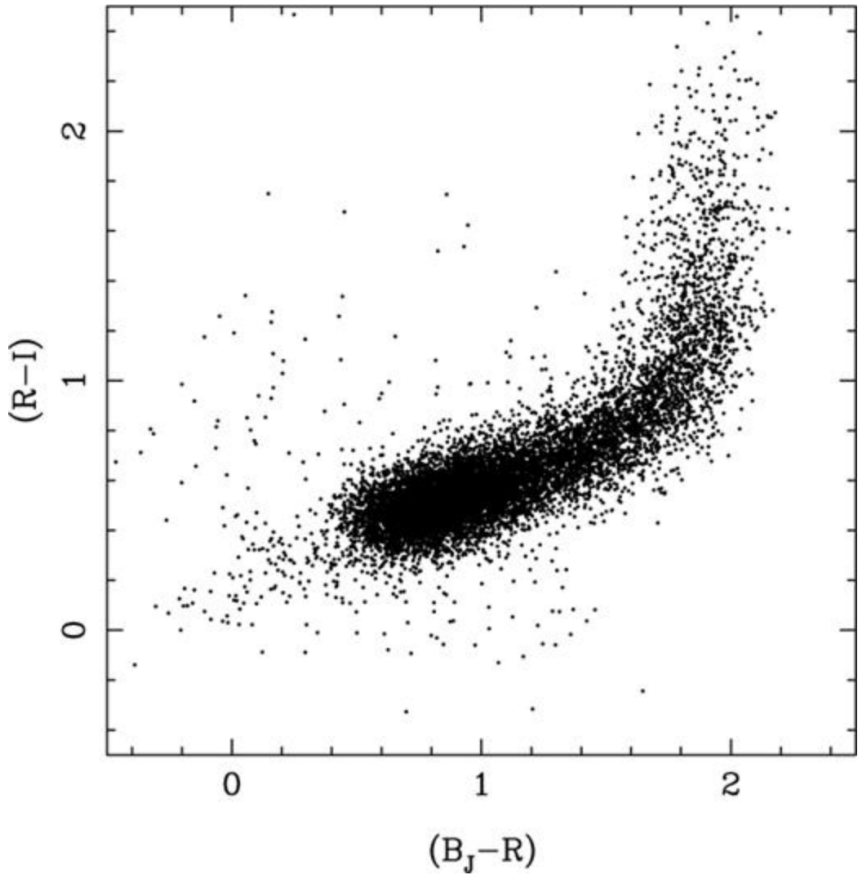
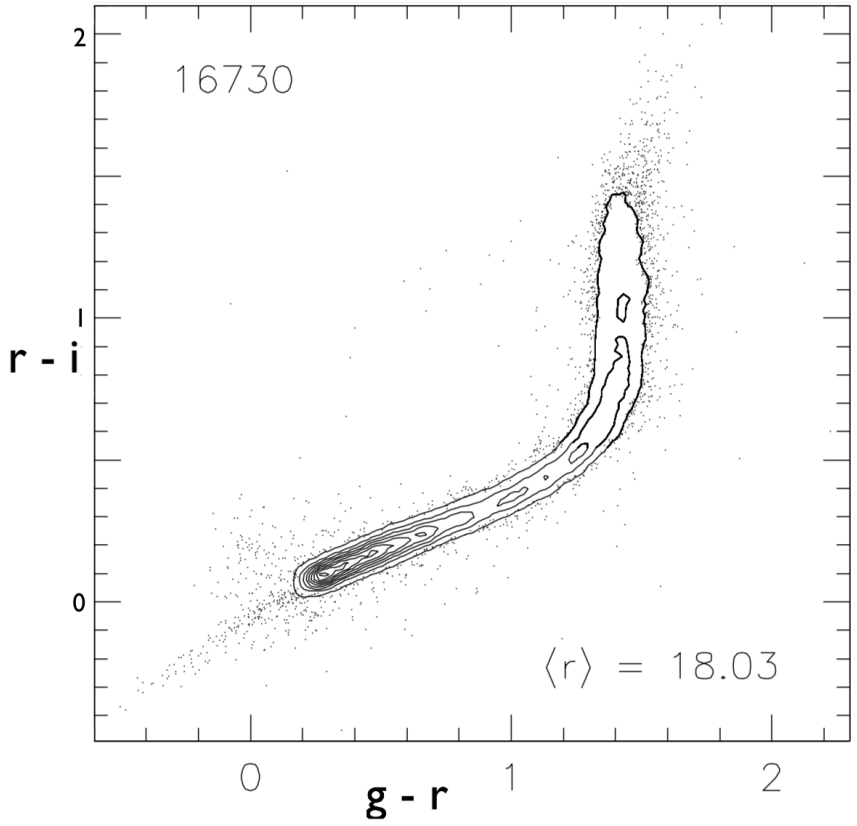
Better Data → Better Science

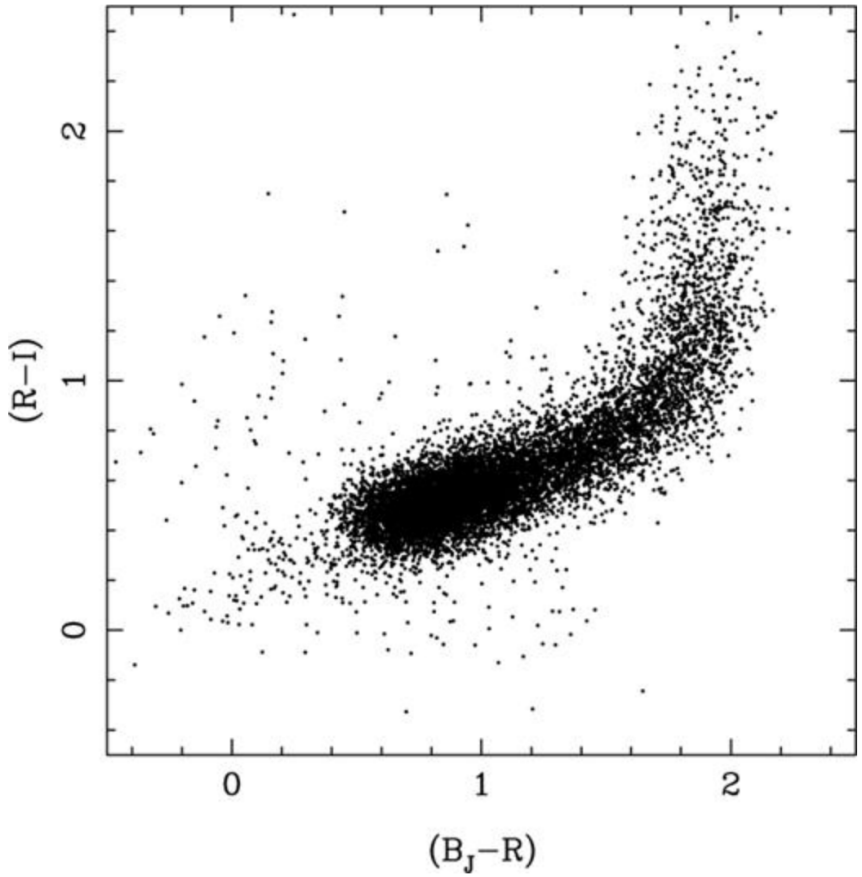


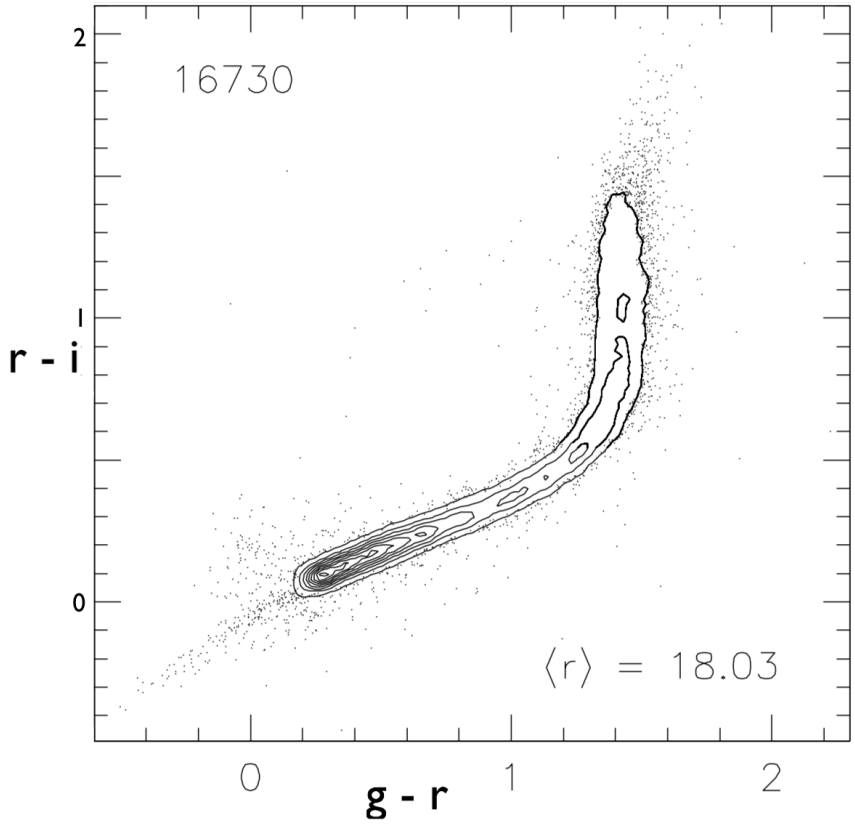
SuperCosmos (Hambly *et al.* 2001)



SDSS, *c.* 2002

Better Data → Better Science





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On the left, scanned Palomar plates; on the right SDSS CCD data.

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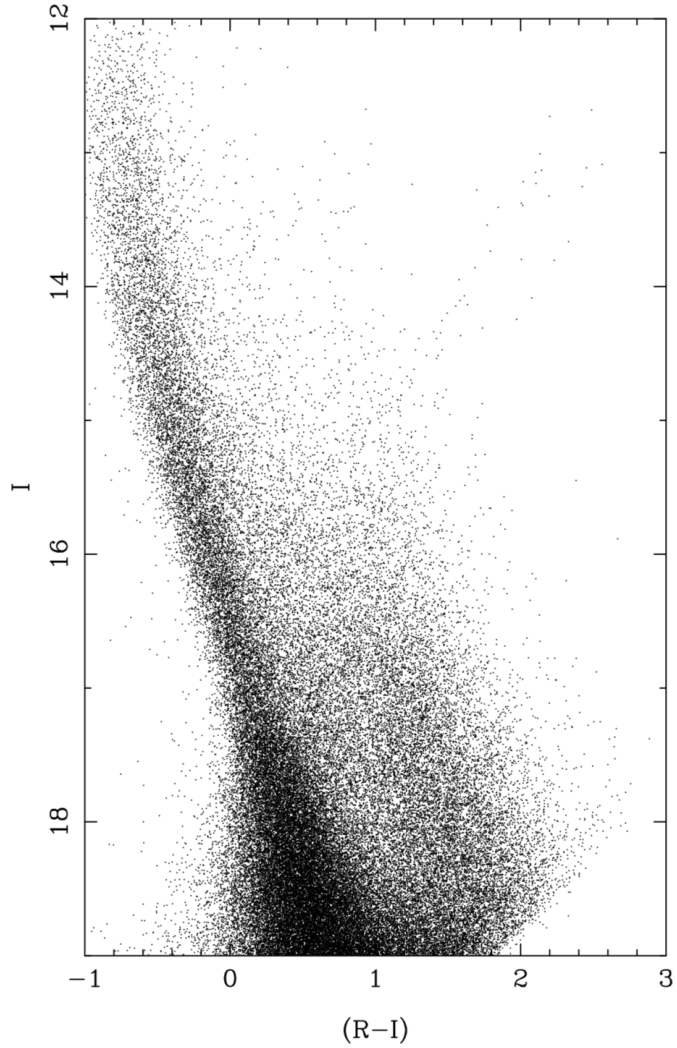

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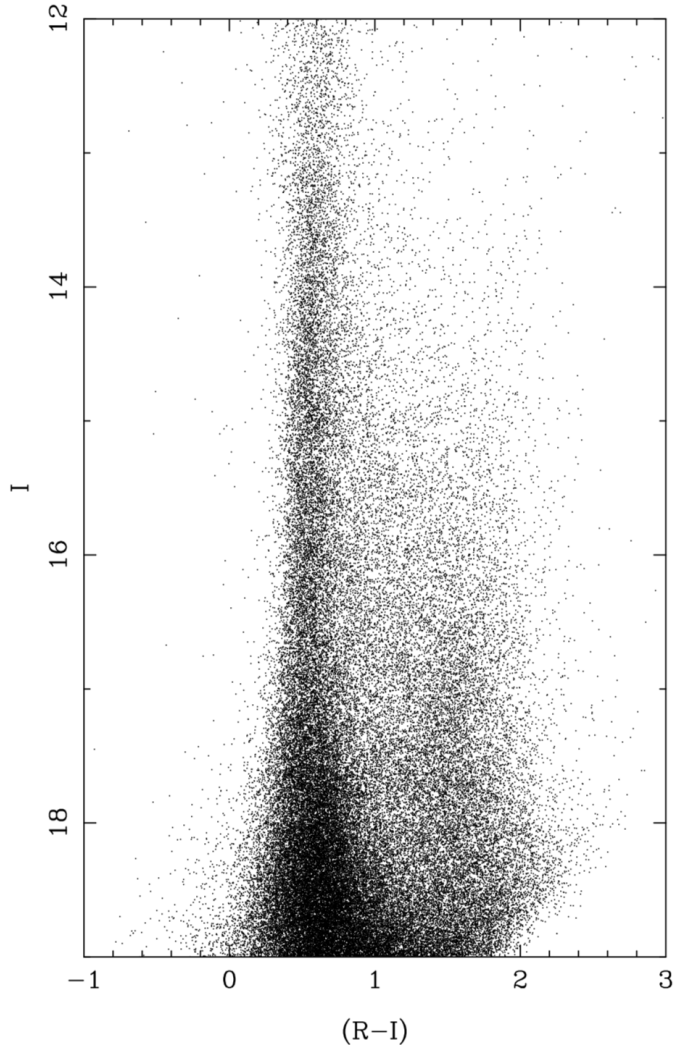

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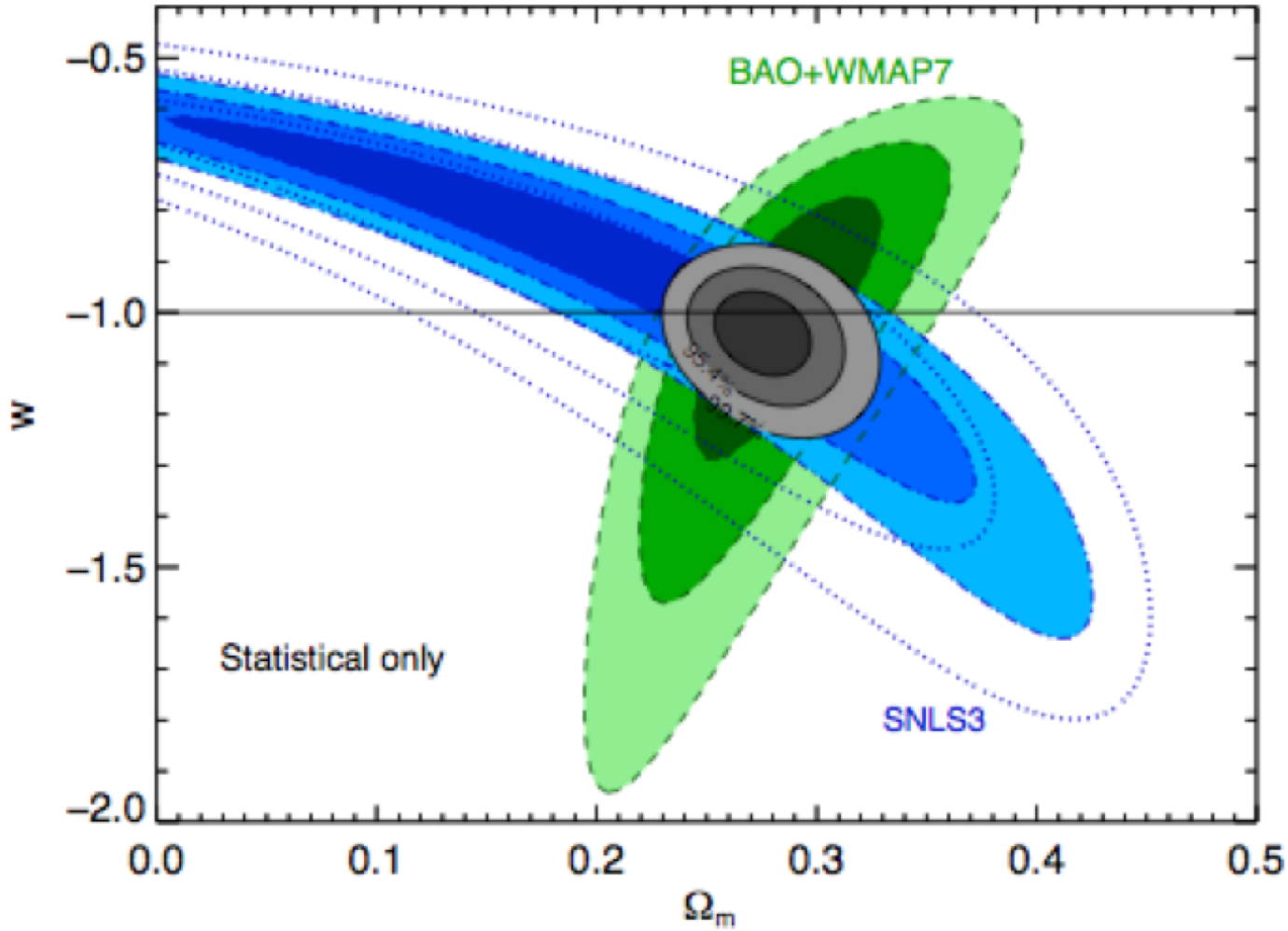

Betoule *et al.* SNLS

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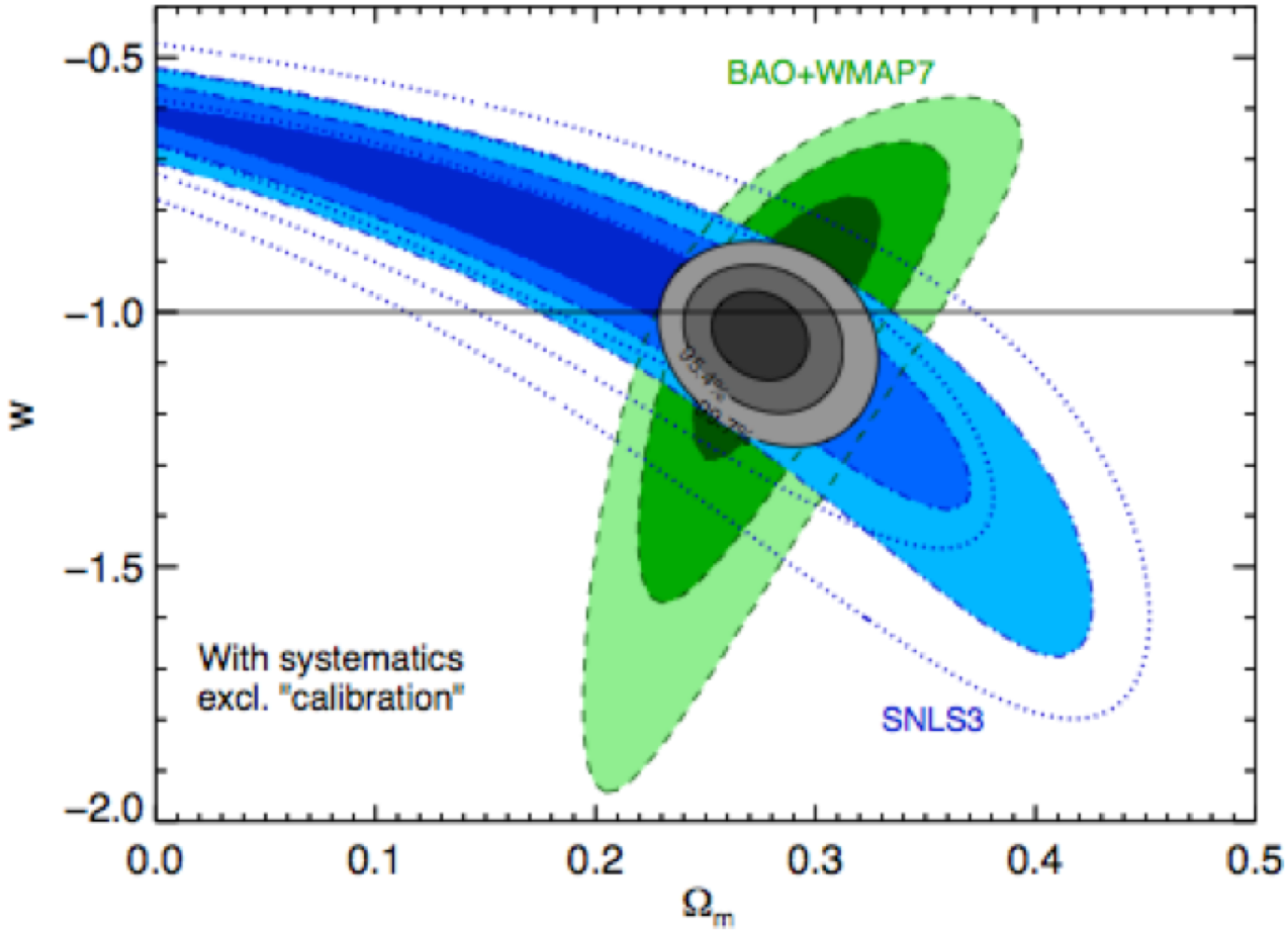

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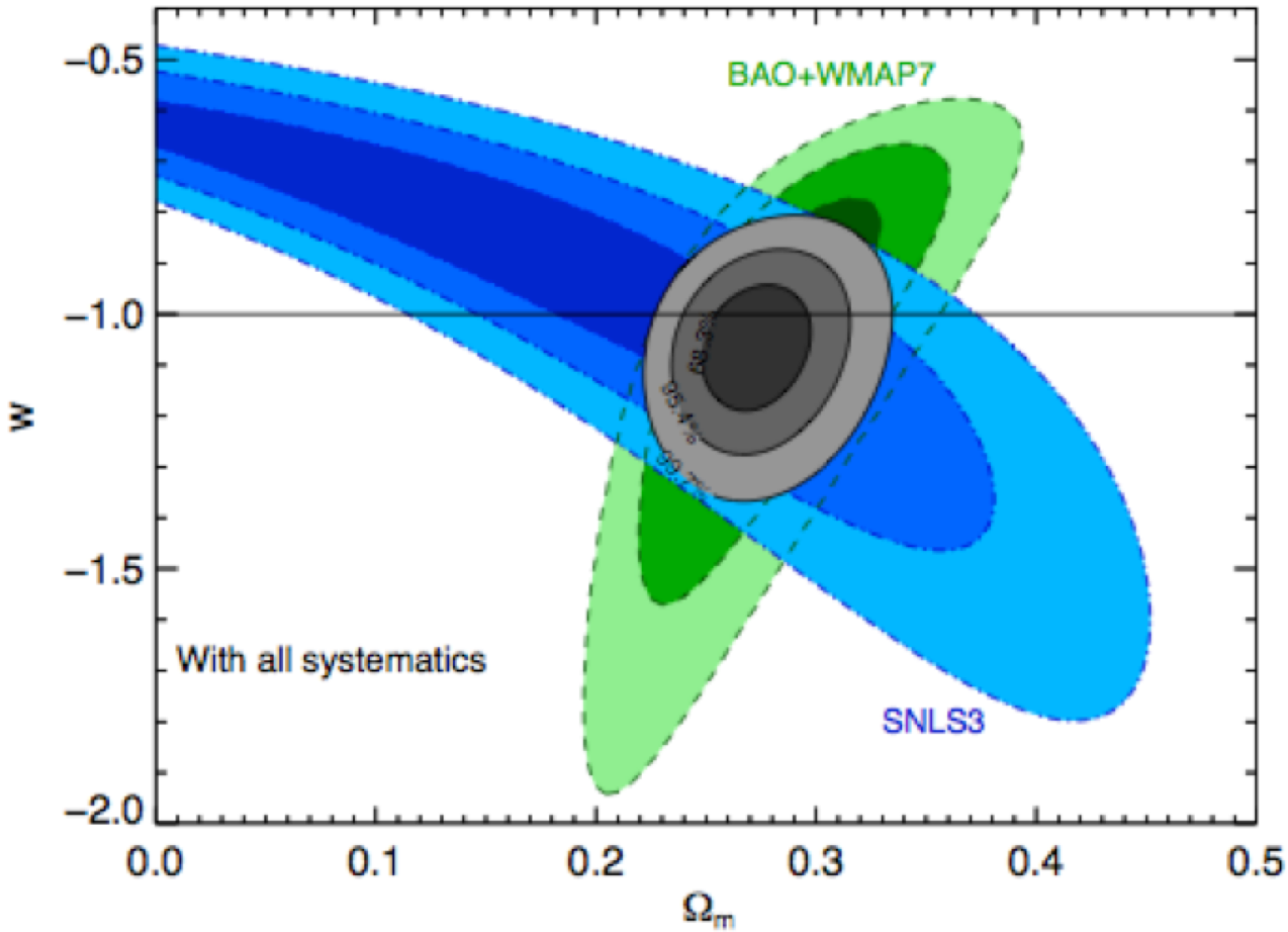

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  Only about 50% of SNLS's variance in Ω_m based on *c.* 200 high-z SNe Ia is statistical. LSST will detect *c.* 5×10^5 SNe Ia, of which maybe 20000 will be useful for cosmological analysis.

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Software can contribute to systematic errors.

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For example, a statistical model for an image containing a star (with known PSF ϕ) at $\boldsymbol{x}$ is

$$I(\boldsymbol{x}) = A\phi(\boldsymbol{x} - \boldsymbol{x}_0) + \boldsymbol{\epsilon}$$

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where I have subtracted the background level. If the noise $\boldsymbol{\epsilon}$ has known variance σ^2, and if I know the position, the (unbiased) optimal linear estimator for the flux A is

$$\hat{A} = \frac{\sum_i \phi(\boldsymbol{x}_i - \boldsymbol{x}_0) I(\boldsymbol{x}_i)/\sigma_i^2}{\sum_i \phi(\boldsymbol{x}_i - \boldsymbol{x}_0)^2/\sigma_i^2}$$

and this is the MLE (and attains the Cramér-Rao bound) if the noise is Gaussian.

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If the star is faint, the noise is the same in every pixel ($\sigma_i^2 = \sigma_0^2$) and this reduces to

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How should we choose w?

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There are similar discussions to be had about galaxy photometry, but they are harder as the uses of the fluxes are more complex (and non-linear); *e.g.* as inputs to photo-z codes used to estimate weak lensing kernels.

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- Astronomers have to learn the tools of software engineering

SDSS and Hipparcos

This part of my presentation started out with a conversation with Michael Perryman (then P.I. of GAIA) about Hipparcos and SDSS.

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Many are being ignored by XXX and YYY too.

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The advice in this talk comes from a PCA analysis of my involvement in

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- PFS (Ask me about my job at `http://web.astro.princeton.edu/jobs`)
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Any resemblance to actual projects, living or dead, or actual events is largely coincidental.

No animals were harmed in the writing of this talk.

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First the good news

Some of us have learned a lot about software engineering:

- C
- TCL
- cvs
-
-
- GNATS
-

Actually SDSS didn’t do too badly.

Douglas Adams (The Hitchhiker’s Guide to the Galaxy. 1978)

Orbiting this at a distance of roughly ninety-two million miles is an utterly insignificant little blue green planet whose ape-descended life forms are so amazingly primitive that they still think fortran is a pretty neat idea.

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Unfortunately our new-found wisdom sometimes makes the job of managing software groups harder; some people love the journey more than the destination, others are Luddites who don’t care about technical debt.

Project Managers

Robert Lupton "Lesson 1: You need a Project Manager"

You need a strong and impartial project manager. SDSS is a collaboration of a large number of institutions and we have never managed to take technical decisions unimpeded by politics.

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I no longer innocently believe that all we need to do is to hire a project manager, as they mostly come from quite another world. We *do* need them, of course, but we need to choose them carefully.

The problem[s] with project managers

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- Appoint a DM Project Manager; believe what you are told

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- Treat DM as a subcontract; believe what you are told
- Appoint a DM Project Manager; believe what you are told

So we have a recursive problem. How do we manage the DM Project Manager?

The problem[s] with project managers

Many project managers come from hardware backgrounds. They are comfortable writing contracts with requirements for stiffness and mass and knowing that the sub-contractor will deliver (and that the milestones mean something).

Strategies that I have witnessed for managing Data Management (DM):

- Ignore the problem
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- Treat DM as a subcontract; believe what you are told
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So we have a recursive problem. How do we manage the DM Project Manager? Or, better, how should we find managers who don't need managing?

People

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A piece of good news:

Janel Garvin, Dr. Dobbs Journal (2015-10-01)

So, all told, developers are not the lonely, antisocial nerds that they are portrayed to be, nor are they free-wheeling socialites.

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The resolution is that the shortage is of the best engineers, not the median:

> *If the best software developer can do the work of 10, 20, or even 100 run-of-the-mill employees, a single-person company that attracts such a superstar can compete effectively against a much larger enterprise*
> *[. . .]*
> *In some cases, software developers who fall at the low end of the productivity curve may be essentially nonproductive or even counterproductive*

Single point failures

Robert Lupton "Lesson 9: Avoid single points of failure"

OK, so this is totally obvious, but there are subtler aspects:

- If one person is allowed to become essential it implies that it’s proved impossible to find someone else who could fill their rôle
  In consequence, if they are on the critical path, and problems arise, it’s hard to add resources to solve the problem.
- If someone with an essential job isn’t very good, then an essential component of your system isn’t going to work very well.

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Robert's Corollary

Roberts' paradox implies that we'll almost always have single points of failure

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is of intrinsically higher worth? And which is a more valuable skill to teach our students?

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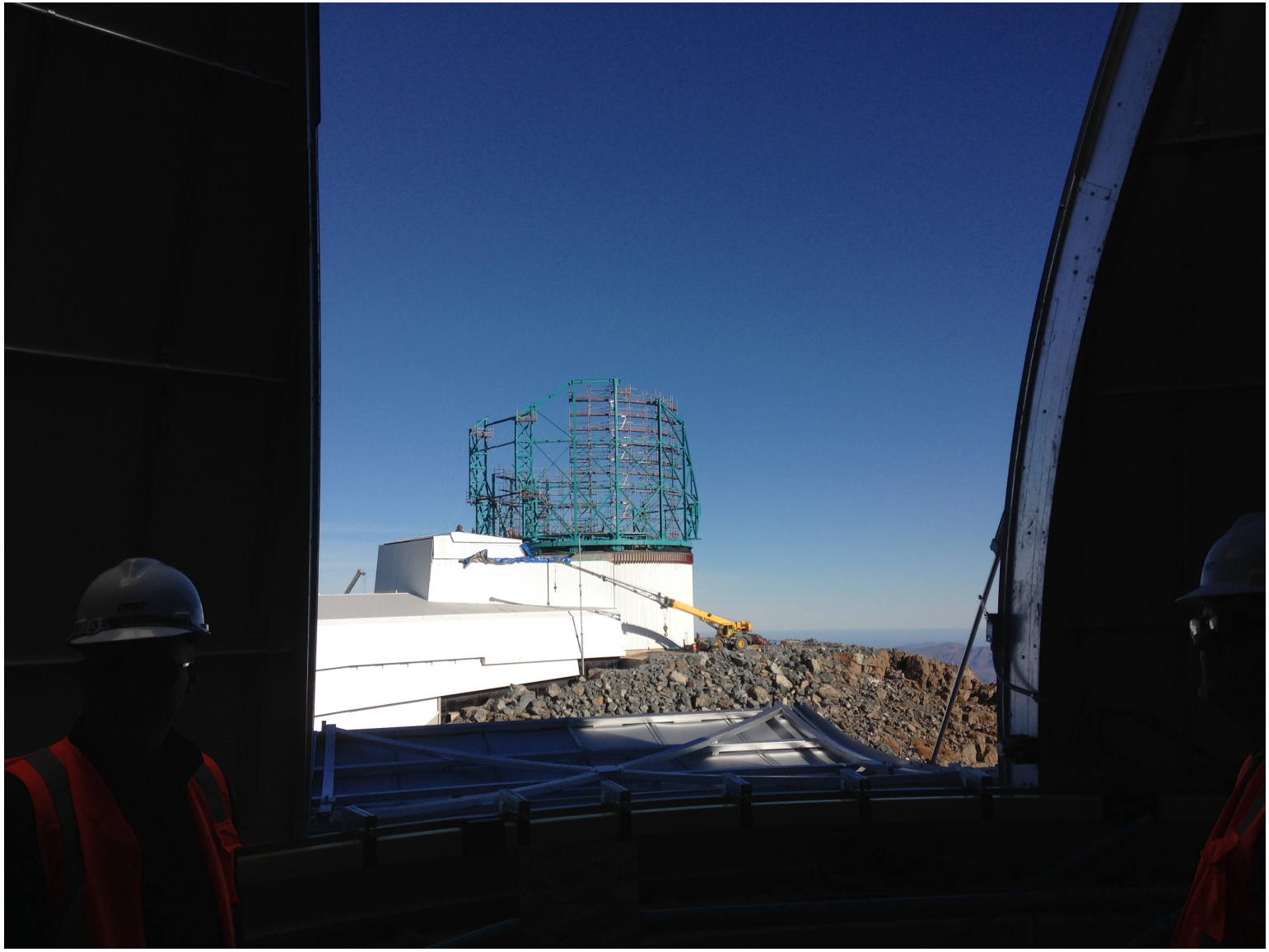

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Scientific Software: Art, Engineering, or Science?

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Scientific Software: Art, Engineering, and Science. And Fun.

LSST Status this Week

A Condor over Cerro Pachón

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