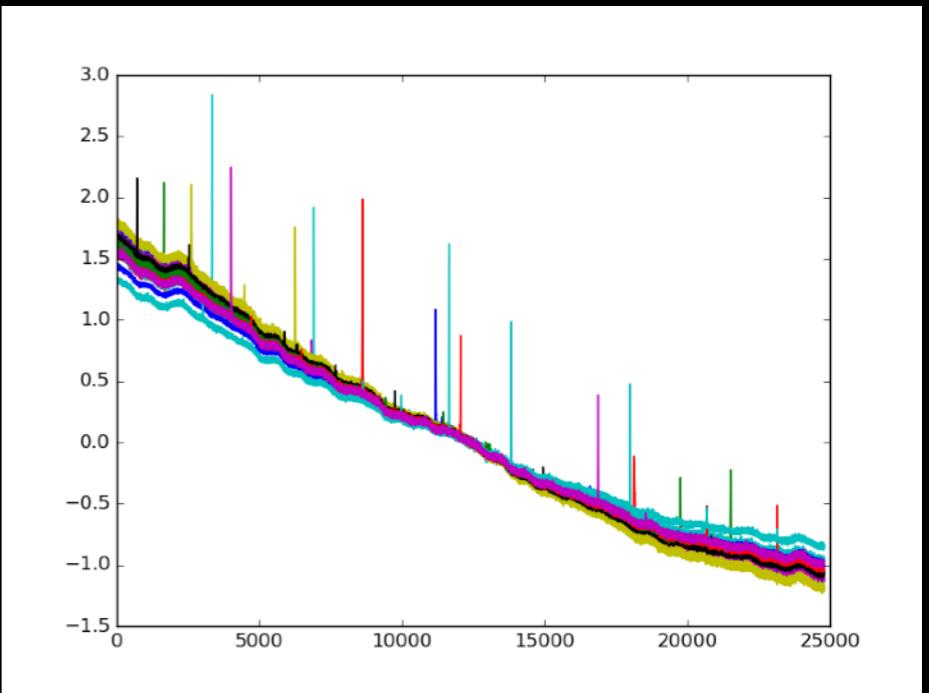


CMB Mapmaking

Typical Data

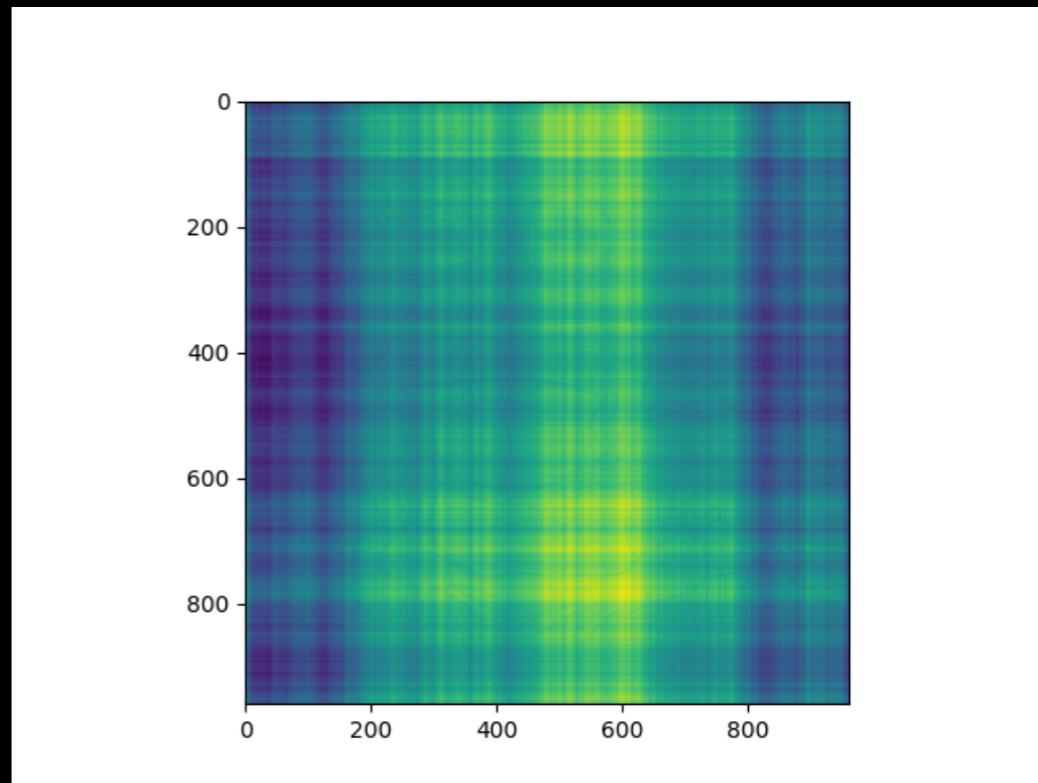
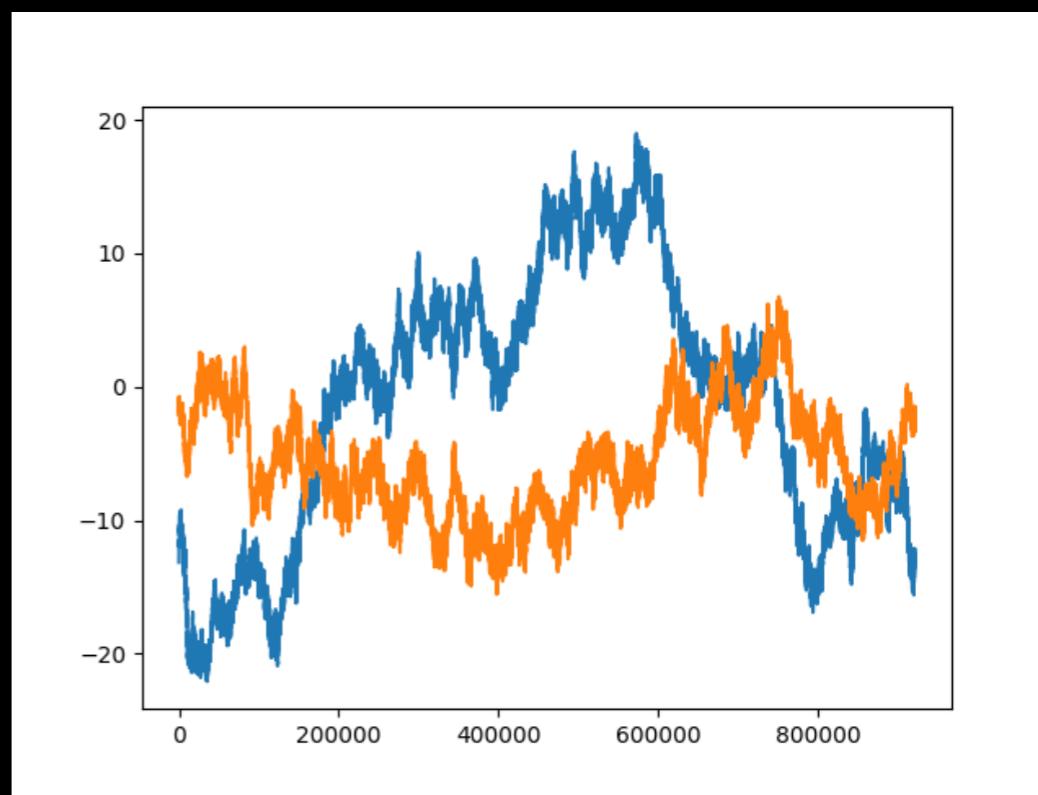
- What we have - a bunch of detectors read out their temperature.
- What we want: a map of the sky.
- How are we going to do this?
Most naive solution - make a map by averaging all data within a map pixel.



Above - real data from a ground-based mm array.
each color different detector.

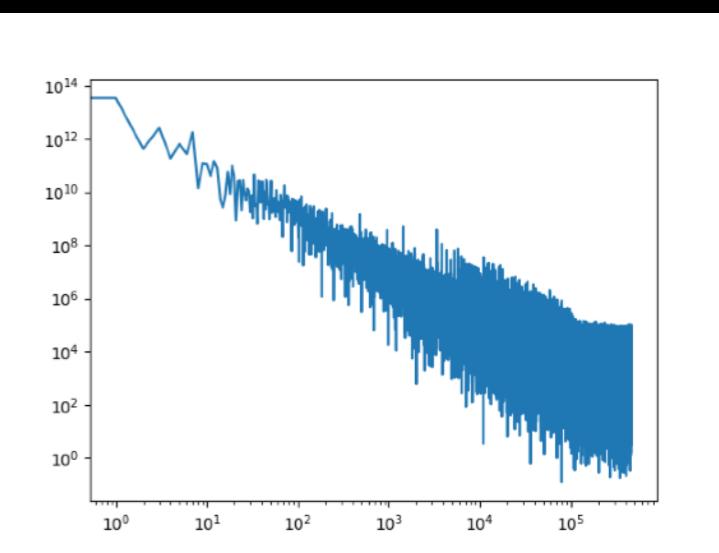
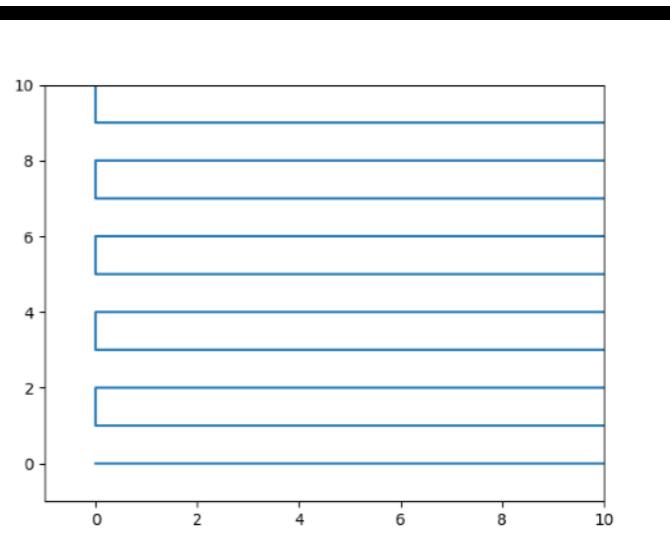
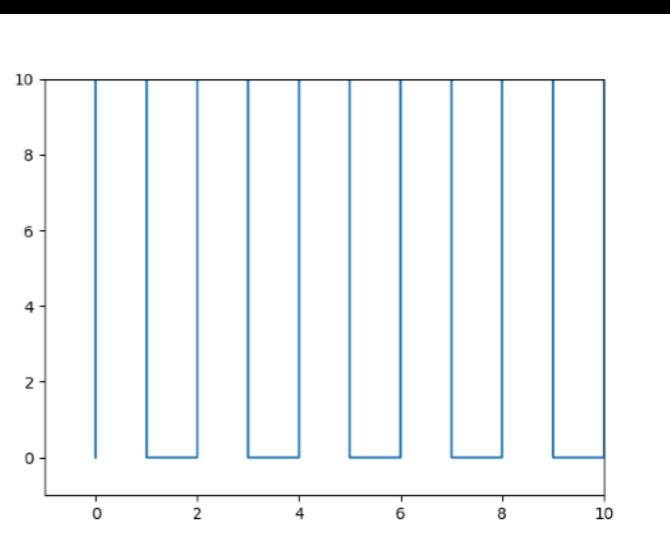
Naive Map

- Averaging data in map pixels *does not work*.
- Top: simulated data based on an input map with realistic noise. One scans EW, one scans NS.
- Bottom: naive map from averaging data. Could you do science?



Pink (1/f) Noise

- The problem: noise is larger on long timescales. The longer I average, the worse.
- Low-frequency noise couples to scan patterns (top,middle) to make stripes.
- Typically, we have more noise at low-frequencies, with white noise floor (bottom).
- This is common in nature, with noise variance= $k^{-a}+n$ for white noise n and index a. because $a=-1$ is so common, we call this 1/f noise, even for $a\neq-1$.



What can we do?

- When in doubt, write down likelihood/ χ^2 .
- We'll assume that $d=Am_t+n$, where d is our data, m_t is a set of true model parameters (in this case, a map of the sky with one param for each pixel), A is a matrix that tells us how to convert m to d , and n is our noise.
- Under Gaussianity, the likelihood of having observed data given a set of model parameters is $\exp(-1/2 (d-Am)^T N^{-1} (d-Am))$ where $N_{ij} = \langle n_i n_j \rangle$.

Maximizing the Likelihood

- We can ask for the map of the sky that maximizes the probability of getting the observed data. This happens when $\text{grad}(L)=0$. for ease, work with $\log(L)$
- Calculus with matrices is just like regular calculus, as long as you preserve order.
- $-2\log(L)=(d-Am)N^{-1}(d-Am)$. we call this χ^2 . The m that *maximizes* the likelihood will *minimize* χ^2 .
- $\nabla\chi^2=-2A^TN^{-1}(d-Am)=0$, or $A^TN^{-1}Am=A^TN^{-1}d$.

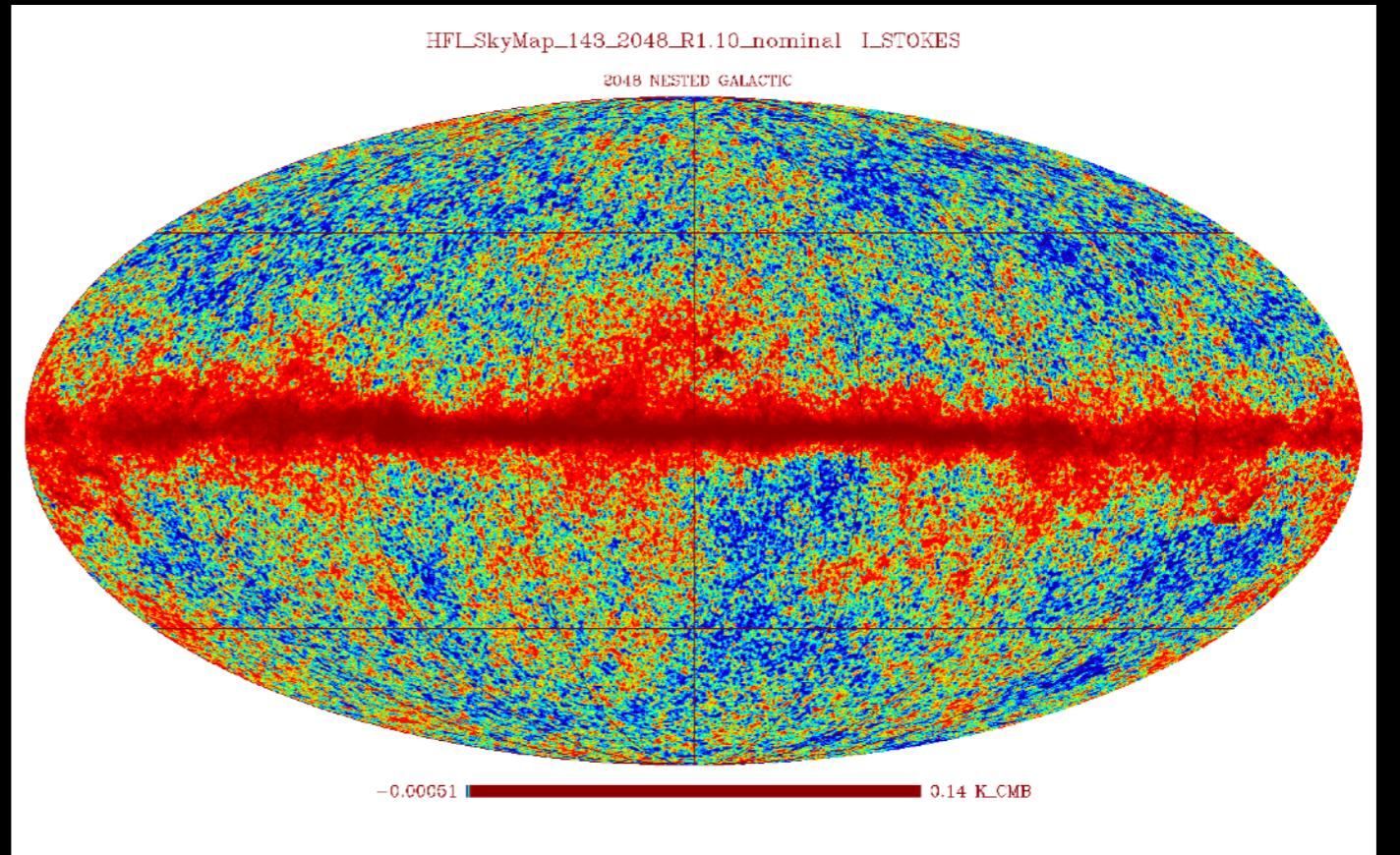
First Glimmer of Hope

- If we can solve $A^T N^{-1} A m = A^T N^{-1} d$ then maybe we can make good maps of the sky?
- We're going to have to figure out N , though, and the invert it.
- Explicit solution would be $m = (A^T N^{-1} A)^{-1} A^T N^{-1} d$. In general, this will be out of our computational reach. We'll see the matrices are just too large.

Giant Matrix Problems

- Solving $Ax=b$ is a huge field.
- We've seen least-squares fitting is one case:
 $(A^T N^{-1} A)x = A^T d$. $A^T d \rightarrow b$, $A^T N^{-1} A \rightarrow A$
- Solving Poisson equation ($\nabla^2 V = \rho(x)$) is another.
- Many problems can be cast this way. If you can cast it, then you can use the considerable power of linear algebra to solve!

Planck



- Let's say we have managed to make $A^T N^{-1} A$. How big is it?
- Planck - say maps are $n_{\text{side}}=1024$. have $12 * n_{\text{side}}^2$ pixels $\sim 12e6$ total.
- But, we have polarization - so $\sim 40e6$ total pixels.
- How long would it take to invert $A^T N^{-1} A$?
- How much storage would it take?

Planck Cost

- Let's say we have managed to make $A^T N^{-1} A$.
- Planck - say maps are $n_{\text{side}}=1024$. have $12 * n_{\text{side}}^2$ pixels $\sim 12e6$ total.
- But, we have polarization - so $\sim 40e6$ total pixels.
- How long would it take to invert $A^T N^{-1} A$?
 - operation count $\sim 2n^3 = 2 * 40e6^3 = 1.28e23$ flops. 1 core $\sim 2.5e9 * 4 * 8 \sim 80e9$ ops/s. Total of $1.5e12$ seconds, or 47,000 core-years.
- How much storage would it take?
 - $40e6^2 * 8$ bytes/pixel = 12 million gigabytes of RAM.
- Direct solution not feasible. NB - CMB-S4/SO are orders of magnitude worse!

Eqn. Pieces - $A^T A$.

- What do the pieces of $A^T N^{-1} A m = A^T N^{-1} d$ look like?
- $\langle d \rangle = Am$. Matrix A takes map m and puts into data d . We'll end up needing an operator that takes m and puts into d . Simplest (and common!) is to assign each data point to a map pixel. Then work for Am is linear in the number of data points.
- We also need A^T . This takes data and adds into a map (the “dirty map” from radio astronomy). Again, if all I need is to make $A^T d$, then work is linear in d .

Eqn. Pieces - N^{-1} .

- Nearby data clearly have correlations in their noise.
- Lifesaver - any signal that is *stationary* (statistics independent of time) is *uncorrelated* in Fourier space.
- We can Fourier transform our data, and model the noise in Fourier space. Then, we get $N^{-1}d$ by Fourier transforming d , dividing by our noise model, and Fourier transforming back.

Could I verify Solution?

- Say someone gave me the answer. Could I confirm?
- Apply A , N^{-1} , A^T as series of operators. Make Am , $N^{-1}(Am)$, and $A^T(N^{-1}Am)$.
- Cost to make $A^T N^{-1} Am$ depends on # of data points.
- Planck 143 - 12 detectors, ~100 Hz, 4 years. Totals ~150e9 samples.
- Am takes n_{data} operations - 150e9.
- FFT-based N^{-1} takes $2 * \log_2(\text{chunk_length}) * n_{\text{data}}$. 1 day=100*86400, $\log_2 \sim 25$. Total ops $50 * n_{\text{data}} \sim 7.5 \text{e}12$.
- $A^T(N^{-1}Am)$ takes n_{data} again, 150e9.

Could I verify ctd.

- Total operation count $\sim 1e13$, dominated by noise.
- My $80e9$ ops/s core would take 125 seconds. (In practice, memory bandwidth is a limiting factor, so A, A^T comparable to N^{-1})
- Data volume $\sim 150e9 \times 8 \sim 1-2e12$. Terabytes of RAM is possible, though non-trivial.
- So, if someone gave me a guess at the solution, I could check if it was correct.

Getting to a Solution

- Can't directly solve, so will have to try to solve iteratively by checking how good solutions are.
- One possibility: start at a guess, find gradient, minimize χ^2 along downhill (gradient) direction.
- If m is guess and m^\dagger is new step, have
$$\chi^2 = (d - A(m + m^\dagger))^T N^{-1} (d - A(m + m^\dagger)) = (r - Am^\dagger)^T N^{-1} (r - Am^\dagger)$$
 where $r = d - Am$
- gradient of $\chi^2 = -2A^T N^{-1} (r - Am^\dagger)$. But, we are at our current guess so $m^\dagger = 0$, and $\text{grad}(\chi^2) = -2A^T N^{-1} r$.
- Making this gradient takes same operations as checking solution so we can do this.

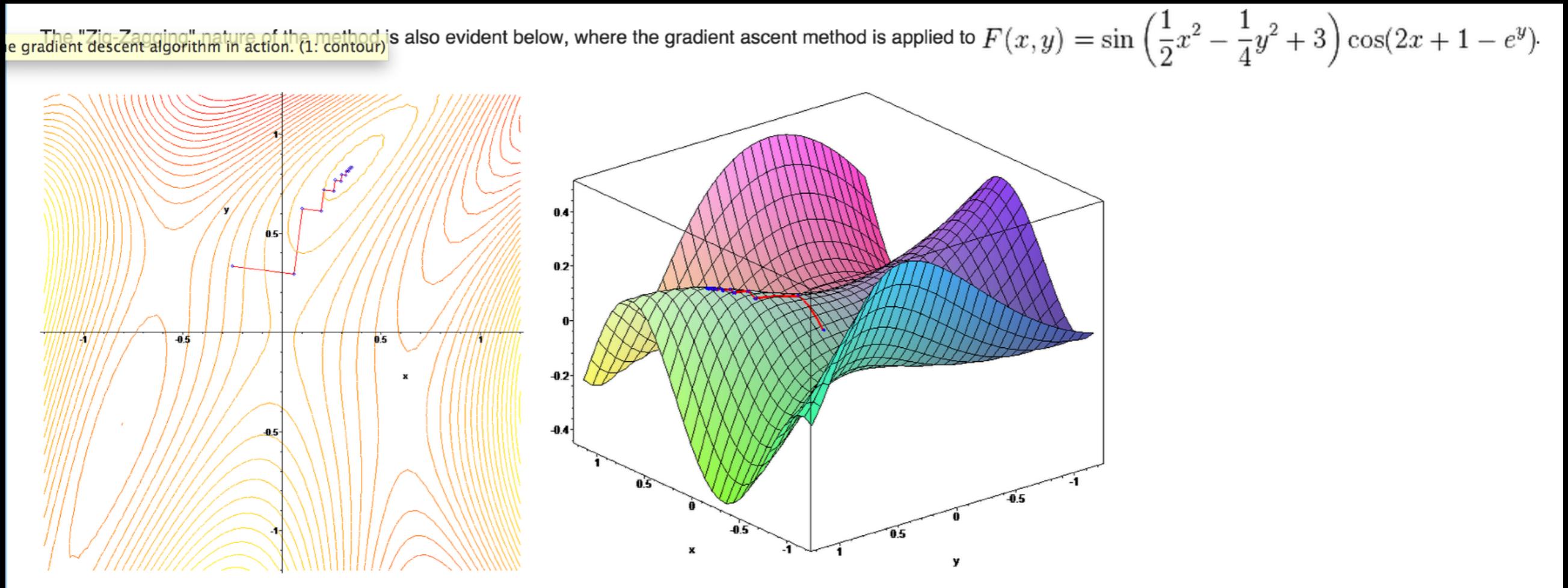
Minimizing Along Direction

- Let v be my direction (proportional to $A^T N^{-1} r$), and q the distance I step. So, $m^\dagger = vq$. What is q ?
- $\chi^2 = (d - A(m + m^\dagger))^T N^{-1} (d - A(m + m^\dagger)) = (r - Avq)^T N^{-1} (r - Avq)$
- Minimize w.r.t q , and have $v^T A^T N^{-1} A v q = v^T A^T N^{-1} r$
- q is a scalar, so $= v^T A^T N^{-1} r / v^T A^T N^{-1} A v$
- should look familiar, where my new A is Av

Scheme to Minimize

- We have a way to try to solve (enormous!) least-squares now.
- step 0: guess a solution. Could be zero...
- step 1: calculate residual: data-current prediction (\mathbf{Am})
- step 2: calculate downhill direction
- step 3: go downhill until minimum
- step 4: add this step to current guess (update \mathbf{m})
- repeat steps 1 through 4, until we make it downhill.
- This scheme called “steepest descent”. Is it a good scheme?

Steepest Descent



No! From wikipedia. Key point - new direction always perpendicular to old direction. So, step n+2 will be parallel to step n. Zigzagging is inefficient.

Conjugate Gradient

- Problem with steepest descent is new directions tend to lie along old directions.
- If I had a way to stop that from happening, maybe this would work?
- Conjugate gradient is a way to solve $Ax=b$ (where in this case, this A equals our usual $A^T N^{-1} A$) where new steps are A -orthogonal, i.e. $m_i^\top A m_j = 0$ for $i \neq j$.
- Magically, conjugate gradient can stay A -orthogonal to all previous directions without remembering what those directions were!

A-Orthogonality

- Let $x = \sum \alpha_k p_k$ where $p_k^T A p_{k'} = \delta_{kk'}$.
- We have $Ax = b = \sum \alpha_k A p_k$
- Multiply on left by one of the p_k . Gives us $\alpha_k p_k^T A p_k$
- How would my estimate of α_k change if I added some amount of $p_{k'}$ to x ? It wouldn't, because of A-orthogonality.
- So, if my search directions are A-orthogonal, solving for the next coefficient doesn't mess up the previous ones.

Conjugate Gradient Recipe

- $r_0 = b - Ax_0$ ($b = A_p^T N^{-1} d$, where A_p is our usual pointing matrix)
- $p_0 = r_0$.
- repeat over k :
- $\alpha_k = r_k^T r_k / P_k^T A p_k$
- $x_{k+1} = x_k + \alpha_k p_k$
- $r_{k+1} = r_k - \alpha_k A p_k$. (if r_{k+1} “small enough”, quit)
- $\beta_k = r_{k+1}^T r_{k+1} / r_k^T r_k$.
- $p_{k+1} = r_{k+1} + \beta_k p_k$.

What's going on?

- Not obvious, but CG starts downhill, minimizes, then chooses new direction.
- New direction chosen so that minimizing along it doesn't mess up previous minimizations.
- In practice, first minimization zeroes out residual along largest eigenvalue.
- Next step zaps next eigenvalue residual, etc.
- Guaranteed to converge after n iterations.
- Each step takes n^2 operations, so total work is n^3 . Similar to direct.

CG Code

- Turns out, if many eigenvalues are repeated, CG will zap all of them in one step.
- In practice, many problems have limited eigenvalue spectrum. CG can converge in many fewer than n steps then.
- If $A^T N^{-1} A$ is singular, it has zero eigenvalues. Those get left for last, so CG helpfully leaves solution unchanged.

```
import numpy as np

def simple_cg(x,b,A,niter=20):
    r=b-np.dot(A,x)

    p=r.copy()
    x=0
    rTr=np.dot(r,r)
    for iter in range(niter):
        print 'iter is ',iter,' with residual squared ',rTr
        Ap=np.dot(A,p)
        pAp=np.dot(p,Ap)
        alpha=np.dot(r,r)/pAp
        x=x+alpha*p
        r_new=r-alpha*Ap
        rTr_new=np.dot(r_new,r_new)
        beta=rTr_new/rTr
        p=r_new+beta*p
        r=r_new
        rTr=rTr_new
    return x

n=1000
A=np.random.randn(n,n)
A=np.dot(A.transpose(),A)
A=A+np.eye(n)*50
b=np.random.randn(n)
x=0*b

x_cg=simple_cg(x,b,A,niter=n/20)
x_true=np.dot(np.linalg.inv(A),b)

print 'mean error is ',np.mean(np.abs(x_cg-x_true)), ' vs mean answer of ',np.mean(np.abs(x_true))
```

```
Jonathans-MacBook-Pro-3:lecture_12 sievers$ python conjugate_gradient.py
iter is  0  with residual squared  983.895633071
iter is  1  with residual squared  935.203900616
iter is  2  with residual squared  820.897912224
iter is  3  with residual squared  609.270999934
iter is  4  with residual squared  423.162817458
iter is  5  with residual squared  264.413744162
iter is  6  with residual squared  196.74420023
iter is  7  with residual squared  130.125978601
iter is  8  with residual squared  86.3093893226
iter is  9  with residual squared  57.6543704596
iter is  10  with residual squared  38.538896129
iter is  11  with residual squared  27.0997454239
iter is  12  with residual squared  16.9680122826
iter is  13  with residual squared  10.7500897212
iter is  14  with residual squared  6.42175958411
iter is  15  with residual squared  3.93462615661
iter is  16  with residual squared  2.67854372478
iter is  17  with residual squared  1.70333560593
iter is  18  with residual squared  0.992818638602
iter is  19  with residual squared  0.625901005577
mean error is  7.64533796934e-05  vs mean answer of  0.00541051489099
```

Adding constant to diagonal shrinks eigenvalue spread, makes CG converge faster.

CG Example

- Look at `test_cg.py`, which imports `cg.py`
- `test_cg` will let you try out various matrix sizes and eigenvalue spreads.
- Can you compare the conjugate-gradient answer to `np.linalg.inv`?
- Does # of iterations for CG to converge depend on eigenvalue spread vs. diagonal offset?
- Does # of iterations depend on matrix size at fixed eigenvalue spread?

Preconditioned Conjugate Gradient

- If I have some guess as to A^{-1} , call it A^\dagger , then I could solve $A^\dagger A x = A^\dagger b$.
- If spread in eigenvalues of $A^\dagger A$ is smaller than in A , then I'll converge faster.
- Preconditioned conjugate gradient is a way of putting in an A^\dagger . One thing guaranteed to improve matters is $1/\text{diag}(A)$ (called Jacobi preconditioner)

PCG Example

```
n=1000
A=np.random.randn(n,n)
A=A+np.dot(A.transpose(),A)

diag_off=np.random.rand(n)*1500
A=A+np.diag(diag_off)
#A=A+np.eye(n)*50
#A=np.diag(np.diag(A))
b=np.random.randn(n)
x=0*b

nstep=n/100
#A=np.diag(np.diag(A))
x_cg=simple_pcg(x,b,A,niter=nstep)
x_true=np.dot(np.linalg.inv(A),b)
print 'mean CG error is ',np.mean(np.abs(x_cg-x_true)), ' vs mean answer of

x_pcg=simple_pcg(x,b,A,np.diag(A),niter=nstep)
print 'mean PCG error is ',np.mean(np.abs(x_pcg-x_true)), ' vs mean answer o'
```

```
def simple_pcg(x,b,A,M=None,niter=20):
    r=b-np.dot(A,x)
    if not(M is None):
        z=r/M #we're going to assume preconditioner is diagonal
    else:
        z=r.copy()

    p=z.copy()
    x=0
    zTr=np.dot(r,z)
    for iter in range(niter):
        Ap=np.dot(A,p)
        pAp=np.dot(p,Ap)
        rTr=np.dot(r,r)
        print 'iter is ',iter,' with residual squared ',rTr
        alpha=zTr/pAp
        x=x+alpha*p
        r_new=r-alpha*Ap
        if not(M is None):
            z_new=r_new/M
        else:
            z_new=r_new.copy()
        zTr_new=np.dot(r_new,z_new)
        beta=zTr_new/zTr
        p=z_new+beta*p
        r=r_new
        z=z_new
        zTr=zTr_new
    return x
```

```
[Jonathans-MacBook-Pro-3:lecture_12 sievers$ python preconditioned_conjugate_gradient_example.py
iter is  0  with residual squared  993.692350289
iter is  1  with residual squared  397.64801161
iter is  2  with residual squared  141.974077044
iter is  3  with residual squared  52.7655926274
iter is  4  with residual squared  22.6071116167
iter is  5  with residual squared  9.03590114608
iter is  6  with residual squared  3.65050457705
iter is  7  with residual squared  1.43721347672
iter is  8  with residual squared  0.569656542728
iter is  9  with residual squared  0.214494092134
mean CG error is  8.61619038593e-06  vs mean answer of  0.000853891507154
iter is  0  with residual squared  993.692350289
iter is  1  with residual squared  408.25843097
iter is  2  with residual squared  117.570553779
iter is  3  with residual squared  35.0391245685
iter is  4  with residual squared  11.9505301647
iter is  5  with residual squared  4.27384918747
iter is  6  with residual squared  1.32840959096
iter is  7  with residual squared  0.456547766476
iter is  8  with residual squared  0.146015621509
iter is  9  with residual squared  0.047654992226
mean PCG error is  3.32323964024e-06  vs mean answer of  0.000853891507154
```

Sparseness

- Pointing matrix is very sparse - one entry per line.
- In python, could do this with (where A is now a vector with entries corresponding to non-zero column):

```
for i in range(n):
    Am[i]=m[A[i]]
```
- Extremely slow! However, python has sparse matrix class in `scipy.sparse`. Essentially, only stores non-zero elements of A.
- `A_sparse=sparse.csr_matrix((dat,(range(n),A))` will make a sparse matrix we can use as our usual A. Much faster!

Huge Speed Difference

```
import numpy as np
from scipy import sparse
import time

ndat=1000000
npix=1000
#make a random mapping of data points to pixels
ipix_vec=np.asarray(np.random.rand(ndat)*npix,dtype='int')
ind=np.arange(ndat)
dat=np.random.randn(ndat)
A=sparse.csr_matrix((np.ones(ndat),(ind,ipix_vec)),shape=[ndat,npix])
map=np.random.randn(npix)

t1=time.time()
ATd=A.transpose()*dat
Am=A*map
t2=time.time()
dt1=t2-t1
print 'sparse projection took ',dt1

t1=time.time()
ATd2=np.zeros(npix)
Am2=np.zeros(ndat)
for i in range(ndat):
    ATd2[ipix_vec[i]]=ATd2[ipix_vec[i]]+dat[i]
    Am2[i]=map[ipix_vec[i]]
t2=time.time()
dt2=t2-t1
print 'loop took ',dt2, ' which is ', dt2/dt1,' times slower than sparse'
print 'mean difference in transpose is ',np.mean(np.abs(ATd-ATd2))
print 'mean difference is predicted data is ',np.mean(np.abs(Am-Am2))
```

```
[Jonathans-MacBook-Pro-3:lecture_12 sievers$ python sparse_timing.py
sparse projection took 0.00457787513733
loop took 1.00558996201 which is 219.663038383 times slower than sparse
mean difference in transpose is 0.0
mean difference is predicted data is 0.0
Jonathans-MacBook-Pro-3:lecture_12 sievers$ ]
```

Numba

- Python also has a just-in-time (JIT) compiler called *numba*.
- Addint numba decorators to functions will turn them into compiled code. You can write for-loops in python that run just as fast as compiled!
- Only difference is we've added nb.njit in front of our function. speed up is 150x.

```
import numba as nb
@nb.njit
def map2tod_numba(x,y,map,data):
    n=len(x)
    for i in np.arange(n):
        data[i]=data[i]+map[x[i],y[i]]
```

Simple Mapper

- look at `simple_mapper.py`. It will let us make a map from the data we saw earlier.
- We might have many components of our solution, so m will be a set of maps (mapset). In our case, we only have one, but frequently we have more.
- We also have a bunch of time-ordered data (TODs). Put those into a class that keeps a bunch of TODs.
- We can overload operators, which lets us use our same CG code.

Steps in Simple Mapper

- read the data and pointing information.
- figure out how big your map needs to be.
- fit a noise model to the data.
- make the right-hand side ($A^T N^{-1} d$)
- run conjugate-gradient to get approximate solution to $A^T N^{-1} A m = A^T N^{-1} d$.

Run it and See!

- Look inside simple_mapper. If you run as-is, you'll make the naive map.
- Look at the comments at the end. Uncomment those, and you'll be able to make a maximum-likelihood map!

Extensions

- This framework is actually very powerful. We can adapt to do lots of different things.
- Example - *destriping*. An alternative to solving mapmaking with complicated N is to put $1/f$ noise in the map.
- Solve for low-frequency offsets plus map at the same time, using a white-only noise model should give something very similar.
- This is called destriping. Could you modify simple_mapper to make a destriped map? Possible exercise for later...

Summary

- Minimizing χ^2 is a powerful way to analyze our CMB data (and most non-CMB data as well).
- (preconditioned) conjugate-gradient can be a *very* powerful tool for solving linear algebra problems.
- Far more things can be made to look like linear algebra than you might expect...

Remaining slides can be ignored.
Useful for having many
timestreams with noise in common.

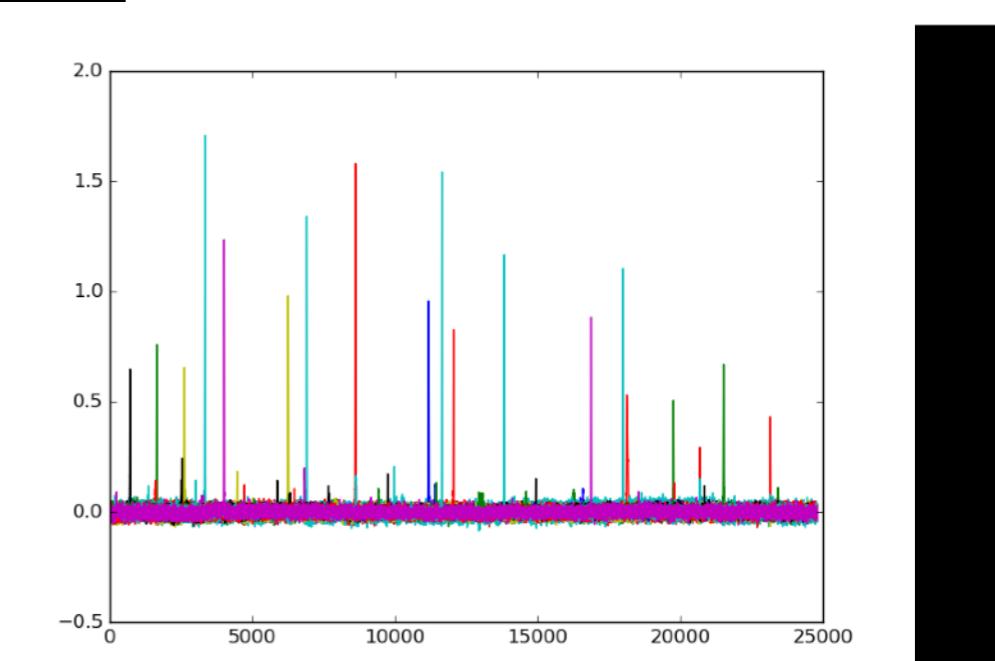
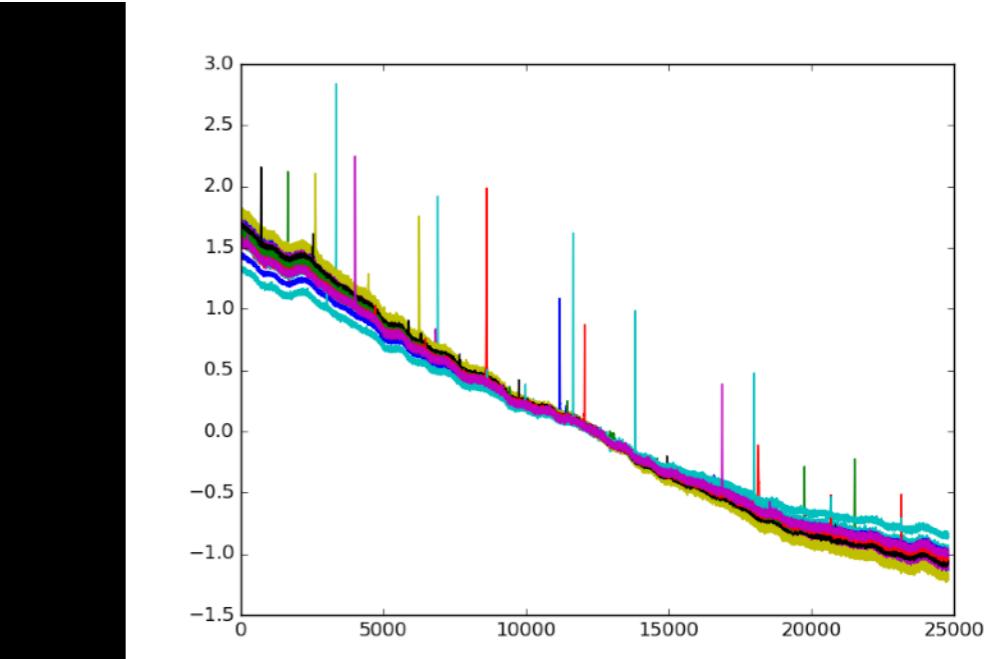
Putting Pieces Together

- Let's look at some actual ground-based data.
- In a very dangerous step, we'll subtract off common mode/detector drifts.
- Middle: raw data.
- Bottom: data with best-fit line+cm amplitude subtracted
- Scan is of a calibrator, so spikes upwards are sky signal.

```
dat_calib=dat['dat_calib'].copy()
ndet=dat_calib.shape[0]
for i in range(ndet):
    dat_calib[i,:]=dat_calib[i,:]-np.median(dat_calib[i,:])

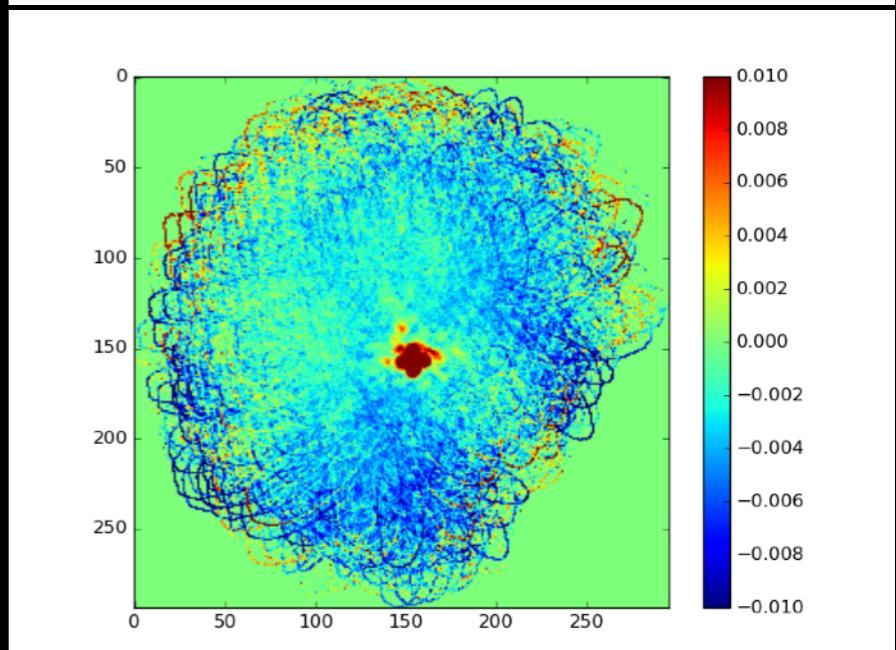
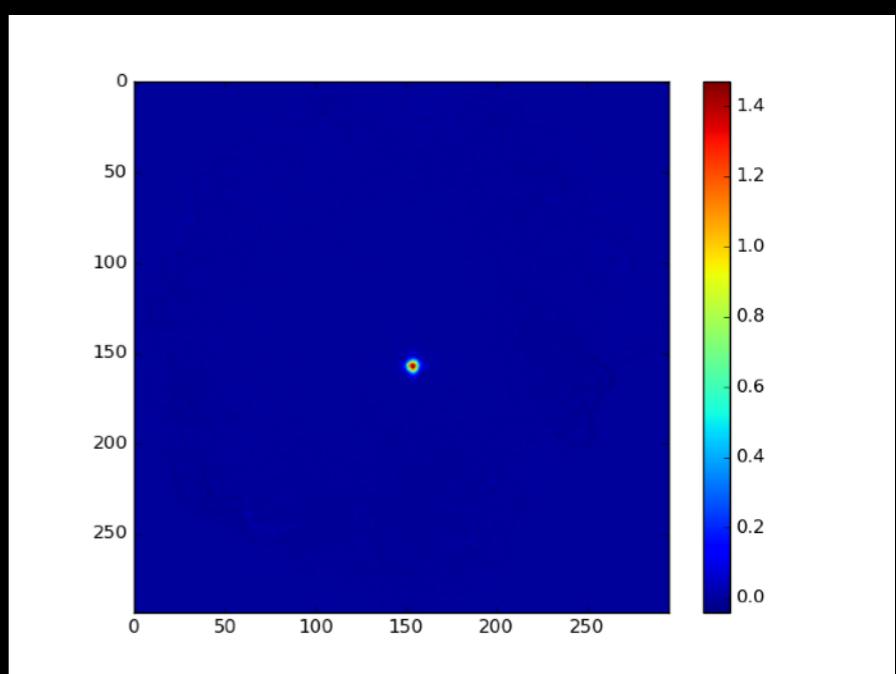
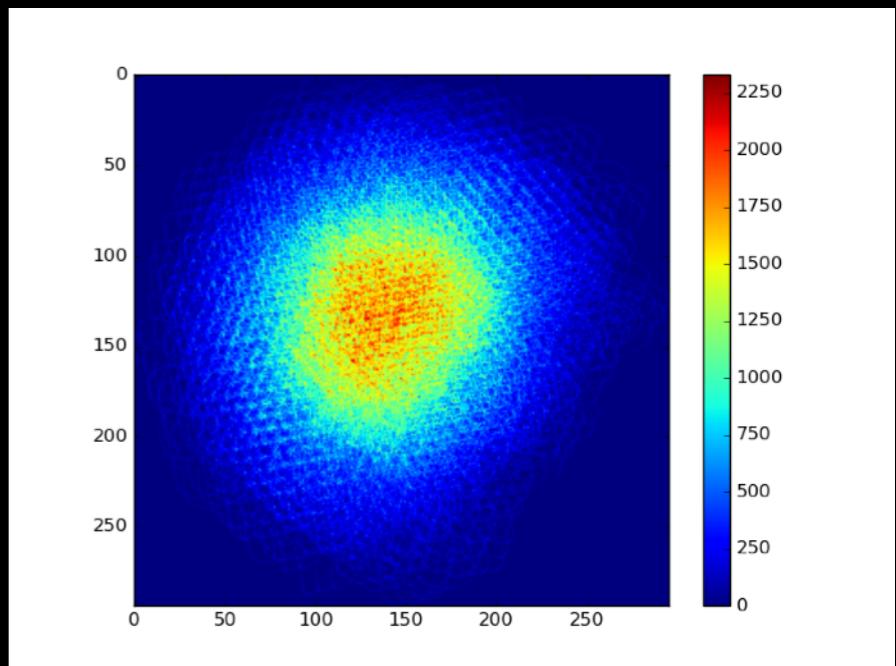
cm=np.median(dat_calib, axis=0)
mat=np.zeros([len(cm),3])
mat[:,0]=1.0
mat[:,1]=np.linspace(-1,1,len(cm))
mat[:,2]=cm

lhs=np.dot(mat.transpose(),mat)
rhs=np.dot(mat.transpose(),dat_calib.transpose())
fitp=np.dot(np.linalg.inv(lhs),rhs)
pred=np.dot(mat,fitp).transpose()
dat_cm=dat_calib-pred
```



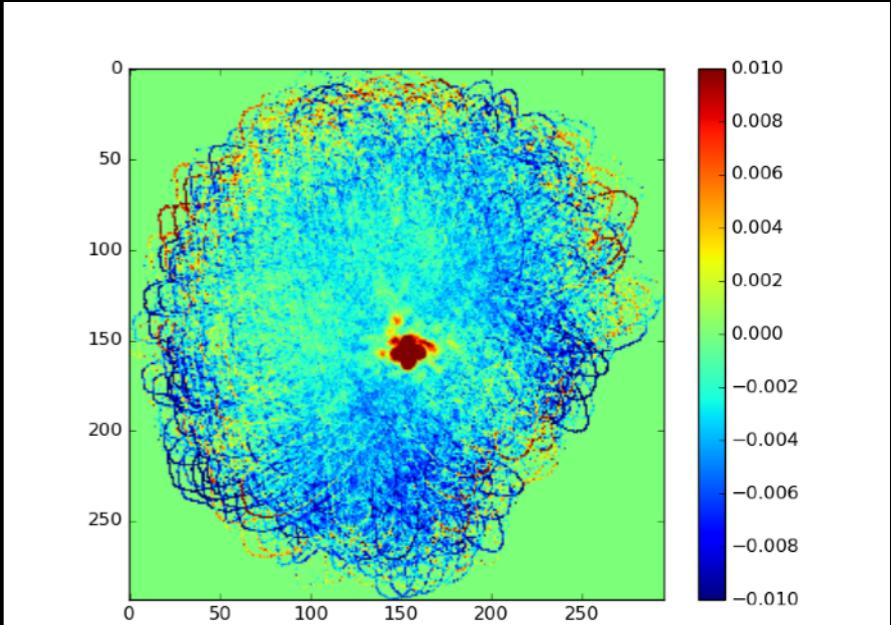
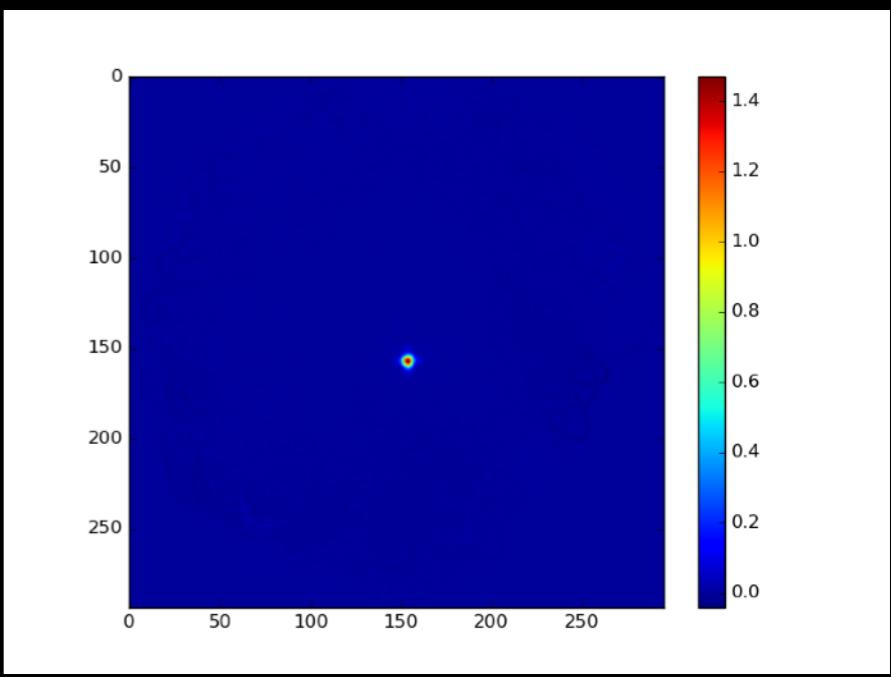
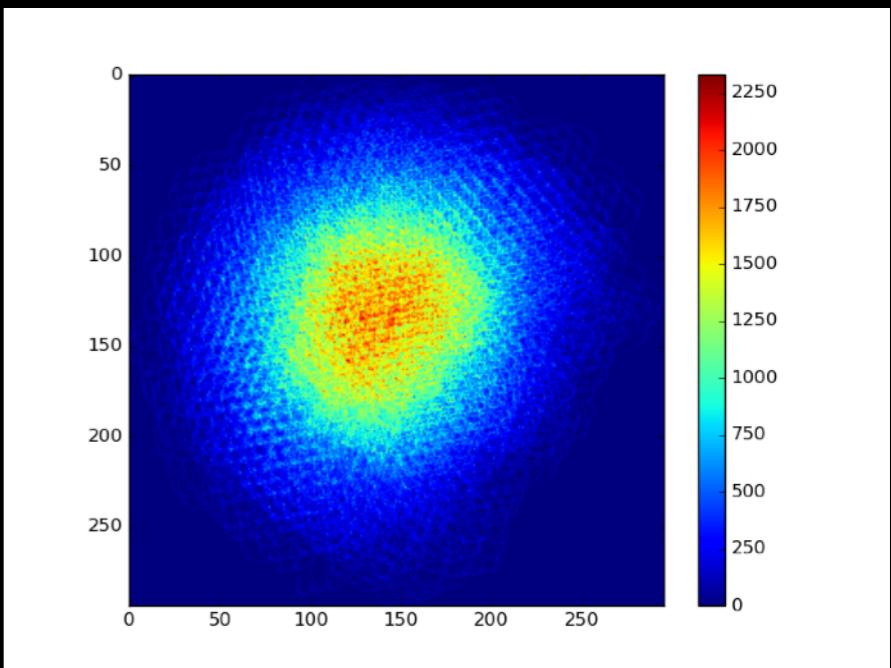
Naive Map

- In fact, naive map of cm-subtracted data is not so awful, at least visually.
- Top: hits. Middle: naive map of CM-subtracted data. Bottom: stretched colorscale.
- Why would this naive map not be good?
- What could we do better?



Naive Map

- In fact, naive map of cm-subtracted data is not so awful, at least visually.
- Top: hits. Middle: naive map of CM-subtracted data. Bottom: stretched colorscale.
- Why would this naive map not be good?
 - CM subtraction removes signal. usually a function of angular scale - introduces a *transfer function*, where map is biased.
- What could we do better?
 - convert CM into a noise, and use a real guess for the noise.



Common Mode as Noise

- A not-crazy model for the noise is each detector has independent noise, plus one noise term constant across all detectors.
- Noise will be a function of frequency, so subtract CM to estimate non-CM part of noise. Do this in Fourier space, as usual.
- What would this noise matrix look like?

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- Noise will be a function of frequency, so subtract CM to estimate non-CM part of noise. Do this in Fourier space, as usual.
- What would this noise matrix look like?
 - Diagonal part from detector noises, plus a common part. $\langle n_i n_j \rangle = CM$, constant across all detectors. Very much like the noise matrix from HW 2.

Sherman Morrison/Woodbury

- Turns out, we can invert this sort of matrix very quickly.
- $(A + vv^T)^{-1} = A^{-1} - A^{-1}v(1 + v^T A^{-1}v)^{-1}v^T A^{-1}$. Woodbury Identity
- Looks long, but if A is diagonal, all these operations are of order n . Much faster than n^3 .
- So, can put in a common-mode as noise rather than subtract.
- If we had many correlated modes, the same fast inverse trick still works. Extension is called the Sherman-Morrison formula. Useful if, say, readout gives correlated noise as well, or atmosphere has structure smaller than array.