

Work Log for November

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November 24, 2014

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1 Goals for the Month

As of October 31st

1. Use Preston's Simulated Yeast, compare to REU yeast
look for estimated $\approx 4 \times \text{true}$
2. Parallelize the Code
`mclapply`, `getOption("mc.cores")`?
3. Wei Chen's Yeast / Real Yeast Genome
4. Generate my own simulated yeast, using a reverse engineered cubfits

2 Progress/Notes

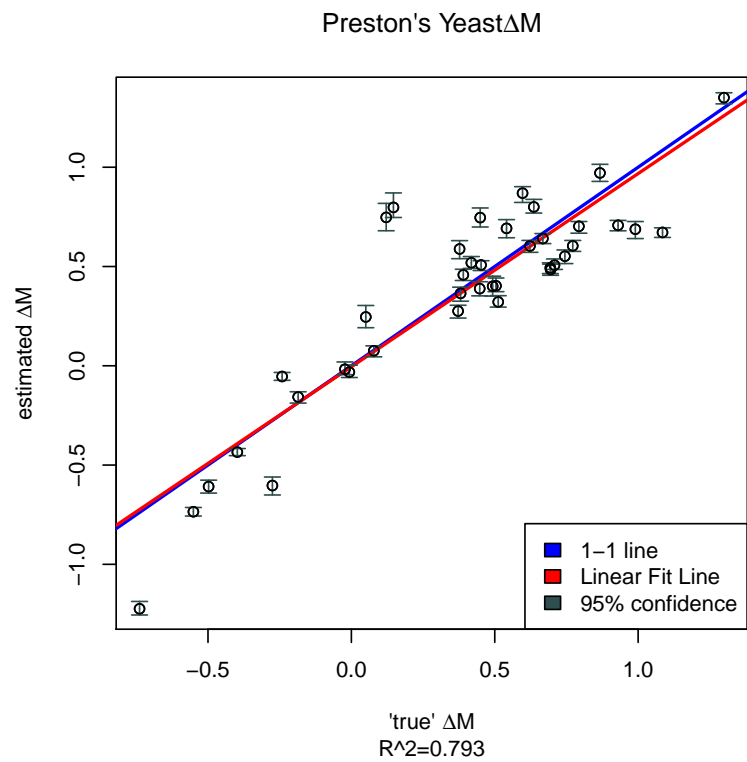
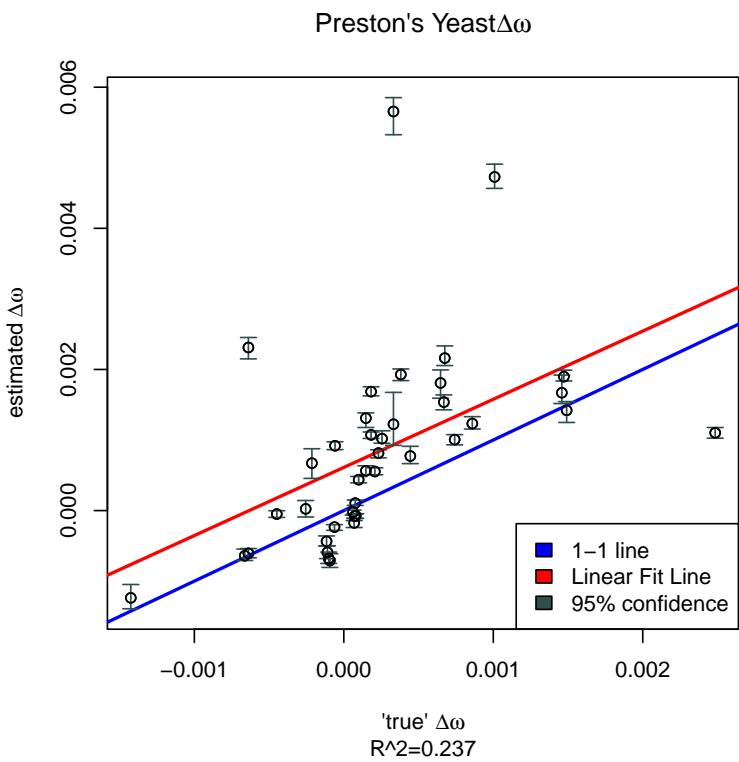
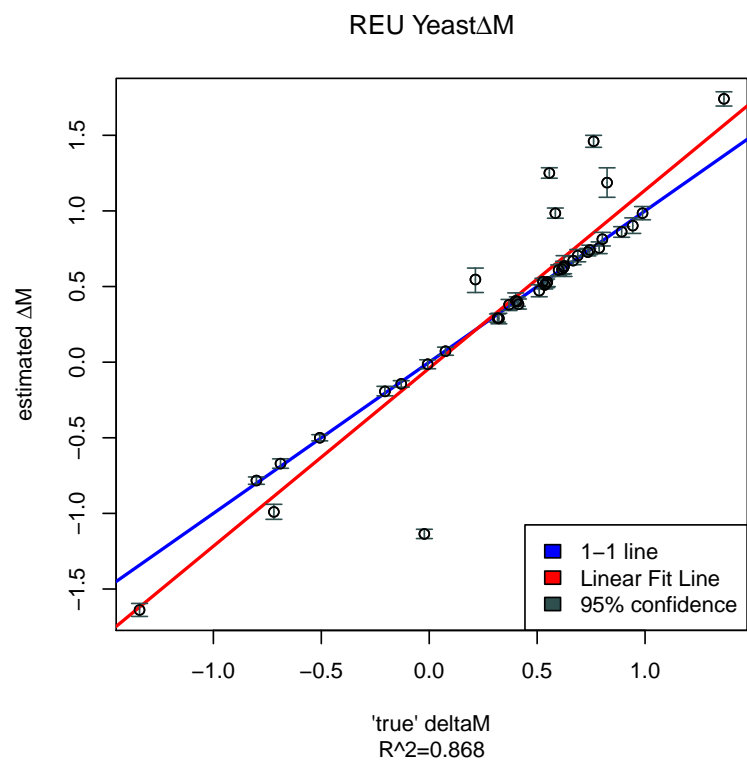
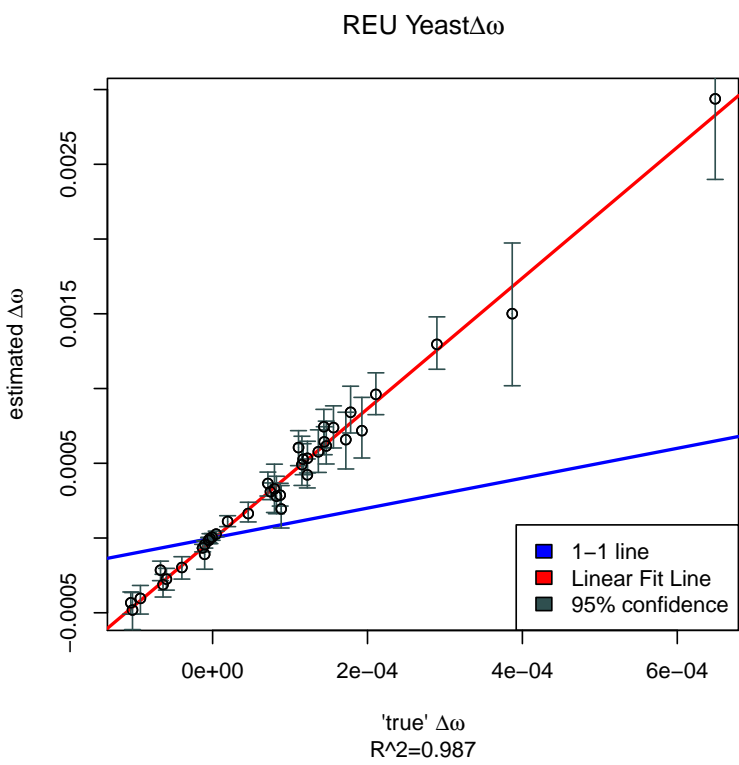
2.1 Use Preston's Simulated Yeast, compare to REU yeast

Here are the results from Preston's simulated yeast...

Notice that the $\Delta\omega$ values are not off by that ≈ 4 factor. We got a pretty good correlation on the $\log\mu$ values, but the ϕ is pretty lousy, and the ω values leave something to be desired.

{{ REMOVED FOR BREVITY. SEE data/1105*.pdf }}

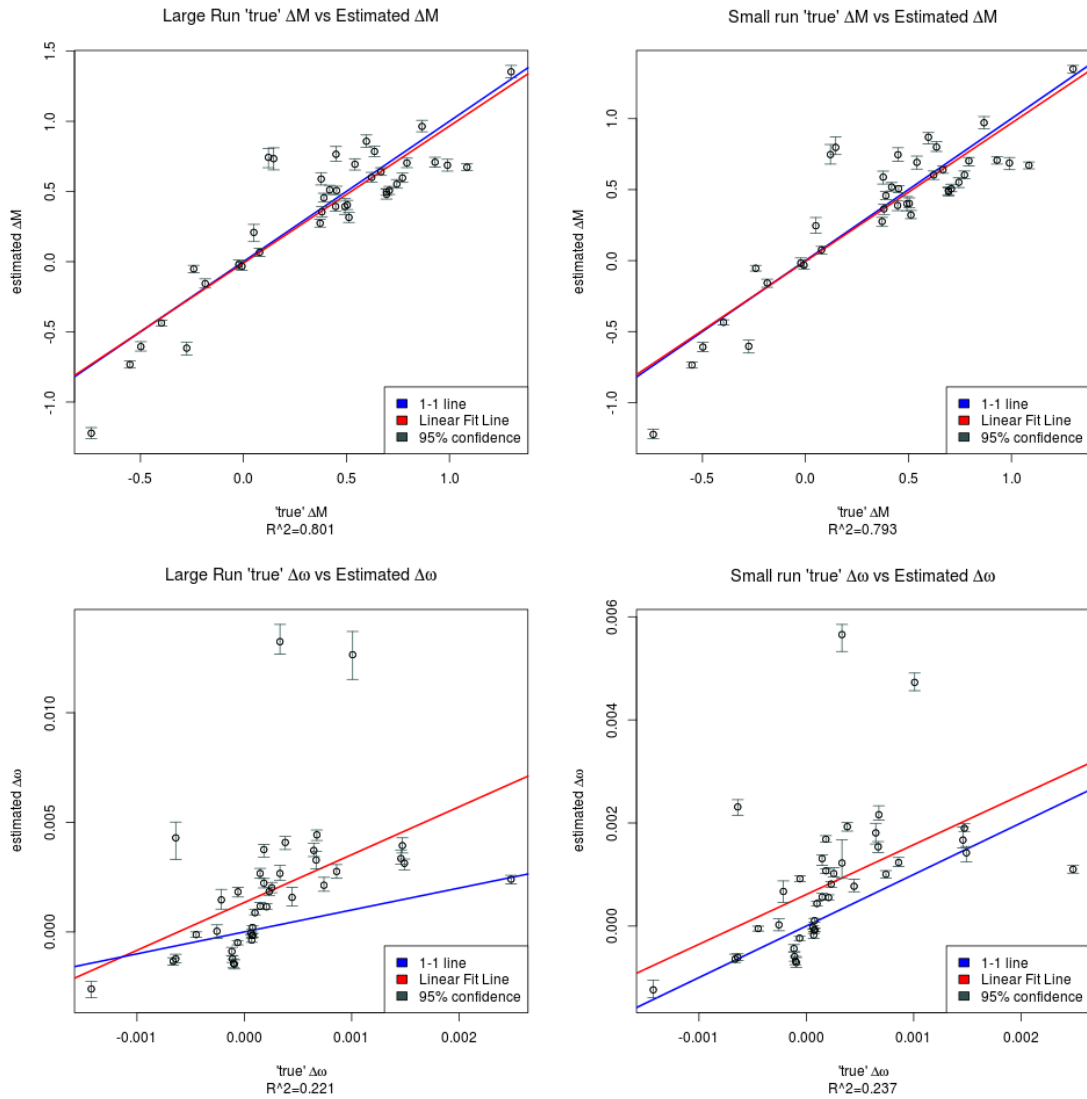
Note how different the $\Delta\omega$ values are between Preston's yeast genome and the REU students' yeast genome.

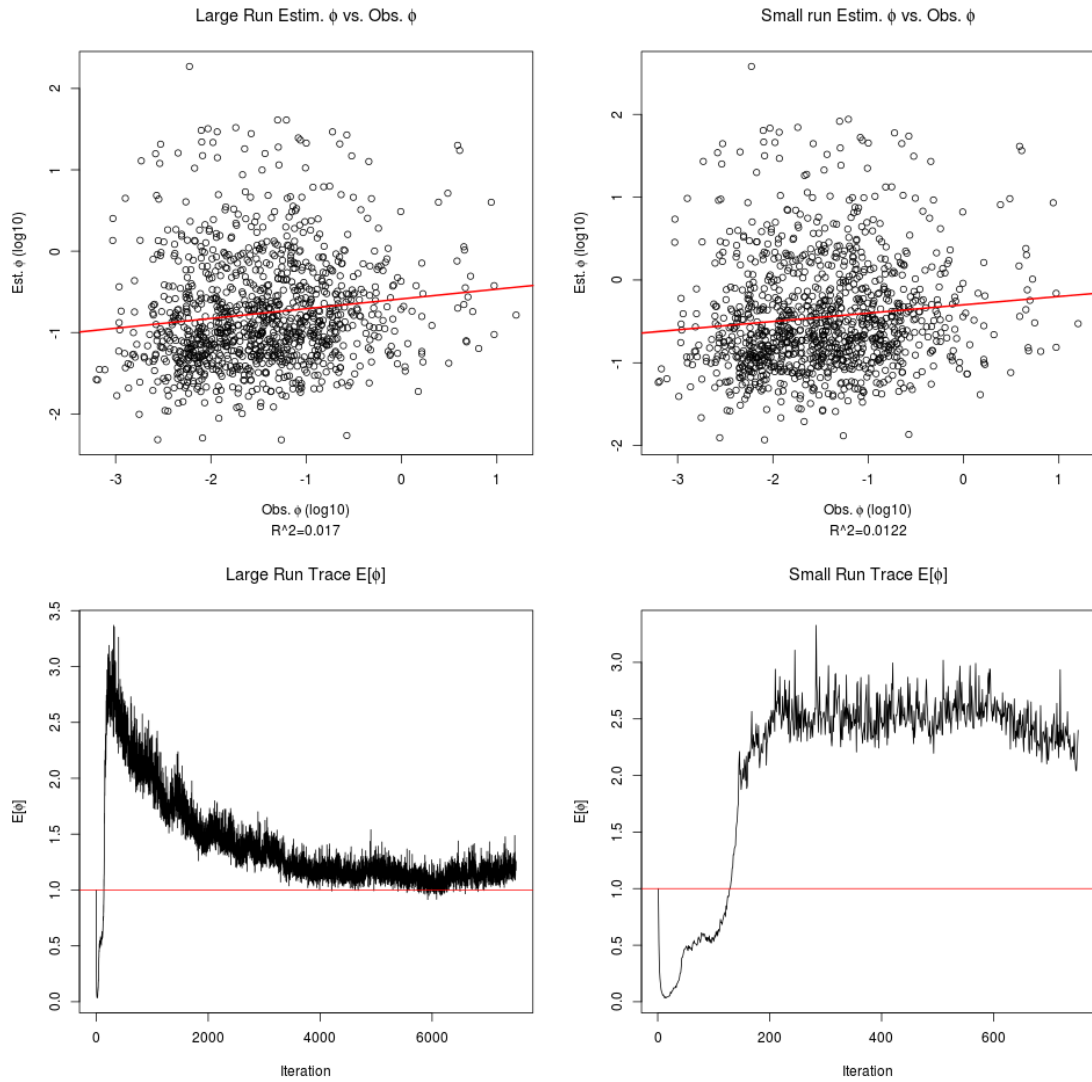


2.1.1 Longer Run?

A longer run creates some interesting results. I did a run that used 7500 samples instead of 750 (which, since I'm thinning by 10, it's actually 75,000 proposals).

Here's the results (Large run is on the left, small run is on the right)





The most relevant thing in my opinion is the $E(\phi)$ graphs. $E(\phi)$ should hover around 1. in the small run, it leapt up to 3, and I was concerned this was an inherent problem in the code. But it appears that the model simply hadn't converged.

2.2 Other Genomes

2.2.1 Entire Preston's Yeast

I fixed an error in the visualize.r results by using the entire genome as the input, and letting the visualize function sort out what values belonged to who. This caused my R^2 value to jump from .02 to .5, a huge improvement.

Because of this, I'm doing a cubfits run with the entire preston's yeast genome, to see how that affectst the results.

2.2.2 Brewer's Yeast

The yeast genome used for the paper, the git repository is

`/export/home/semppr/gitrepos/wcchen/logistic_analysis.git/`

The exported files can be found in

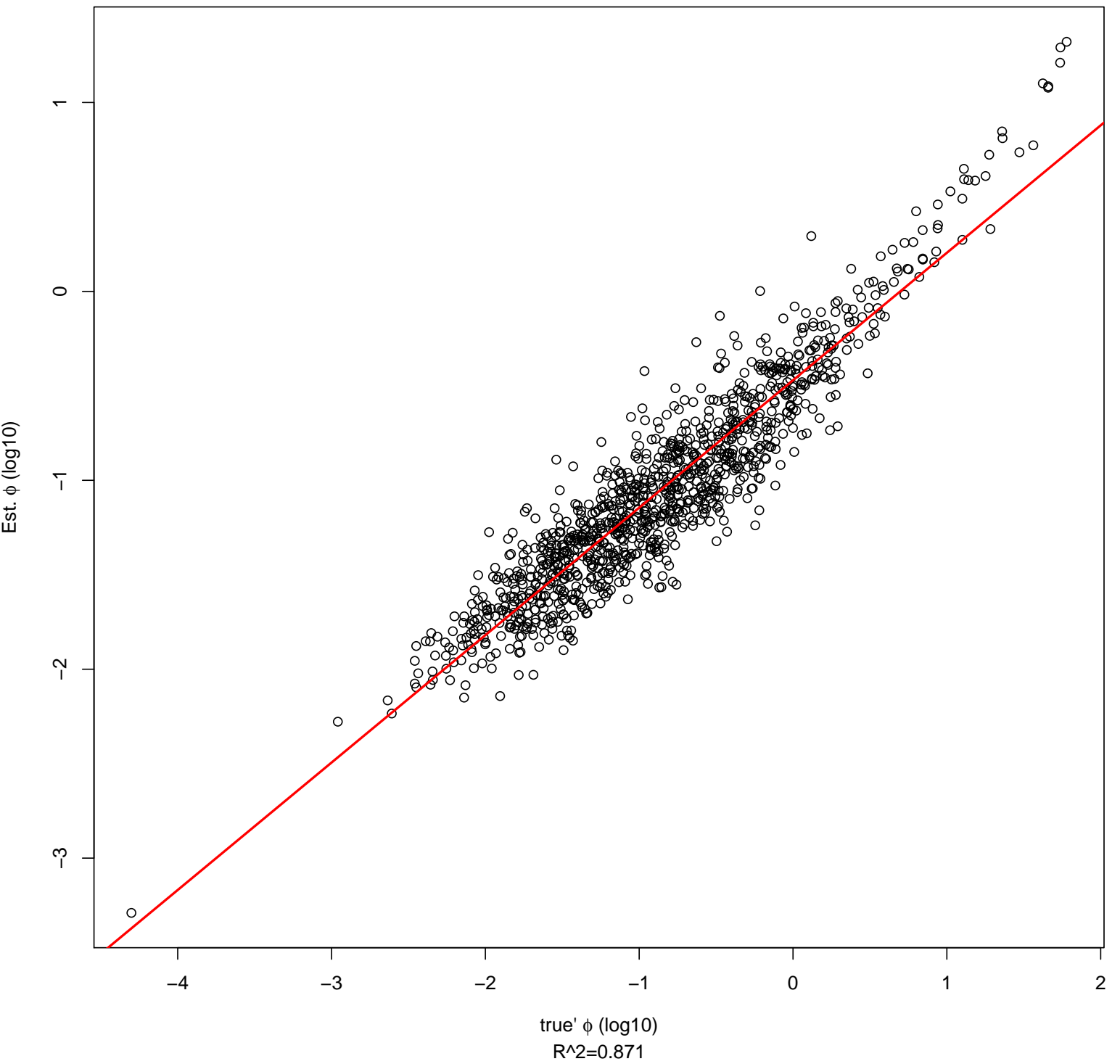
`/home/lbrown/logistic_analysis/p01-paper`

What follows is a comparison of

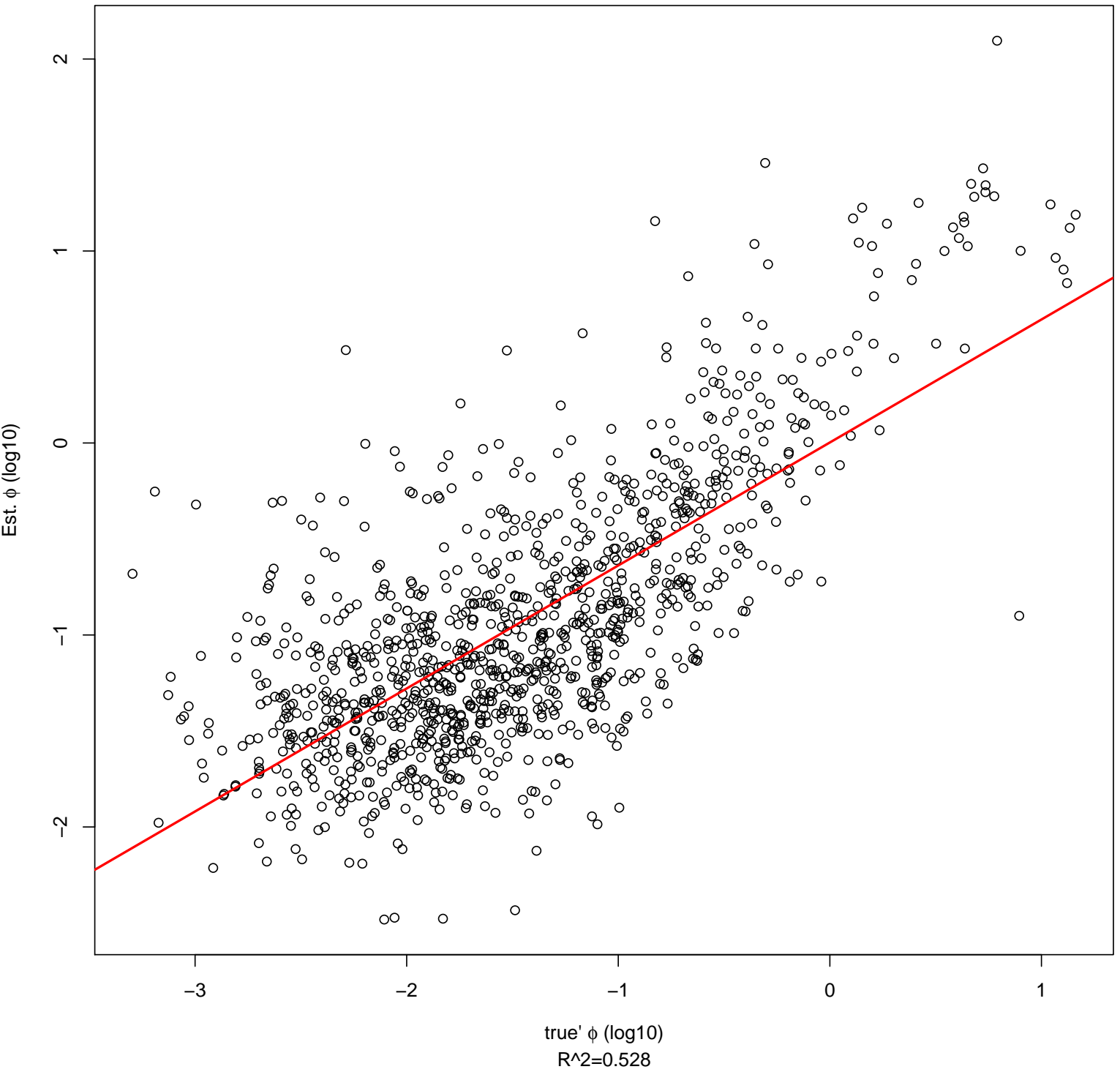
1. A run of a random selection of 1/5th of the genes from the REU simulated yeast
2. A run of a random selection of 1/5th of the genes from Preston's simulated yeast
3. A run of Preston's entire simulated yeast genome
4. A run of the brewer's yeast genome that was used for the 2014 paper

First, it will have the ϕ value comparison, then the codon usage bias for the 'true' ϕ values, and finally the codon usage bias for the phi values generated by the model. Each run was done with $\delta a_{1,2}=0$ and $a_2=4$. Each run ran for 3000 samples with 10x thinning, or 30,000 total proposed values, except for the REU yeast which was 1000 samples, or 10,000 total proposed values. Other collections of runs were done with differing values of $\delta a_{1,2}$ and a_2 , especially for the partial Preston's Yeast, but those runs are not included for brevity.

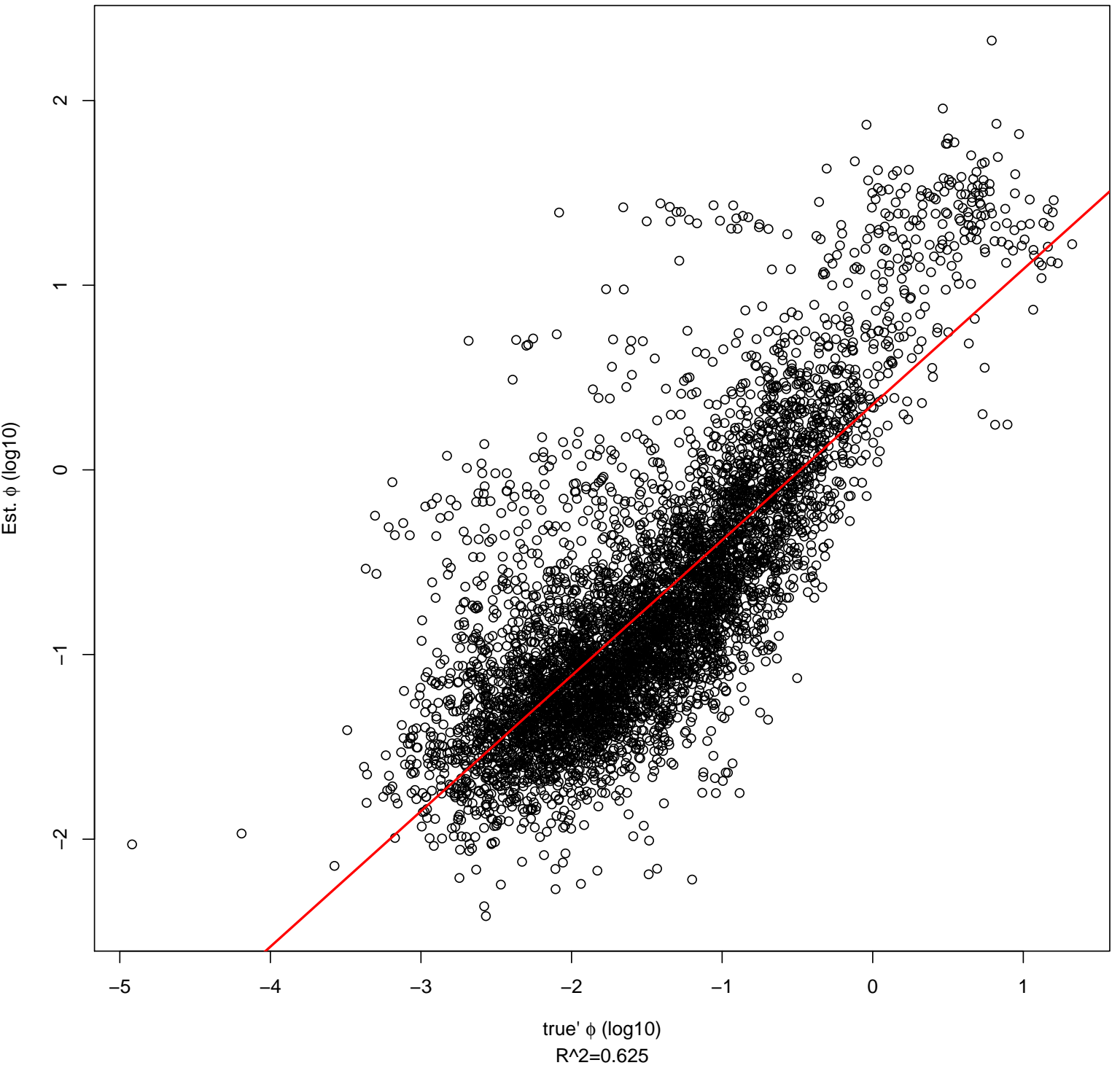
Partial REU13 Yeast, Estim. ϕ vs. 'true' ϕ



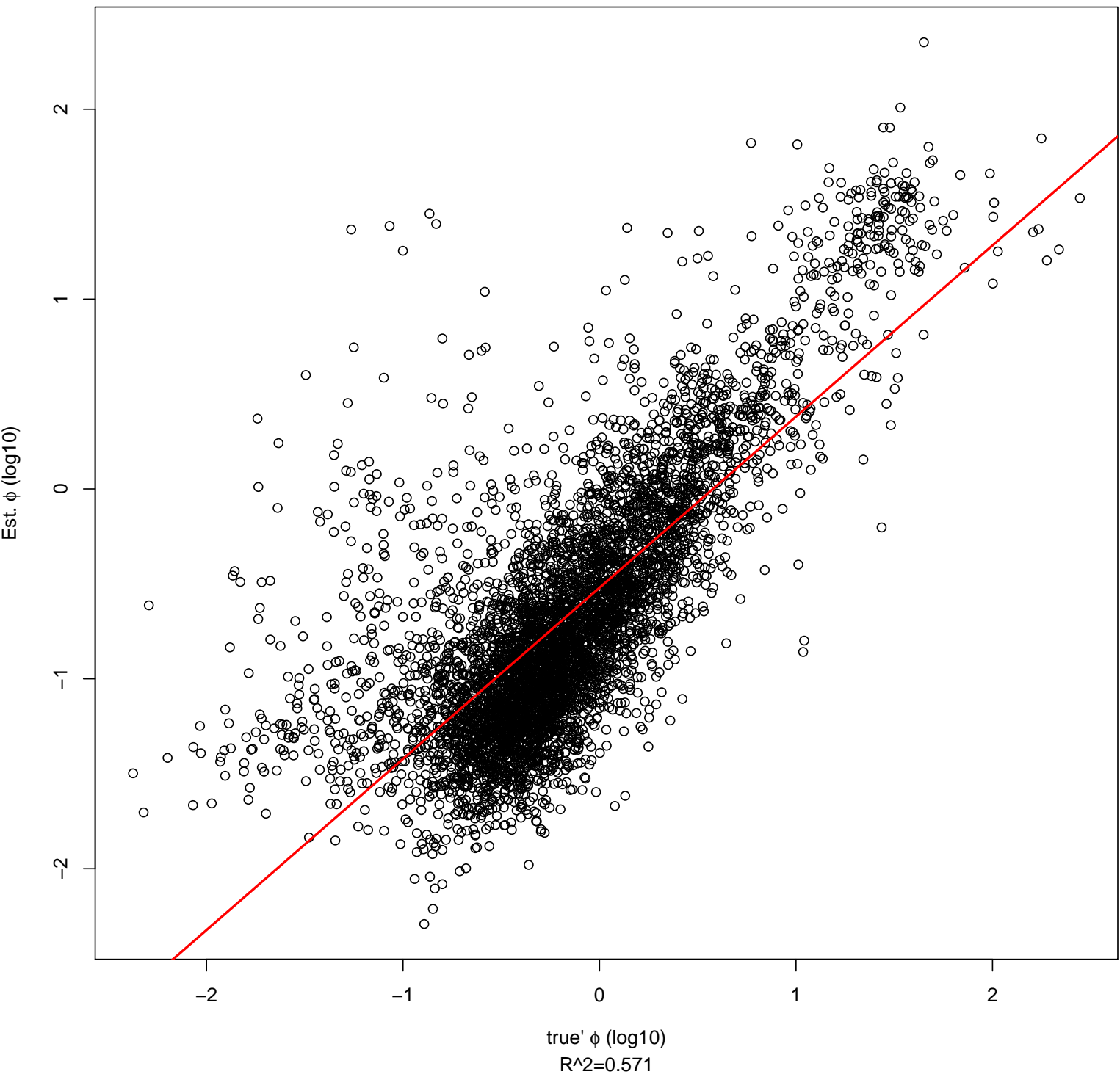
Partial Preston's Yeast, Estim. ϕ vs. 'true' ϕ



Full Preston's Yeast, Estim. ϕ vs. 'true' ϕ

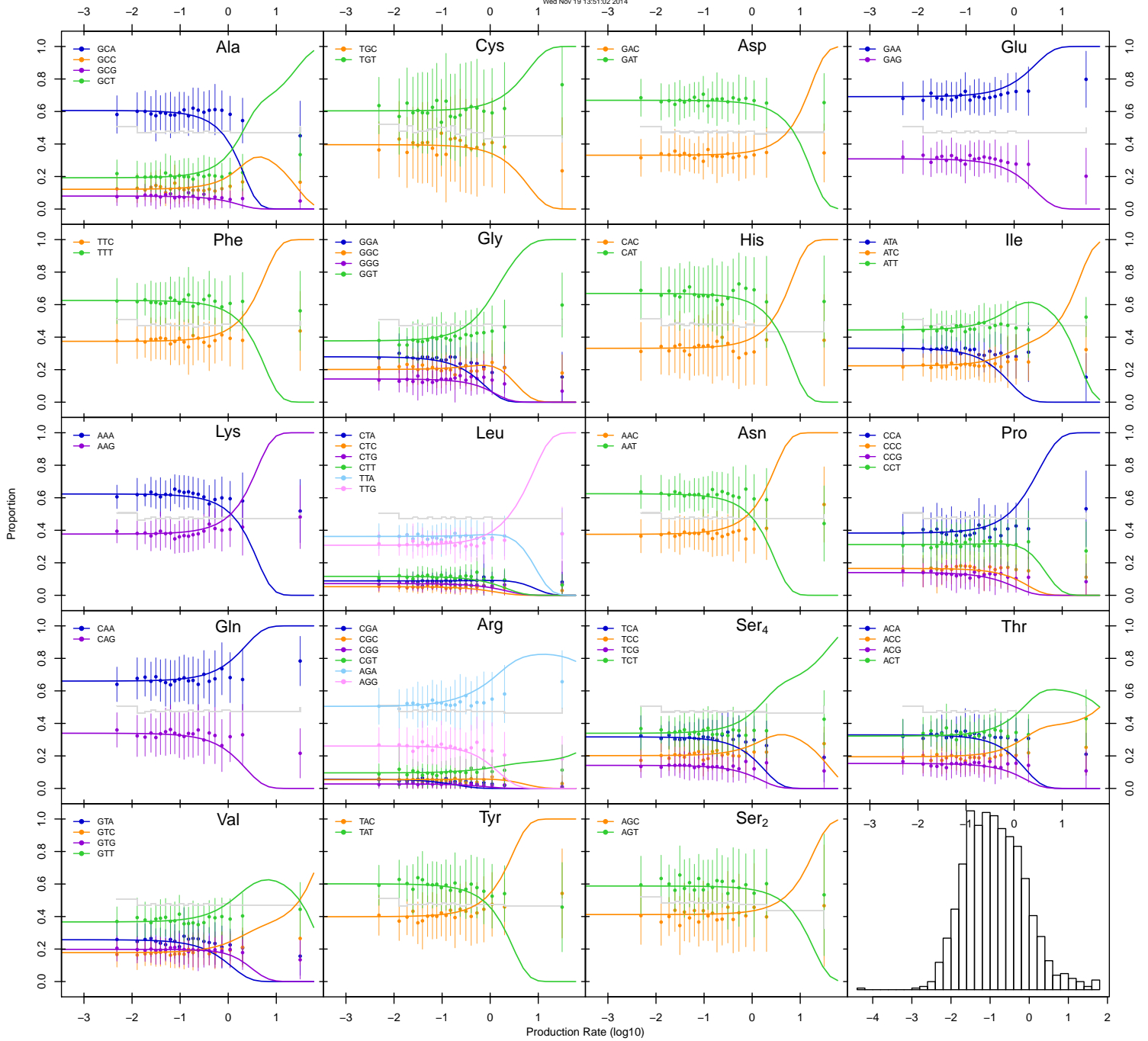


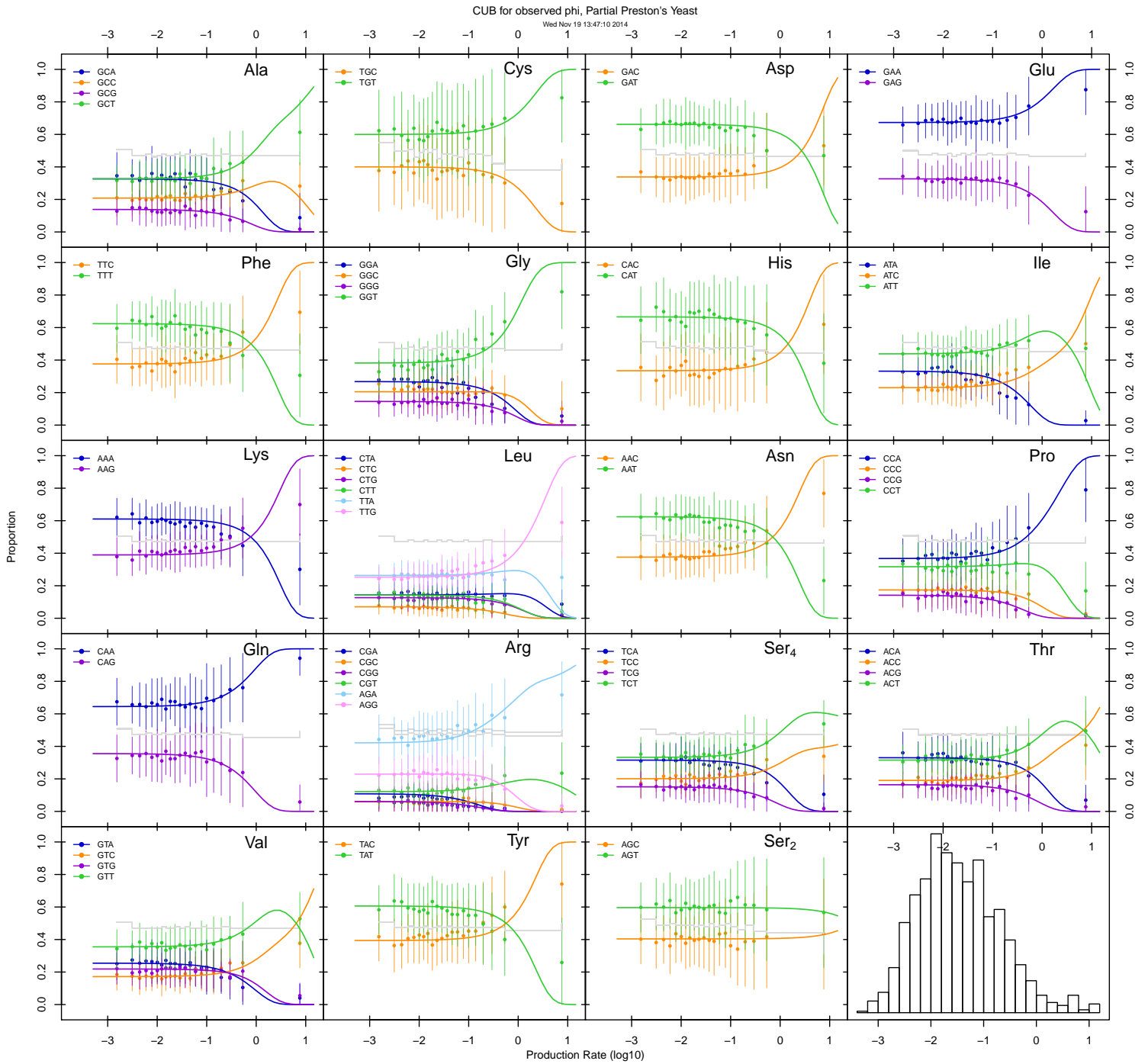
Full Brewer's Yeast, Estim. ϕ vs. 'true' ϕ



CUB for observed phi, Partial REU13 Yeast

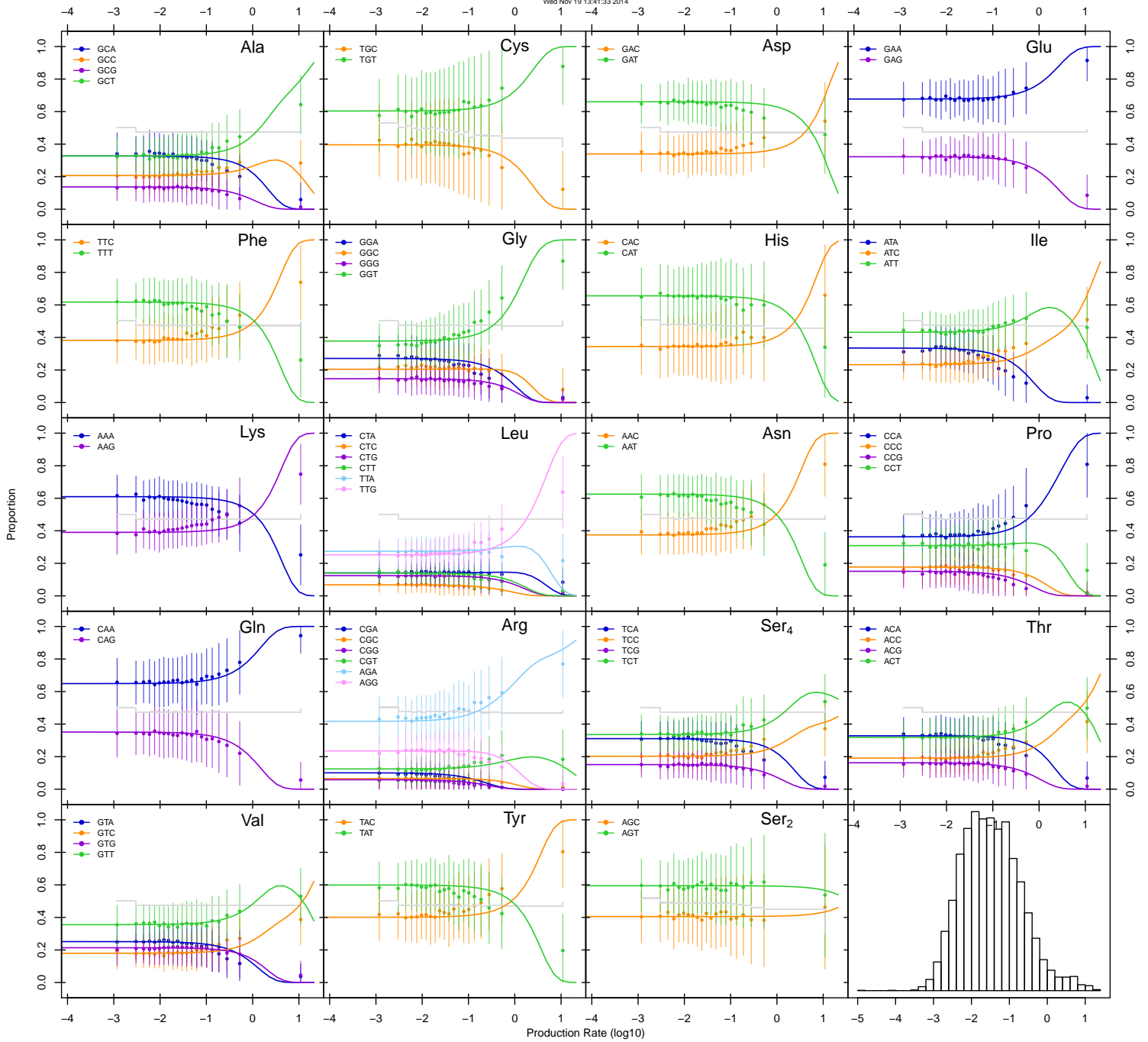
Wed Nov 19 13:51:02 2014





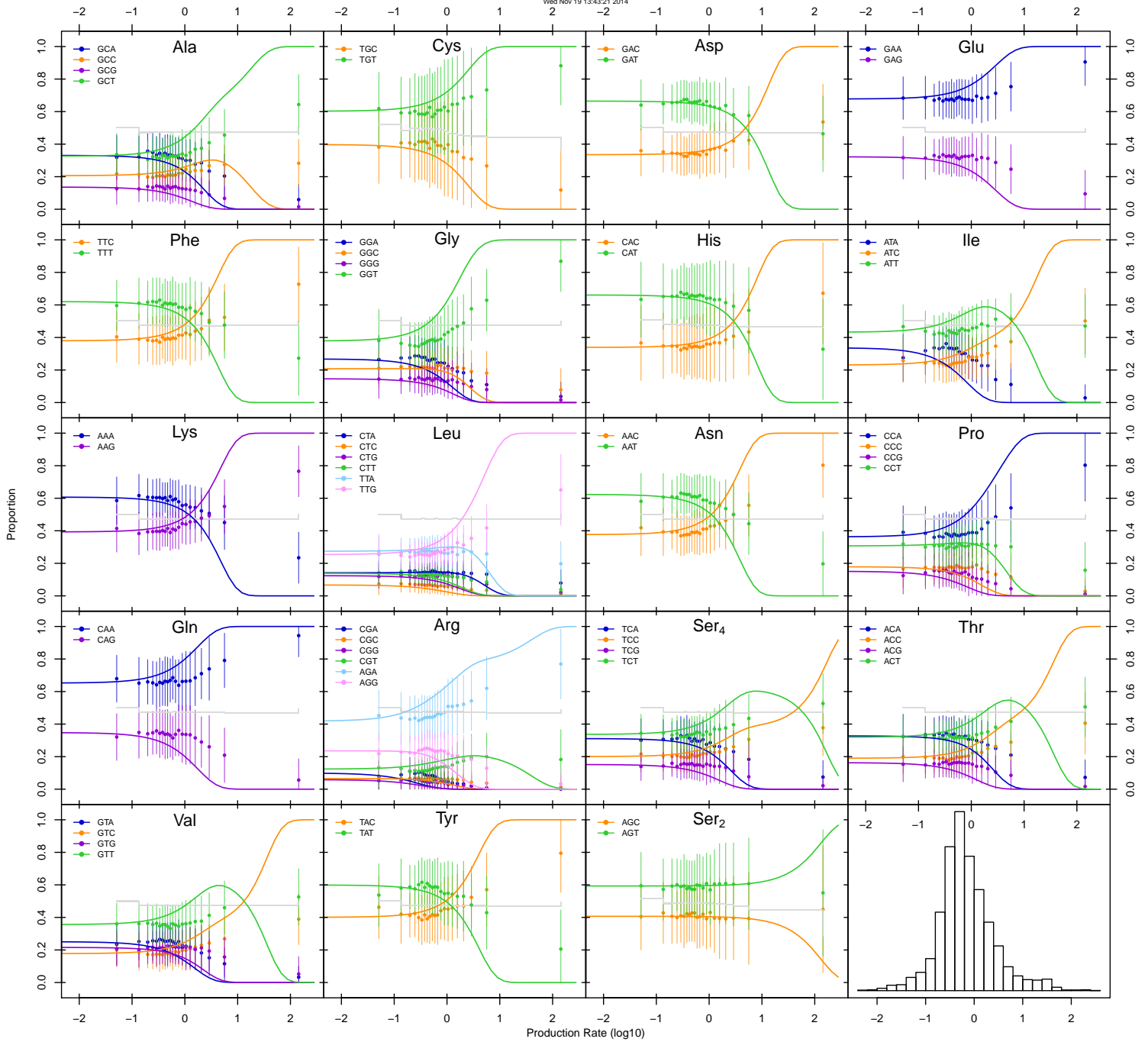
CUB for observed phi, Full Preston's Yeast

Wed Nov 19 13:41:33 2014



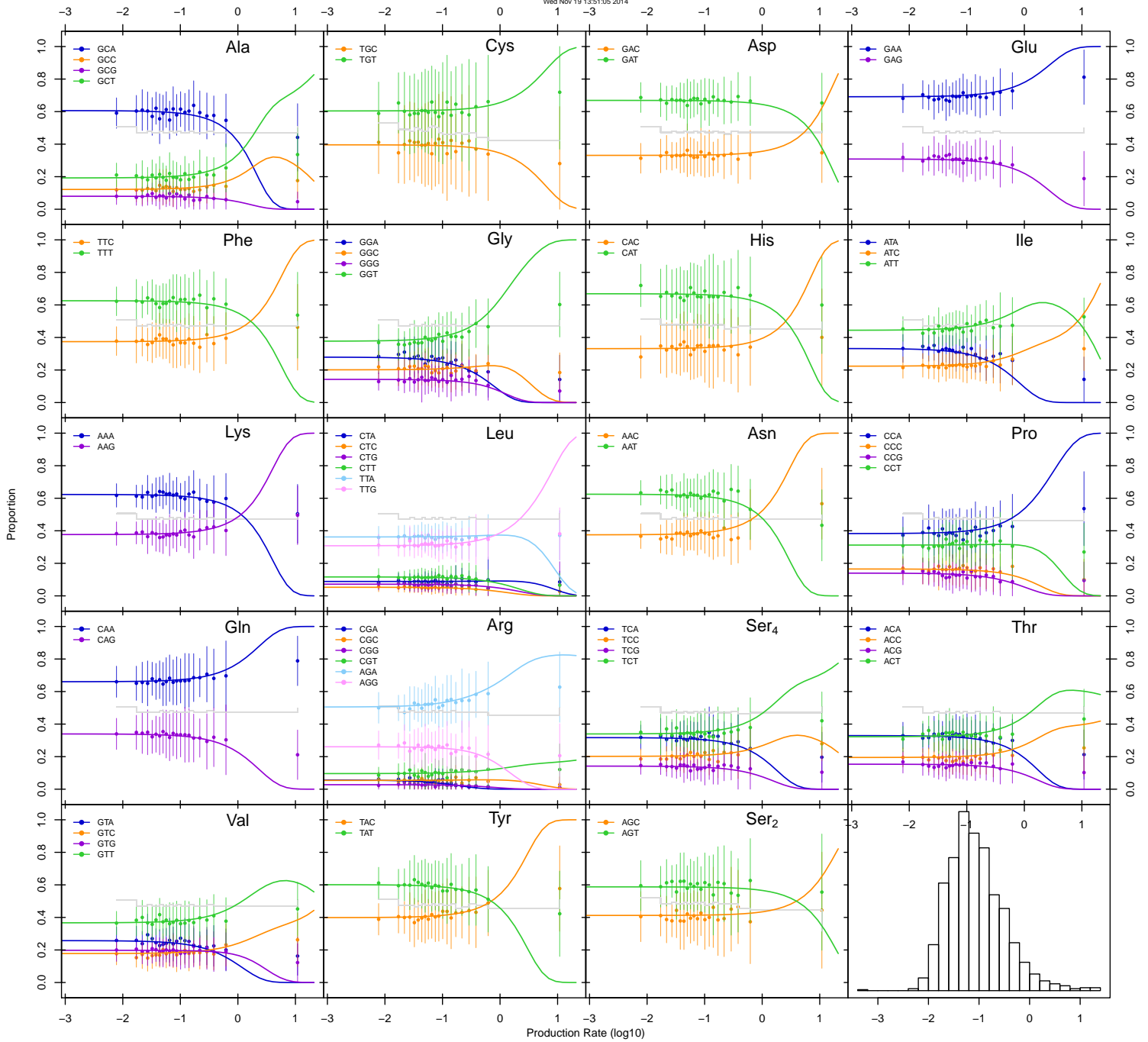
CUB for observed phi, Full Brewer's Yeast

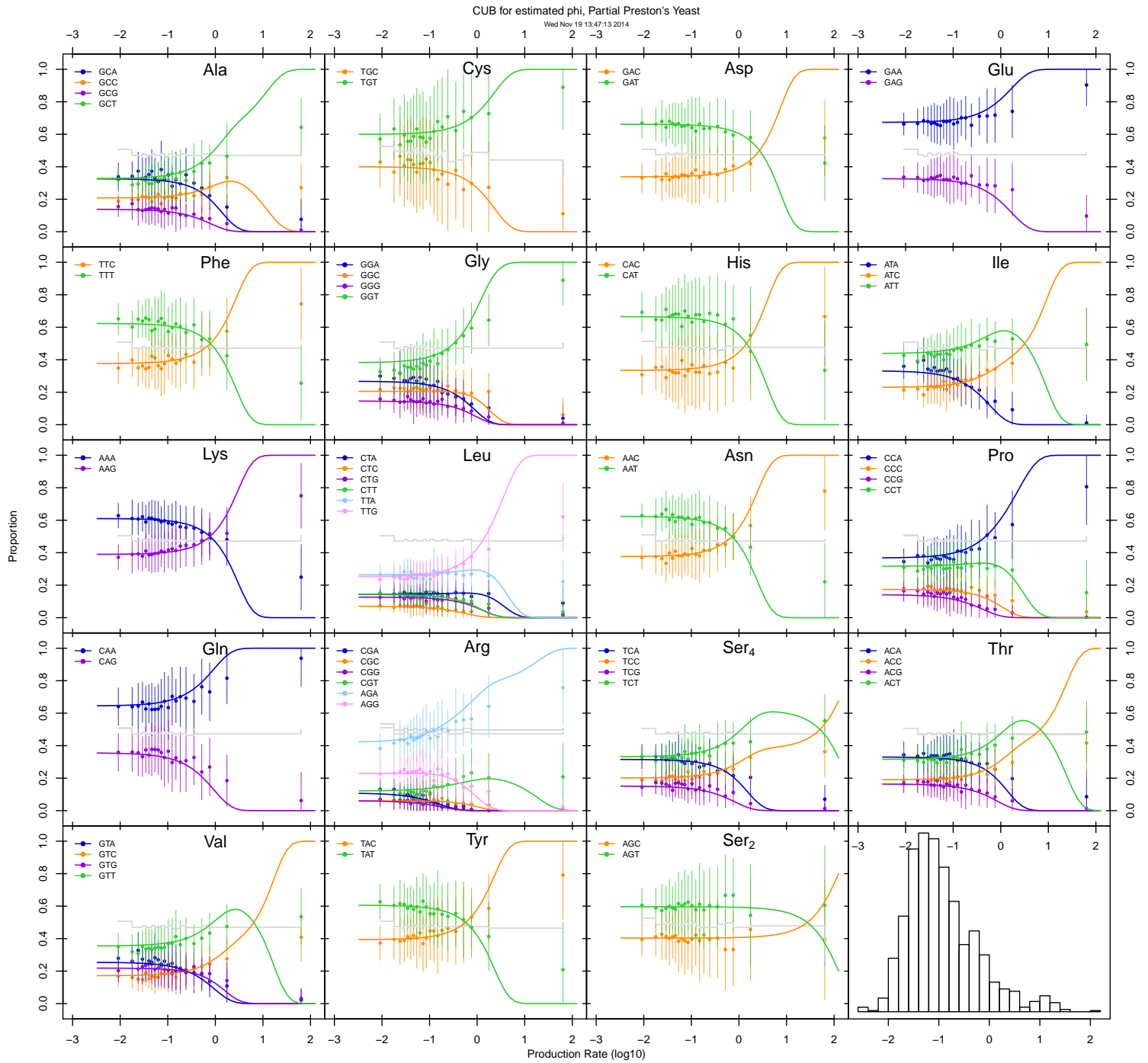
Wed Nov 19 13:43:21 2014



CUB for estimated phi, Partial REU13 Yeast

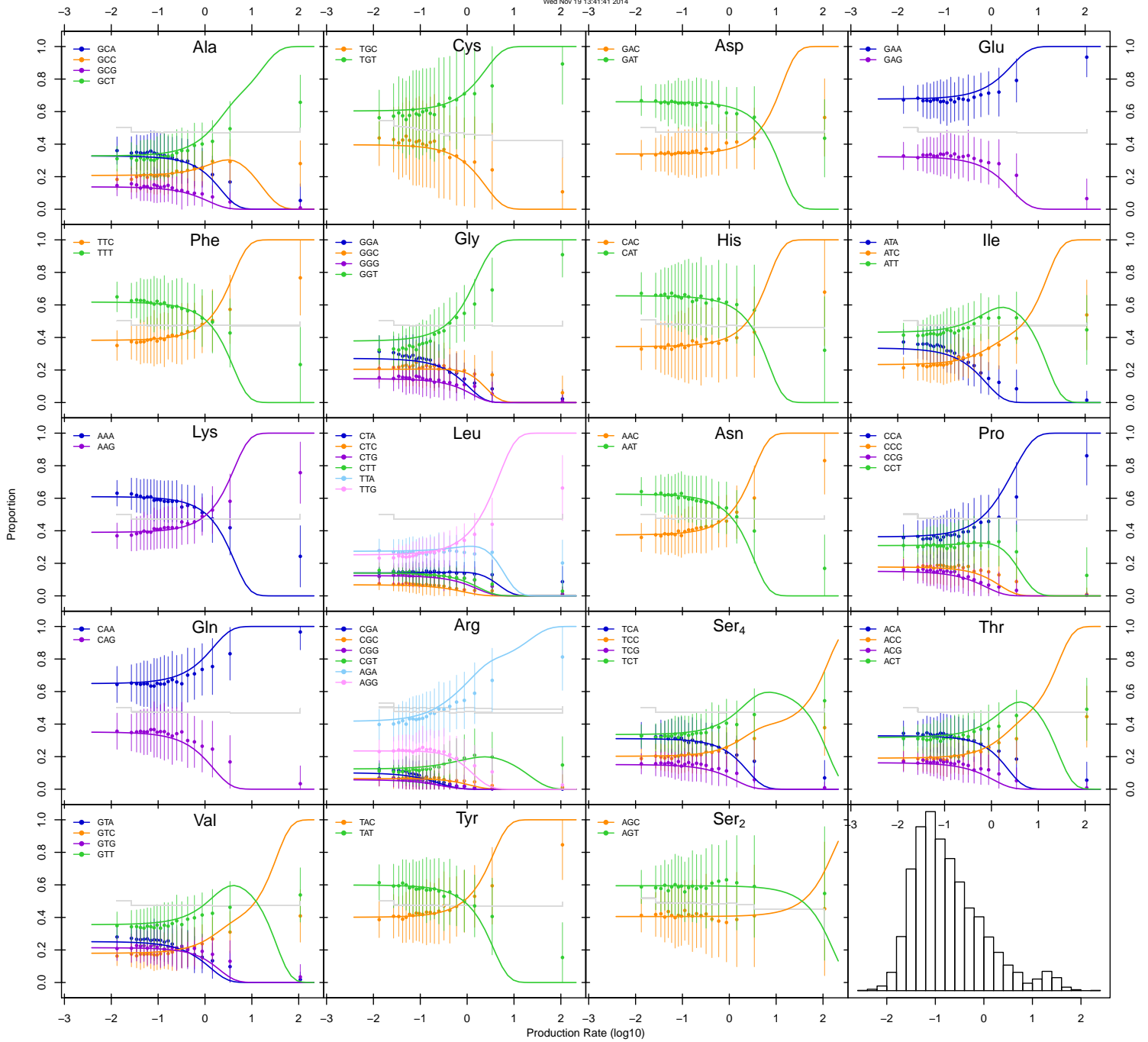
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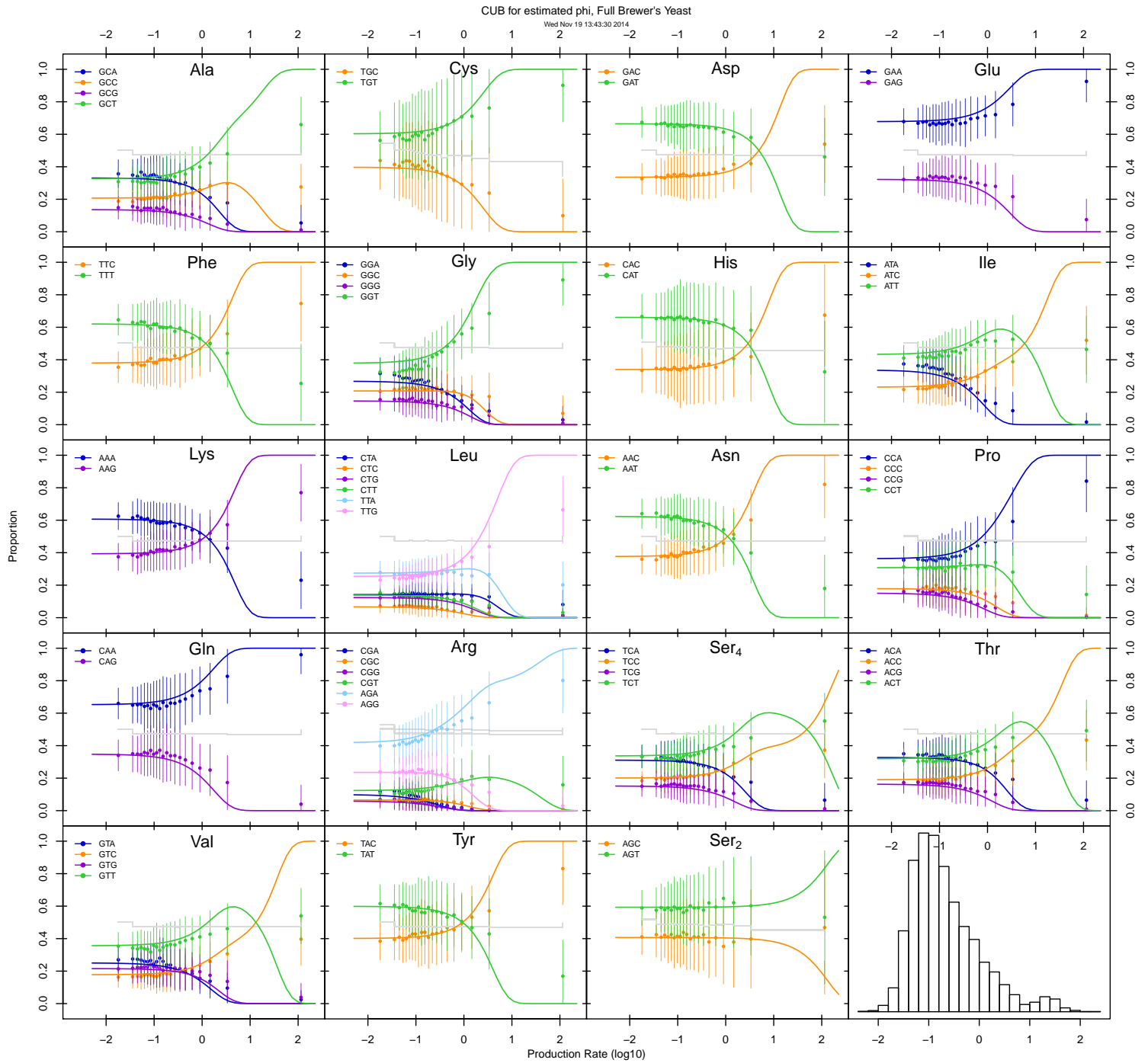




CUB for estimated phi, Full Preston's Yeast

Wed Nov 19 13:41:41 2014





2.3 Generate my own simulated yeast, using a reverse engineered cubfits

Still an interest, but it's fallen down the priorities. The existing genomes seem to do fine.

2.4 Parallelize the Code

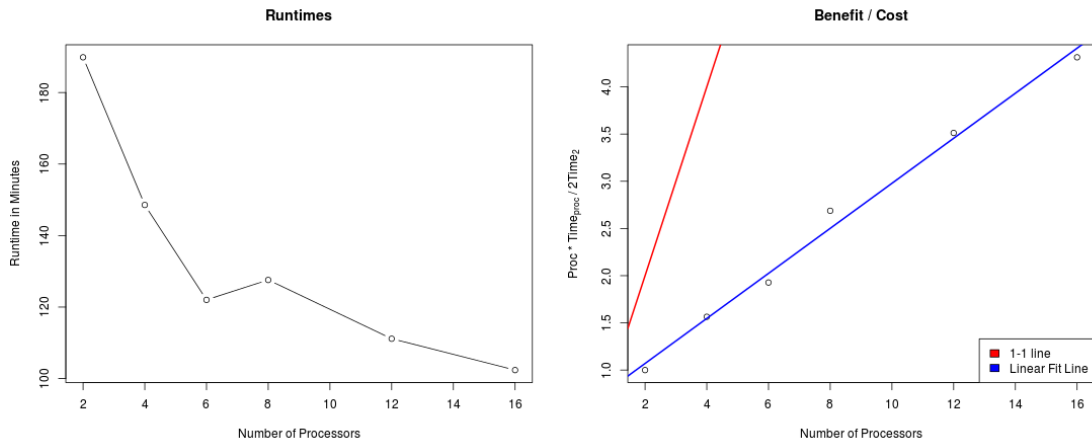
2.4.1 `getOption("mc.cores")`

How to set the number of cores for an `mclapply` call? `mclapply`'s default number of cores is `getOption("mc.cores", 2L)`;

`getOption("(option)", (value))` returns the value previously set to that (option), or otherwise it returns (value). `mc.cores` is not set by default. So first, set `option("mc.cores"=Number_of_Cores)`. Then `mclapply` should correctly get the number of cores.

2.4.2 Timing

As expected, we get diminishing returns on adding additional processors



2.5 Change probability calculation

Our results seem to indicate that the cost of a nonsense error is not high enough. The actual codon usage bias is not very high until you get to very high values of Φ . This doesn't match what we actually see.

In the code, when the posterior probability of a codon is calculated, instead of calculating

$$\Pr(c_i|\phi, i) = \frac{\exp[M_i + \omega_i(a_1 - a_2)y_1 + \omega_i a_2 y_1 i]}{\sum_{u=1}^m \exp[M_u + \omega_u(a_1 - a_2)y_1 + \omega_u a_2 y_1 i]}$$

Wei Chen calculates

$$\Pr(c_i|\phi, i) = \frac{\exp[M_i - \omega_i \phi i]}{\sum_{u=1}^m \exp[M_u - \omega_u \phi i]}$$

This was done for a number of reasons. The y_1 term is just the aggregate of the effective population, ϕ , and a scaling term $-q$. Also, the assumption was that $a_1 \approx a_2 = 4\text{ATP}$.

2.5.1 Adding a_2

So it appears that Wei Chen never accounted for the direct cost of codon addition in the model. Maybe he was counting on it being cancelled by the scaling term q ? In any case, I changed `my.logdmultinomCodOne.r` from

```
xm <- matrix(cbind(1, tmp.phi * reu13.df.aa$Pos), ncol = 2)
```

to

```
xm <- matrix(cbind(1, 4 * tmp.phi * reu13.df.aa$Pos), ncol = 2)
```

Since $a_2 \approx 4$.

Then `xm%%baamat` should be $M_i - 4\omega_i\phi i \approx M_i - a_2\omega_i\phi i$ As intended.

Implementing the change seemed to have no significant effect on the model, with Preston's Yeast or the REU Yeast. The results of the former are in `cubfits/misc/results/np/11-10/*4ATP.pdf`, and the latter are `cubfits/misc/results/ny/11-10/*4ATP.pdf`

This is troubling. I'm subtracting out an additional $3\omega\phi * position$ from each mutation bias, and I'm seeing very little results in actual codon usage bias. I checked the calculations in the browser, and it's accurate.

2.5.2 $\Delta a_{1,2}$

To better account for the parameters of the model, we're going to add another parameter called $\Delta a_{1,2} = (a_1 - a_2)$, and use

$$\Pr(c_i|\phi, i) = \frac{\exp[M_i - \omega_i(\Delta a_{1,2})\phi - 4\omega_i\phi i]}{\sum_{u=1}^m \exp[M_u - \omega_u(\Delta a_{1,2})\phi - 4\omega_u\phi i]}$$

The math part of the change takes place in `my.logdmultinomCodOne.r`, adding an extra row to `xm` and multiplying $\omega\phi\Delta a_{1,2}$, which is `baa[2]*tmp.phi*(new parameter)`

2.5.3 How to set $\Delta a_{1,2}$

Mike suggests a small stepsize, but the big question is, when to we increase or decrease $\Delta a_{1,2}$?

I could add it to the `baa` matrix, and set it using the same `vglm` call in `myfitMultinomialOne.r` that fits the M and ω values, but then it would be different for each amino acid. Of course, I could do that, and then set all of them equal to the (max/min/mean/median) value for $\Delta a_{1,2}$, but is that a bad idea? Also, this would make our VGLM call take longer, and it would disrupt our ability to fit the parameters we are already fitting. Those parameters would also be fit relative to an AA-specific $\Delta a_{1,2}$, even though $\Delta a_{1,2}$ would not be AA-specific.

2.6 Move to Newton

Newton uses R 3.0.1, all my dependencies were build under 3.1.1. Newton HAS R 3.1.0, but not 3.1.1.

2.7 Wrong Names

It's not just a problem in the `chain$b.Mat` data. It's in the `my.fitmultinomOne.r`

2.8 Visualization

2.8.1 'true' values vs simulated values

Changes have been added to `visualize.r`, based on other plotting functions.

I've added confidence intervals (the scale of the interval can be set in `visualize.r`). Cedric didn't have any functions to do so, but I was able to apply the "plotrix" package. I've also installed that package to `"/home/lbrown/cubfits/Dependencies/plotrix"`. Everyone else should have permissions on that directory, in case someone wants to use my edited `visualize.r` function.

2.8.2 Fix plotCUB

The `plotCUB` function right now is calculated based on the ROC model. For the estimated and observed bias, the lines do not line up with the means and confidence intervals.

`plotCUB` generates the line (called `predict.roc`) using the `prop.model.roc` function. It seems to be based on `my.logdmultinomCodOne.r`. I've made the appropriate changes. By correctly using the $\Delta\omega$ values as $\Delta\omega$ (and not $\Delta\eta$), and also multiplying through by the mean position of the amino acid, we actually see a Codon Usage Bias!

I've made the appropriate changes in `plotCUB` so that it can take a_2 and $\Delta a_{1,2}$ as arguments, and actually use them in predicting the CUB for the NSE model. Right now, it takes the position as the mean position of that amino acid, which for *S. Cerivisiae* tends to be ≈ 350 .

The problem should be fixed, and also, shouldn't interfere with running the ROC model.

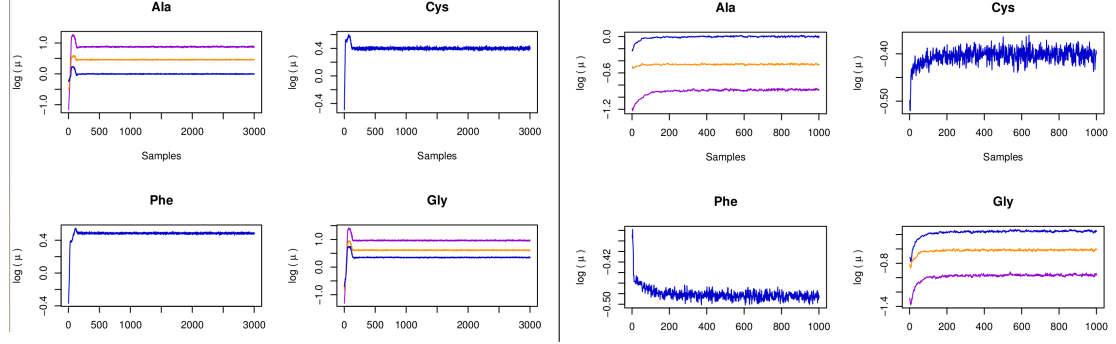
2.9 logMu flip

So as a result of the `deltaEta` switch, the code was multiplying the $\Delta\log(\mu)$ values by -1. As I've described above in the `x%*%baamat` calculation, it actually ended up doing negative mu, and fitting that. To the credit of the model, it was actually just fitting the opposite. Previously, I would just flip the result before plotting it.

I've gone into the `my.logdmultinomCodOne.nse` function and flipped the $\Delta\log(\mu)$ back at the codon probability calculation. The result looks nice so far.

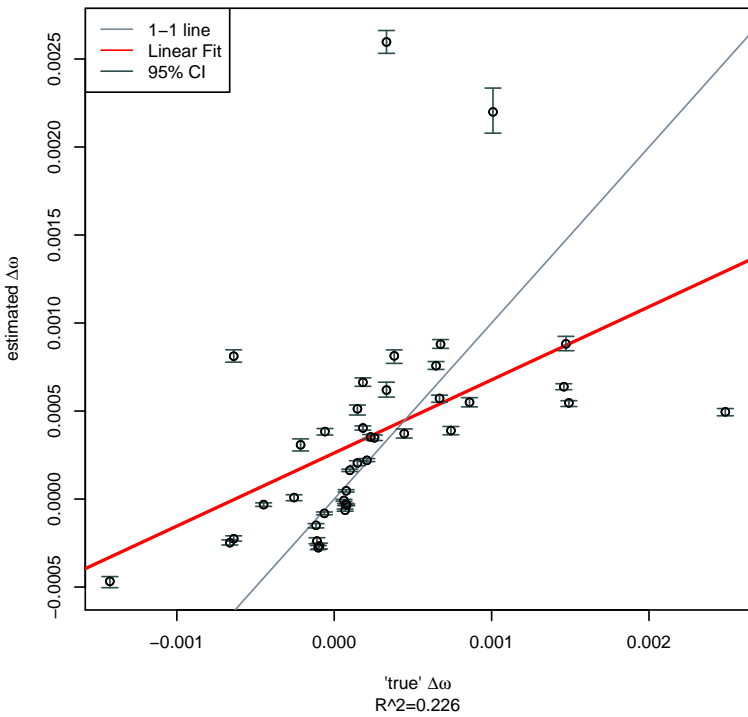
To illustrate, compare these two runs:

Figure 1: The first figure is a run before the logMu flip. The second is after. The second image has very small changes in $\Delta \log(\mu)$, which looks like a more convincing result to me. Look especially at Glycine, at the purple line (codon GGG). Before the logMu flip, it started at about -1.2, went to 1.2, then converged around 1. After the flip, it started around -1.2, and converged around -1.

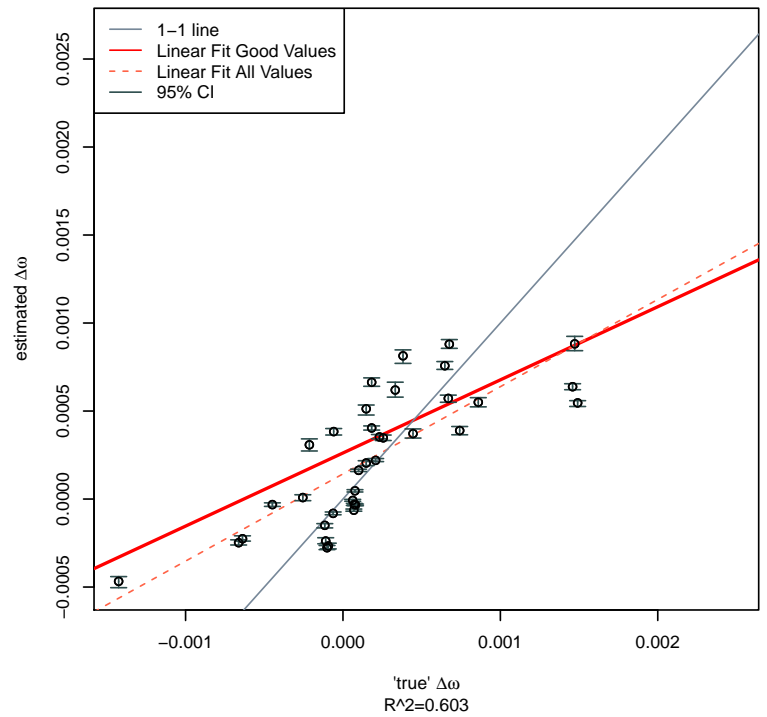


2.10 Problematic Codons

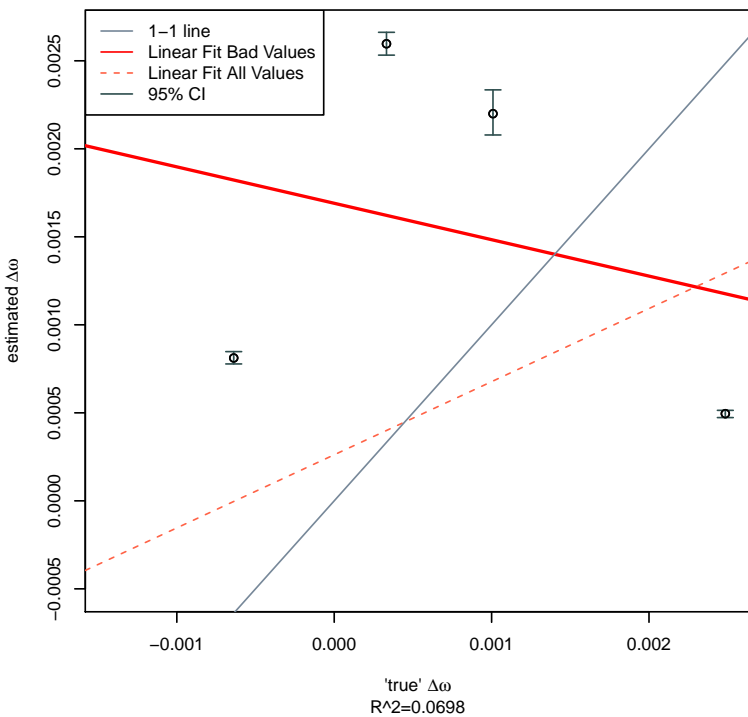
'true' $\Delta\omega$ vs Estimated $\Delta\omega$



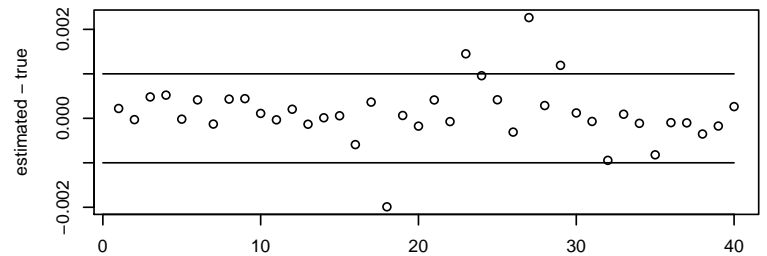
$\Delta\omega$ without problem values



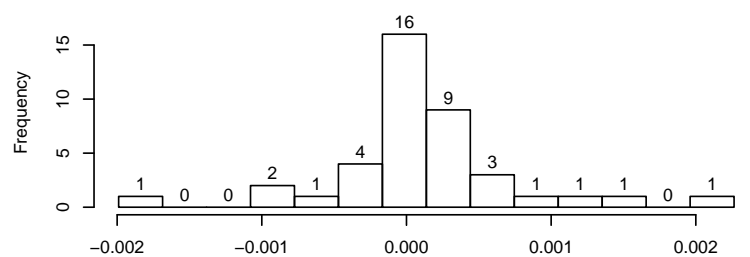
$\Delta\omega$ problem values



$\Delta\omega$ error



Estimated $\Delta\omega$ - 'true' $\Delta\omega$



3 Goals for next Month

1. Future Goal