

Scoring the Parameter Estimation Challenge

This challenge will be scored based only on the following two criteria: 1) The “distance” between simulated and predicted values, and 2) The distance between estimated and known parameters.

1. Distance between simulated and predicted values

The challenge requests predictions of three proteins at times $t_i = 0.5 i$, for $i = 1, 2, \dots, 40$. Let's denote by $p_k^{\text{pred}}(t_i)$ and $p_k^{\text{sim}}(t_i)$ the predicted and simulated levels of protein k at times t_i . Different models require different proteins to be predicted as follows:

Model	Time-courses to predict
1	p2, p4 and p6
2	p3, p5 and p7
3	p4, p8 and p9

Because the initial conditions are given, the real challenging predictions take place after some time has elapsed from $t=0$. We will take that time to be 5. Therefore the squared distance between predicted and measured protein abundances for model j can be taken to be:

$$D_j^{\text{prot}} = \frac{1}{90} \sum_{k=1}^3 \sum_{i=11}^{40} \frac{[p_k^{\text{pred}}(t_i) - p_k^{\text{sim}}(t_i)]^2}{0.01 + 0.01[p_k^{\text{sim}}(t_i)]^2}$$

Note that the squared difference terms are normalized with the variance, and the variance follows the noise model that was implemented in the data provided. The noise model is simply $\sigma_{\text{baseline}}^2 + \sigma_{\text{signal}}^2$, where $\sigma_{\text{baseline}} = 0.1$ and $\sigma_{\text{signal}} =$

$0.1 p_k^{sim} \cdot \sigma_{baseline}$ represents a baseline, signal independent, measurement noise, and σ_{signal} represents a signal dependent measurement noise with a constant coefficient of variation of 0.1.

Also note that we are dividing by 90 ($= 3 * 30$) the number of terms being added. So a noisy but excellent prediction will give a value close to 1, as we should take into account the fact that the models are based on fits to noisy data. We could think could have used protein concentrations in logarithmic scale. However, it is often the case that the protein abundances go to values close to 0, and the logarithm will give a divergence.

A null model will be created from this distance, based on the predictions of all the participants. For example, if there are M participants, we will choose at random one of the M predictions for $p_k^{pred}(t_{11})$, then at random one of the M predictions for $p_k^{pred}(t_{12})$, ..., and finally one of the M predictions for $p_k^{pred}(t_{40})$. We will therefore get a value of D_j^{prot} which would correspond to one possible random choice of predictions amongst all the participants. If we do the same process a large number of times, we will generate a distribution of distance squares, for which a p-value can be estimated for D_j^{prot} . That p-value will be denoted as p_j^{prot} .

2. Distance between estimated and known parameters

The challenge requests predictions of all the parameter for the three models. As protein degradation rates are equal, they are in practice only 1 parameter for each of the 3 models. Hence, Models 1, 2 and 3 have $N_p = 29, 35$ and 49 parameters considered for scoring (instead of 34, 41 and 57 submitted). Let's denote as v_i^{pred} and v_i^{real} the predicted and actual parameter values used in the simulations where i runs between 1 and N_p . The mismatch between estimated and true parameters will be assessed on the log-scale. In this way, a mismatch by a factor of x has the same penalty independently on the nominal value of a parameter. Furthermore, the ratio becomes independent on changes of physical units. Therefore the "distance" between predicted and real parameters can be taken to be:

$$D_j^{param} = \frac{1}{N_p} \sum_{i=1}^{N_p} \left[\log \left(\frac{v_i^{pred}}{v_i^{real}} \right) \right]^2$$

Similarly to the case of the distance between simulated and predicted protein abundance, a null model will be created from the distance between estimated and known parameters, based on the predictions of all the participants. If there are M participants, we will choose at random one of the M predictions for v_1^{pred} , then at random one of the M predictions for v_2^{pred} , ..., and finally one of the M predictions for $v_{N_p}^{pred}$. We will therefore get a value of D_j^{param} which would correspond to one possible random choice of predictions amongst all the participants. If we do the same process a large number of times, we will generate a distribution of distance between known and estimated parameters, for which a p-value can be estimated for D_j^{param} . That p-value will be denoted as p_j^{param} .

3. There will be no scoring based on used credits

There is no standard or obvious way of scoring in which it is optimal to spend some but not all the credits. We will ignore for this challenge the amount of credits spent. Therefore participants are encouraged to spend the whole budget.

4. Overall score over the three gene networks

For each of the three models, each team will have a p-value for the time trace predictions and a p-value for the parameter predictions. We will take the overall score to be a function of the product of all the p-values. More specifically:

$$Score = -\log \prod_{j=1}^3 p_j^{prot} p_j^{param}$$