Data-driven codon optimization in Saccharomyces cerevisiae

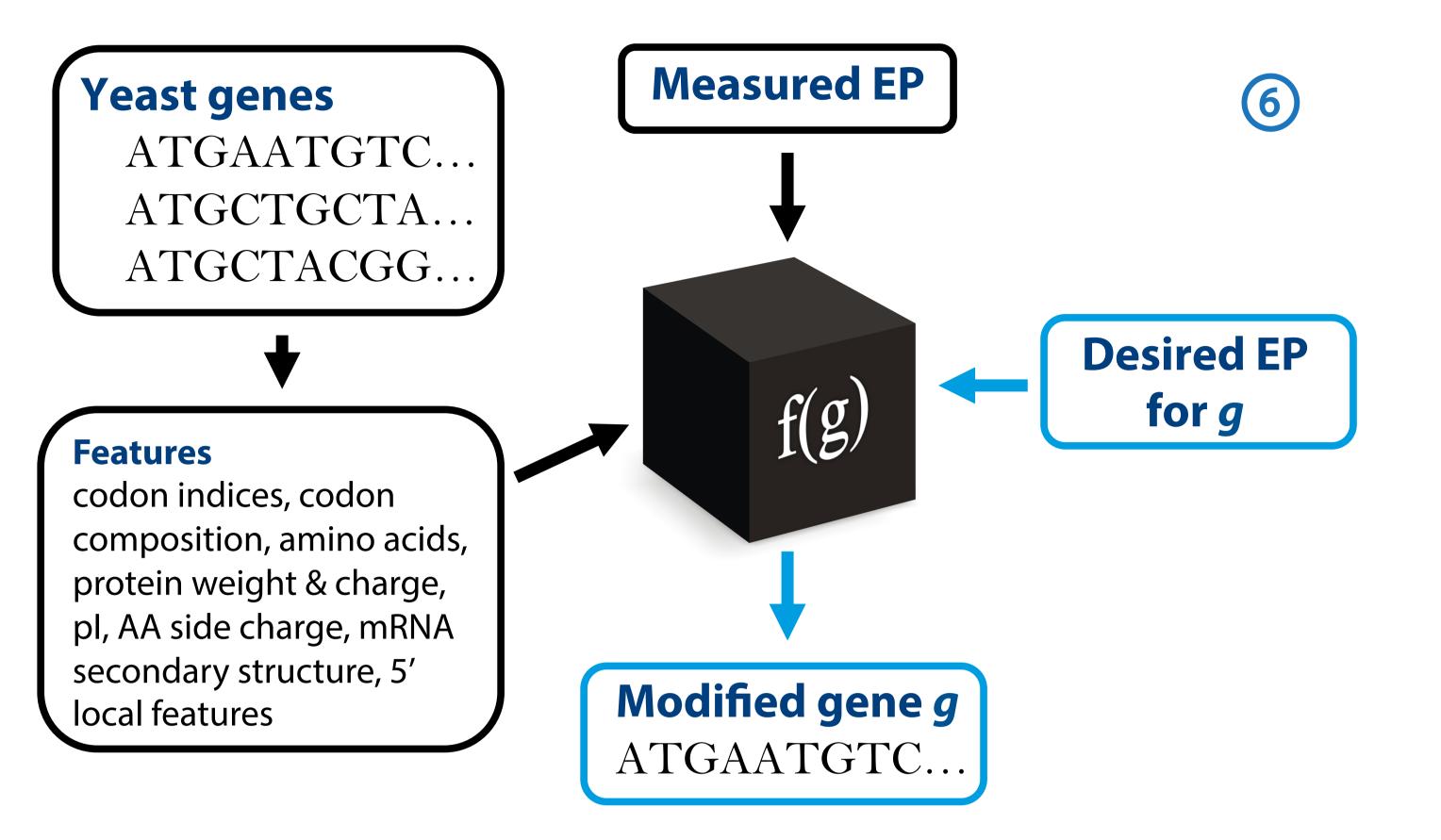
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Choice of codons influences gene translation rates

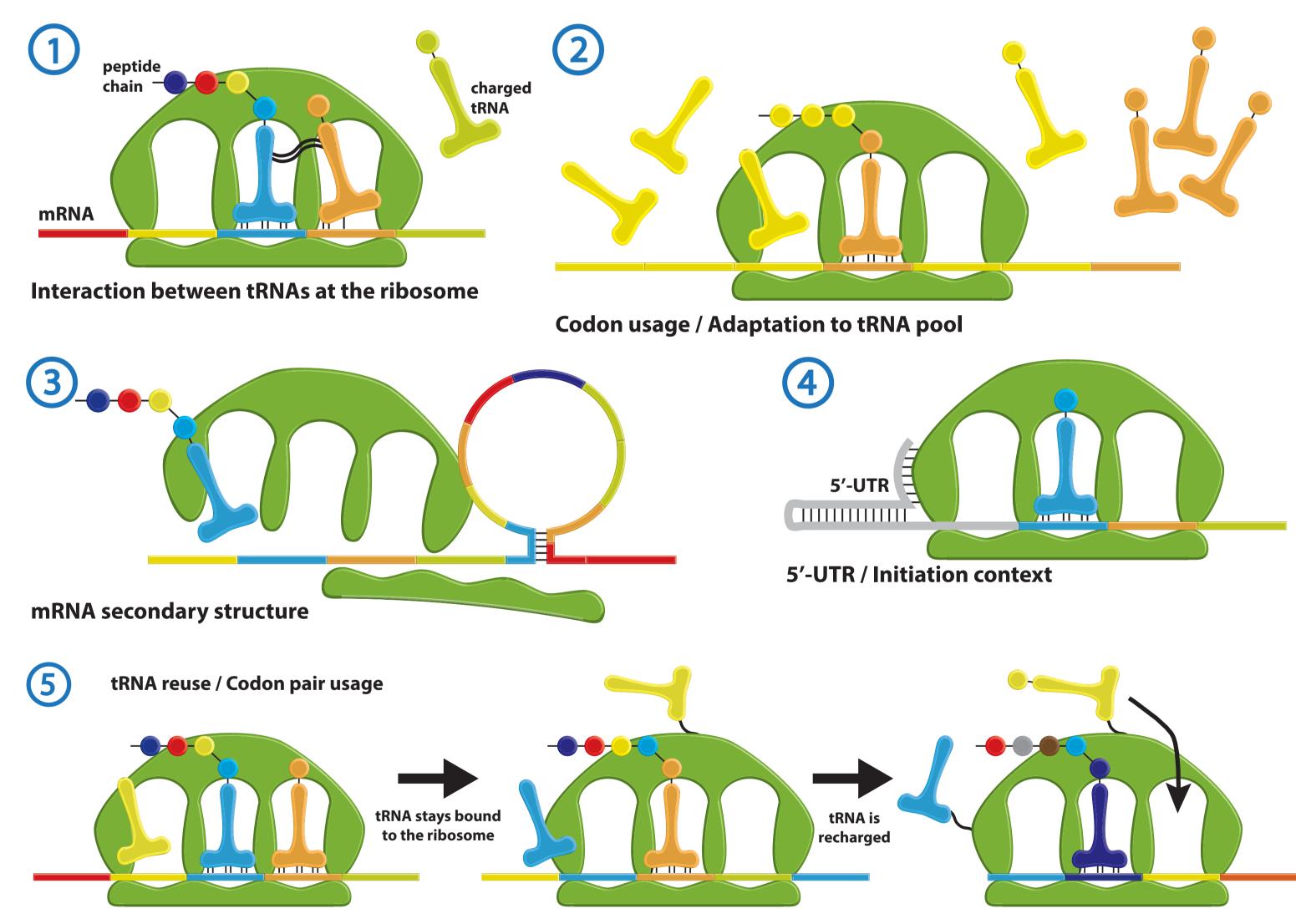
Most of the 20 amino acids are encoded by 2 to 6 synonymous codons, which are rarely used at equal frequencies. Biased choice of synonymous codons is more evident in highly expressed genes, which can exclusive use a single codon per amino acid. This observation is often employed to prove that synonymous codons are not translated at equal rates.



The difference in translation rates between organisms presents a challenge for heterologous protein expression, when a donor gene can have little or no expression in a new host organism. The process of adapting gene's sequence for (more) efficient translation, called *codon optimization*, is instrumental for heterologous expression of single genes or complete pathways.

Multiple mechanisms determine translation rates

Numerous hypothetical mechanisms (1-5) have been suggested for explaining the observed difference in translation rates between synonymous gene encodings. However, none of the mechanisms are completely understood and little is known about interactions between different mechanisms, making it difficult to rationally adjust gene translation.

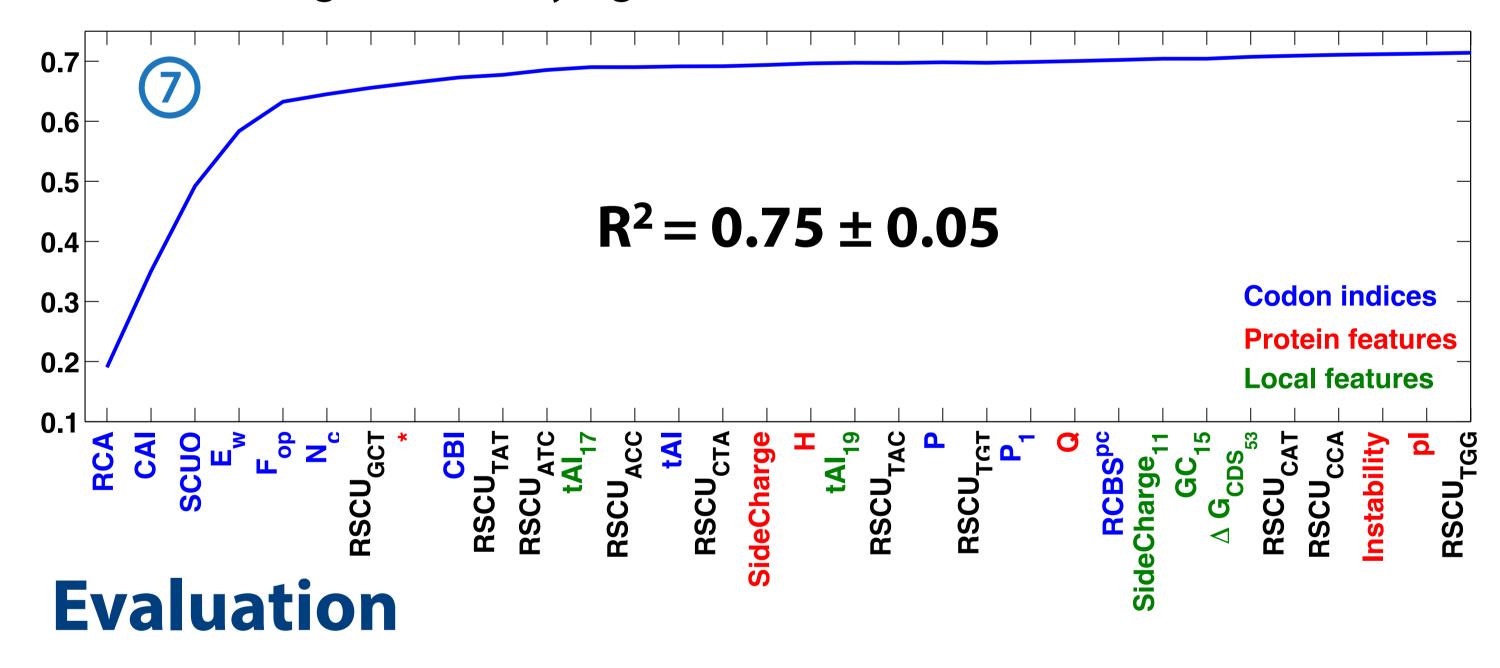


We use a non-linear regression approach for learning a predictor of *Expected amount of Protein* (EP) in *S.cerevisiae*, defined as mRNA levels x Ribosome density [4], from multiple sequence features. We then invert this predictor to see which codon substitutions increase the prediction **6**.

Predictor training and evaluation

Support Vector Regression (v-SVR) and backward feature selection have been used to train a predictor with $R^2=0.75\pm0.05$ (10-fold CV) and 79 features (see 7) for the first 30 features). The regression combines features describing multiple translation mechanisms in a single predictor, allowing to make predictions about translation rates without understanding the underlying mechanisms.

Sequence-based features can be used for predicting translation rates



We synonymously changed sequences of the PAL1 and 4CL genes involved in plant flavonoid biosynthesis such that they would give maximum predicted EP (8), (9). We also codon optimized them using JCat [5].

8 4CL Type	Codons changed	EP, folds	PAL1	Type Codons changed	EP, folds
cDNA	0	1	cDNA	0	1
JCat	338	1035	JCat	414	403

Gene sequence-based features (such as CAI [1], tAI [2] or TPI [3]) have been devised for mechanisms 1-5 and have been shown to correlate with mRNA or protein levels. These correlations, capturing linear relationships between individual features and gene expression, have been used for codon optimization. However, such an approach does not take the potential interactions between different features (mechanisms) and cannot explain their combined effect on translation rates.

Optimized EP 344 1976 Optimized EP 438 855

In silico predictions suggest an achievable 2-fold increase in translation rate compared to genes codon optimized using an existing method. These results are currently being verified in the lab by measuring mRNA levels, protein levels and enzymatic activity of original and optimized PAL1 and 4CL versions.

References

[1] Sharp & Li NAR (1987); [2] dos Reis *et al. NAR* (2003); [3] Friberg *et al. LNBI* (2003); [4] Ingolia *et al. Science* (2009); [5] Grote *et al. NAR* (2005).



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