

how can machines learn protein engineering ?

– one possible approach of machine learning concept to predict and improve enzyme activities.

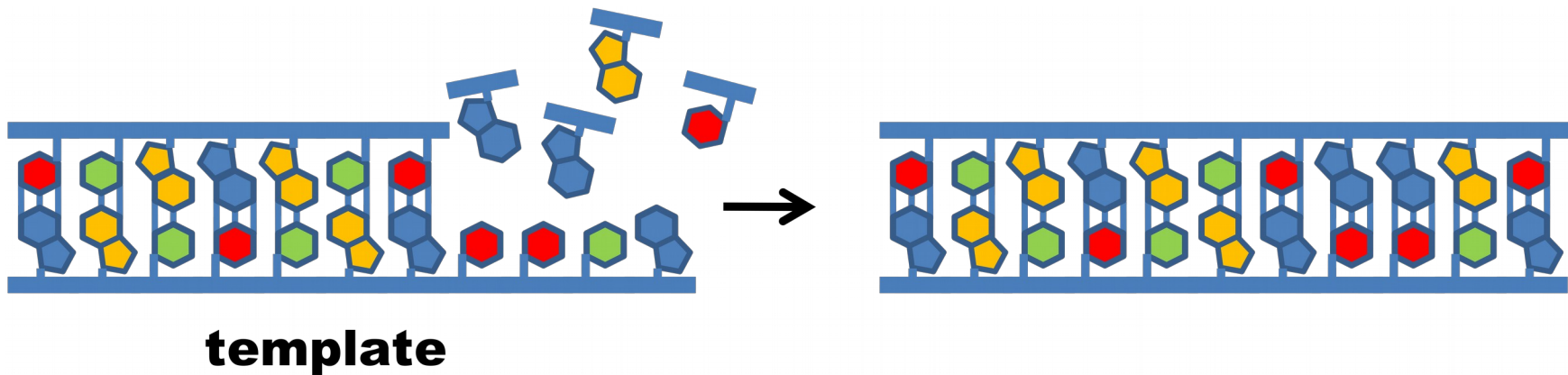
before we start talking about enzymes,
we should talk about RNA

RNA condensation and template directed extension reactions

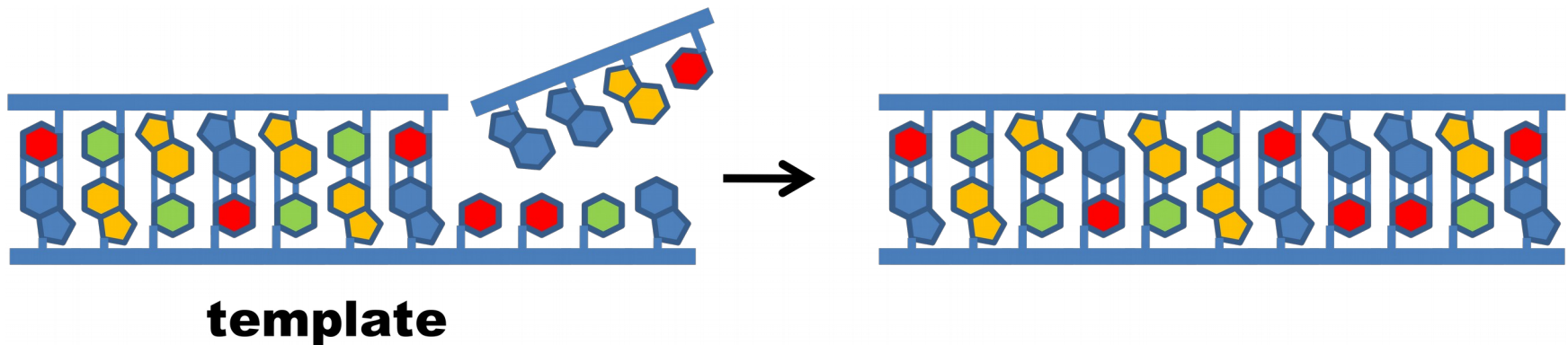
work performed at University of Southern Denmark Odense (SDU)
in **Steen Rasmussen's** and **Pierre-Alain Monnard's** group
together with **Philipp M.G. Löffler** (main experimenter)

template-directed nucleotide condensation/ligation

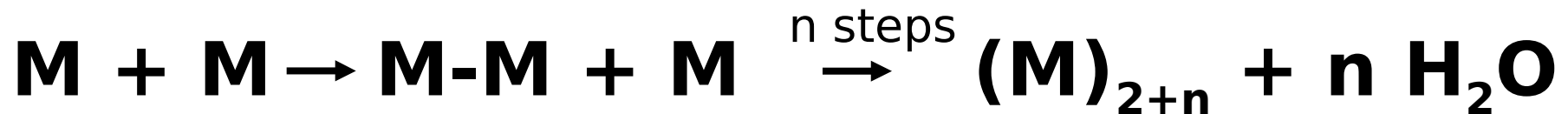
(a) Primer extension with monomers



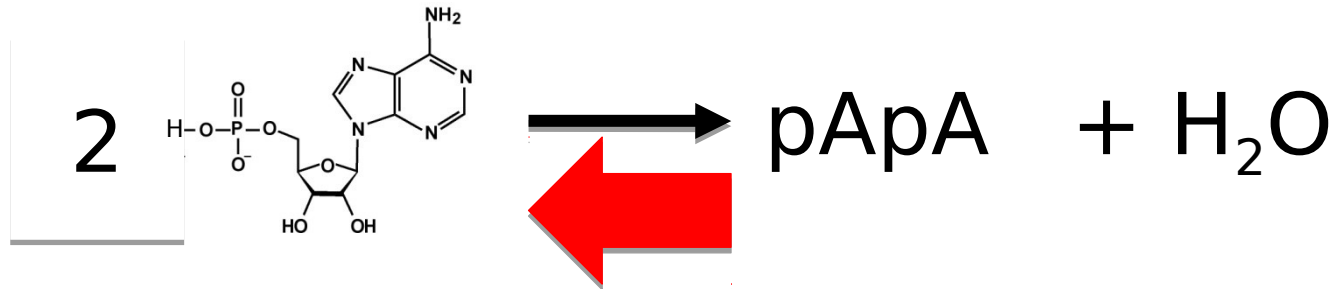
(b) Template directed ligation



condensation of RNA monomers



In aqueous solution condensation reactions are **not** favored,
BUT the reverse reaction, DECOMPOSITION, is favored



Activation of monomers, compartmentalization and/or CATALYST (e.g. METAL ions, surface,....) are needed !

RNA self-replication in HOMOGENEOUS aqueous phase

Monomers template-directed polymerization

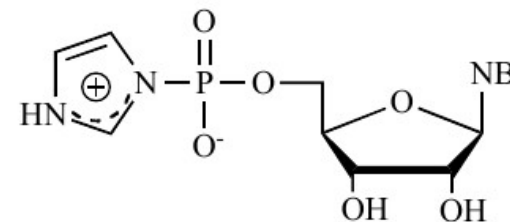
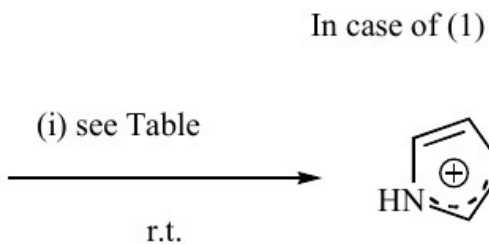
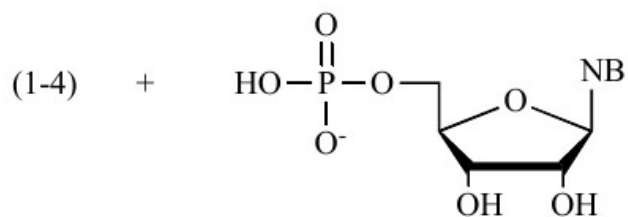
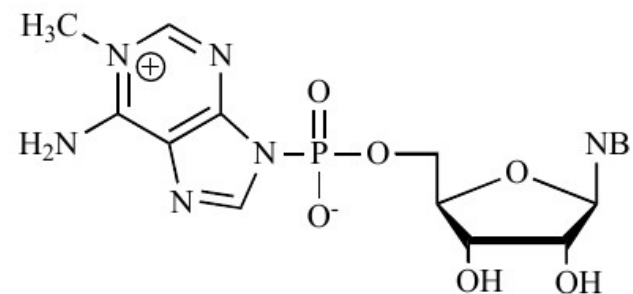
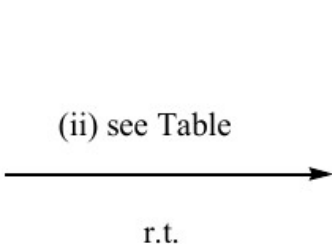
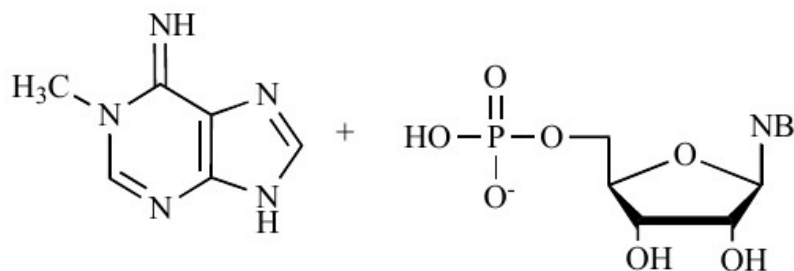
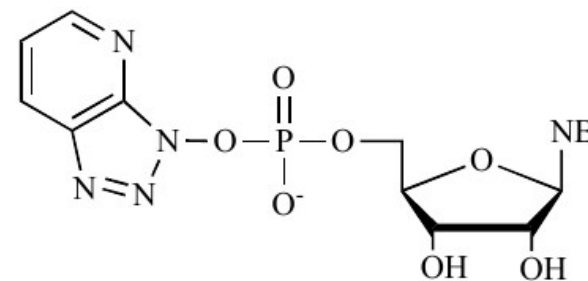
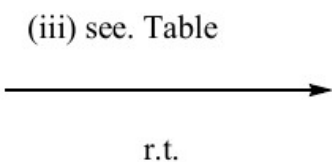
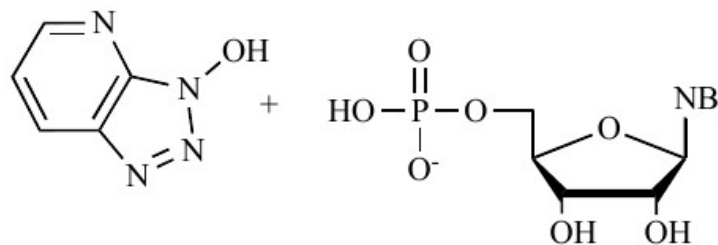


Orgel et al. (1980-1997)

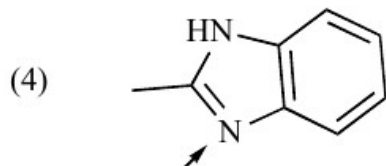
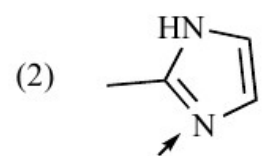
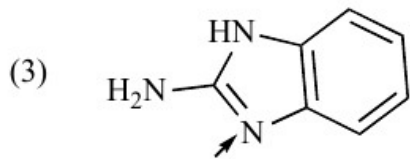
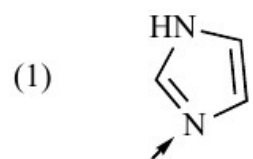
Template with at least 60 % C \Rightarrow Poly G efficiently formed

Consecutive AA (UU to be polymerized) \Rightarrow Block (U too hydrophilic)

\Rightarrow **NO AMPLIFICATION POSSIBLE WITH MONOMERS**

(a)**(b)****(c)**

Imidazole derivative variants



Coupling agents

Conditions

(i) (PyS)₂DMF/DMSO, P(Ph)₃, (Et)₃N, Ar, dry

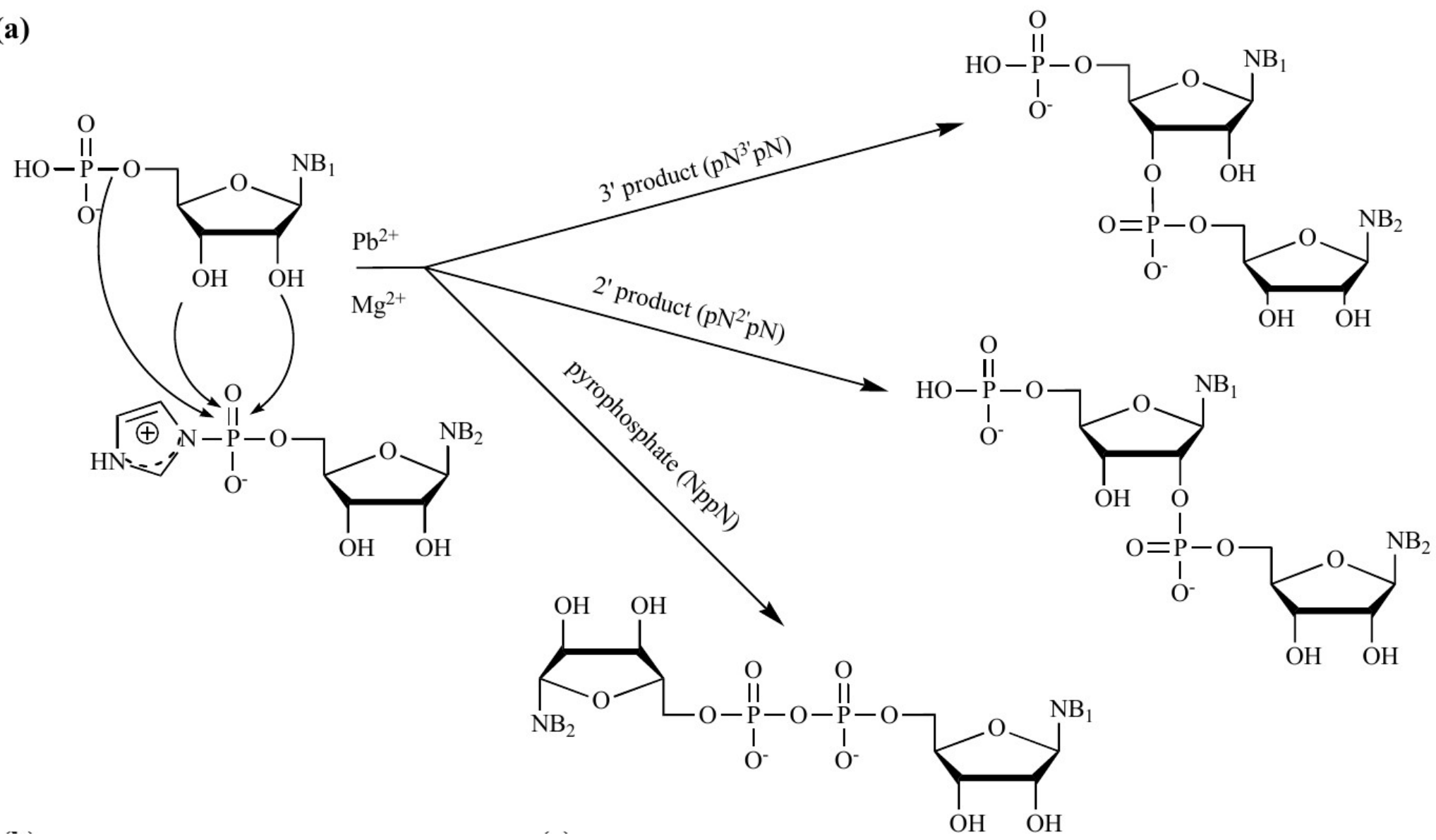
(ii) EDC

H₂O, NaOH, pH 5

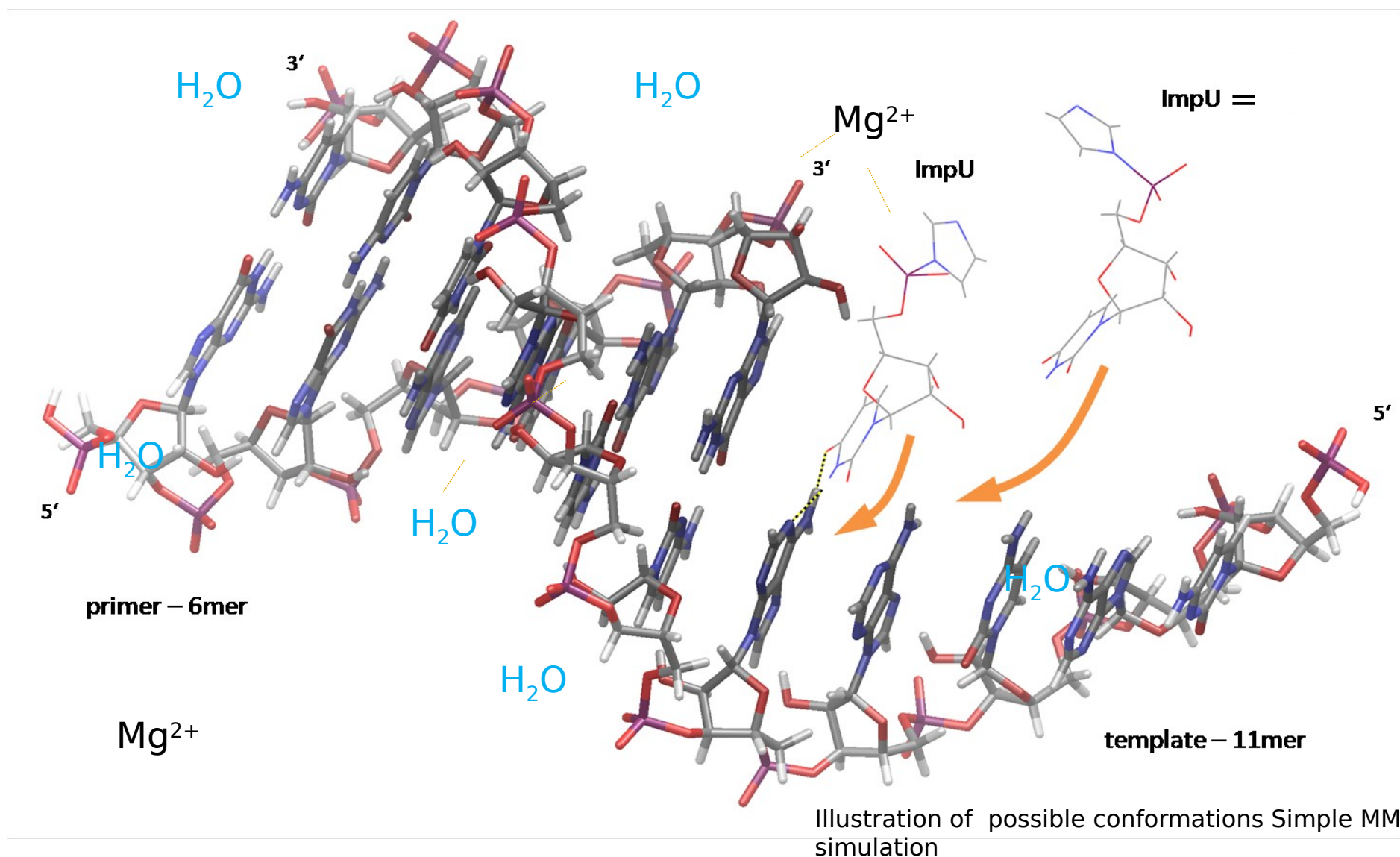
(iii) HATU

DMF, DIEA, Ar, dry

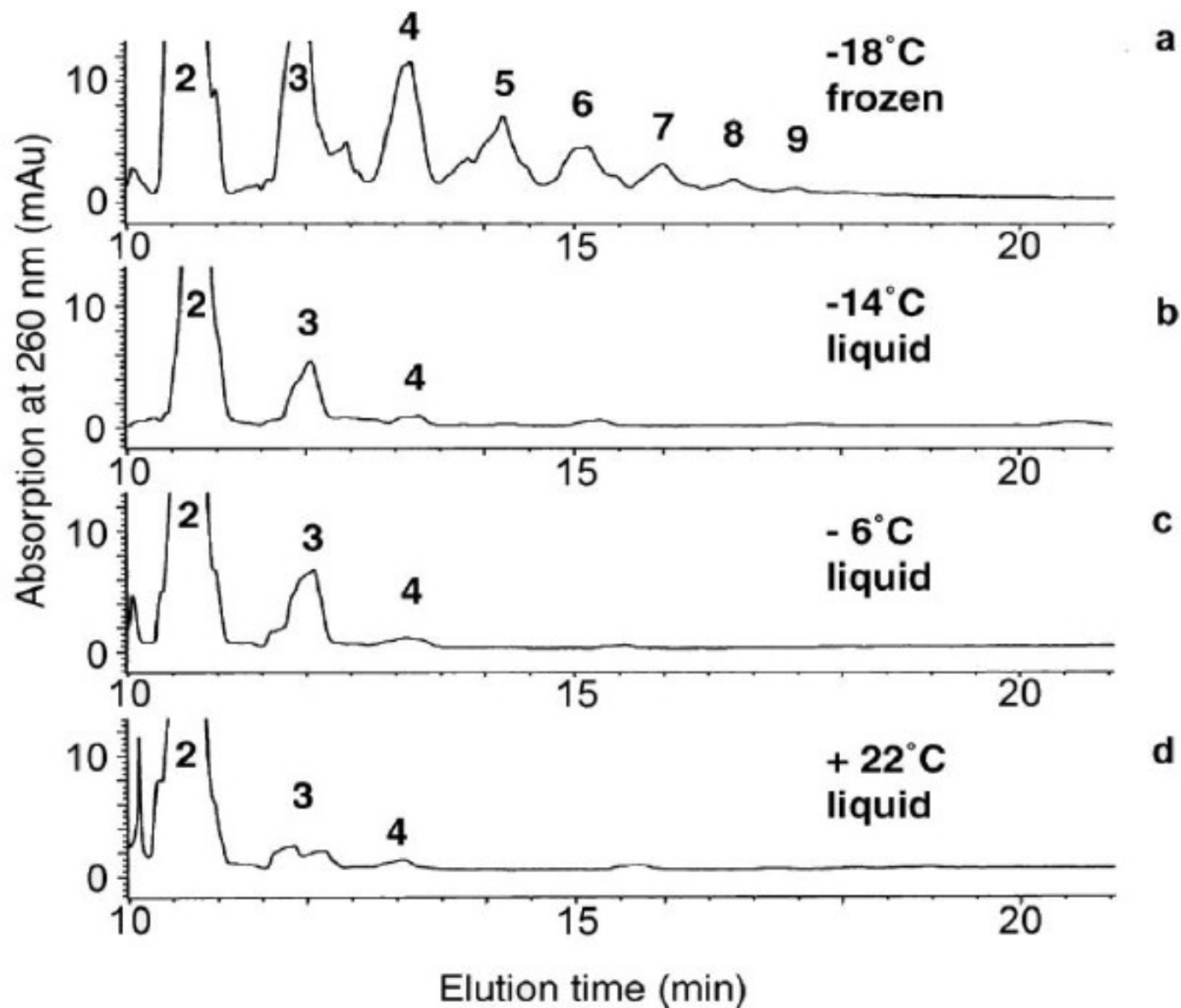
(a)



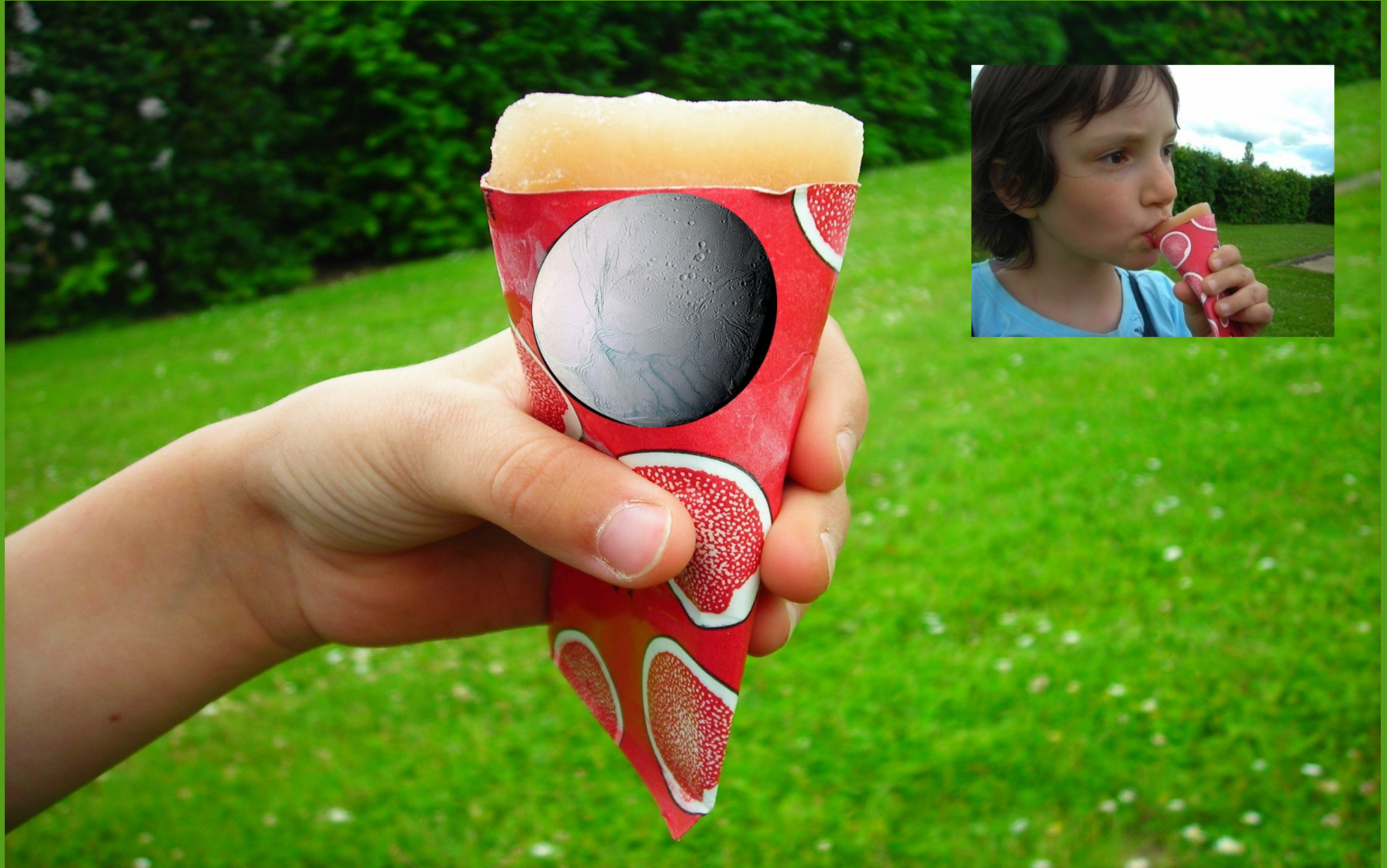
Condensation of nucleotides (ImpU) on a template



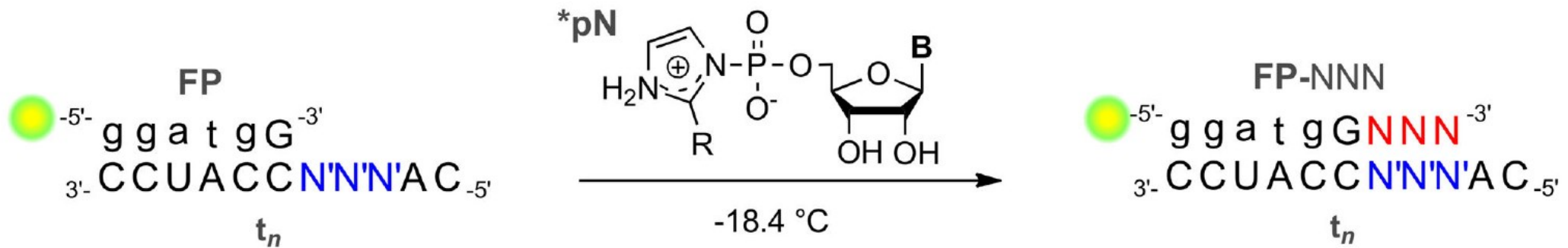
temperature dependence of oligomerization



eutectic ice



primer extension experiment designs



t_1 3'-CCUACCCCCAC-5'

t_2 3'-CCUACCAACAC-5'

t_3 3'-CCUACCAUCAC-5'

t_4 3'-CCUACCAAGCAC-5'

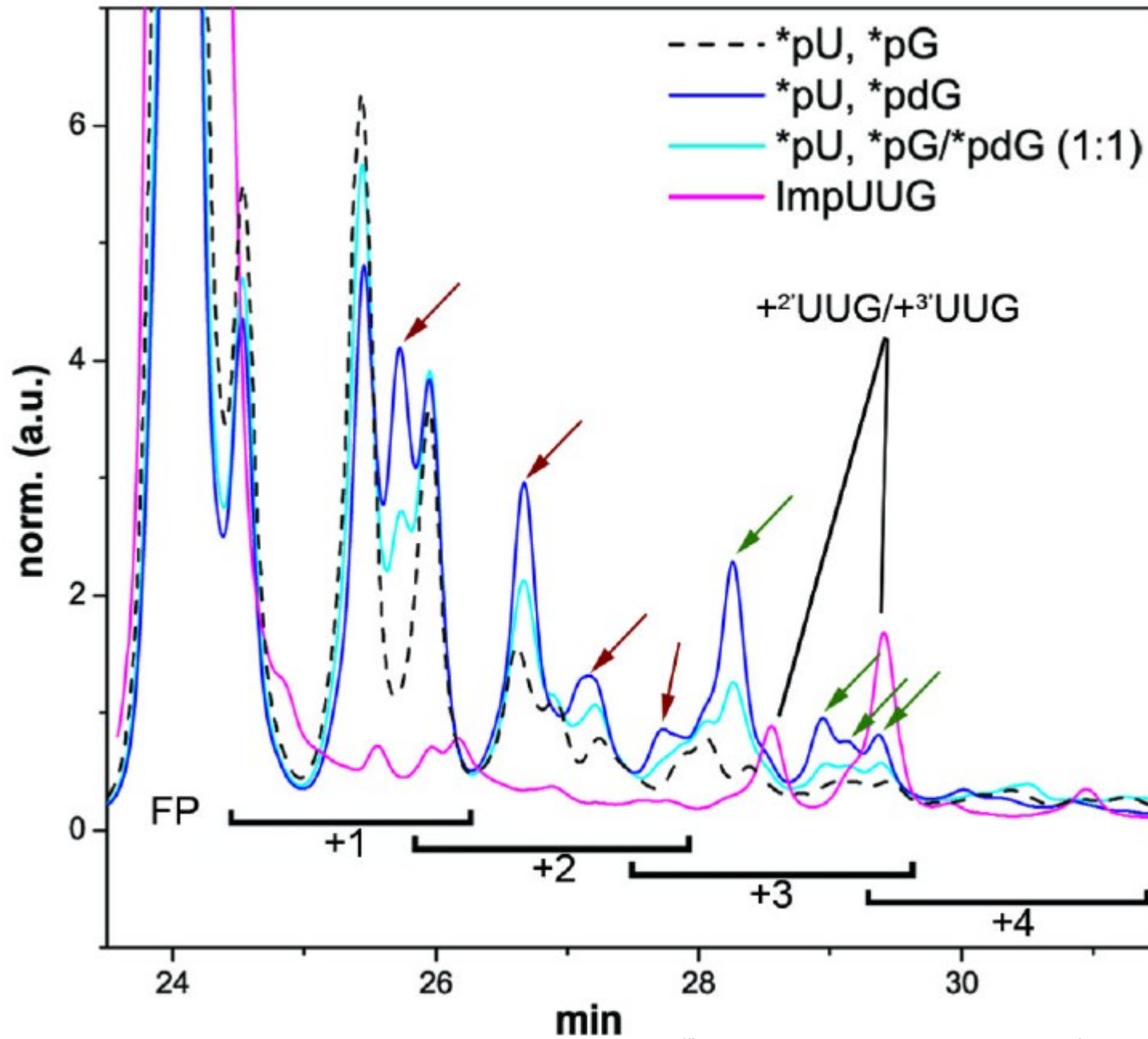
***pNs:**

N = U, A, C, G or dG

R = H (ImpN);

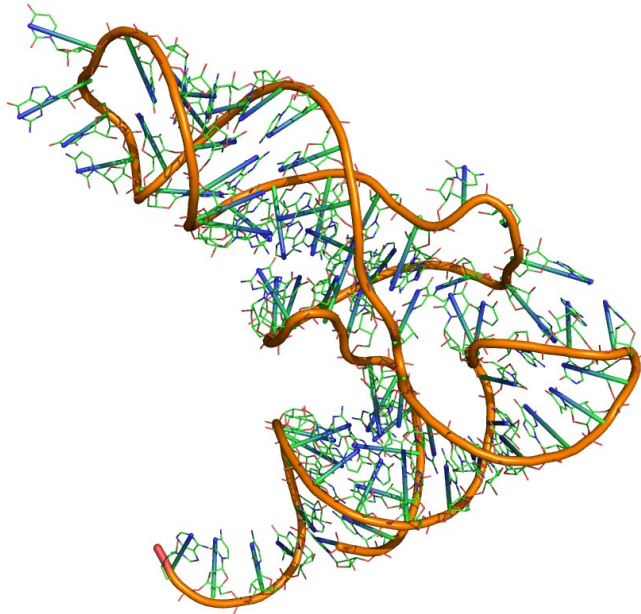
CH₃ (2-MeImpN)

template directed primer elongation



RNA condensation and
folding is just the beginning

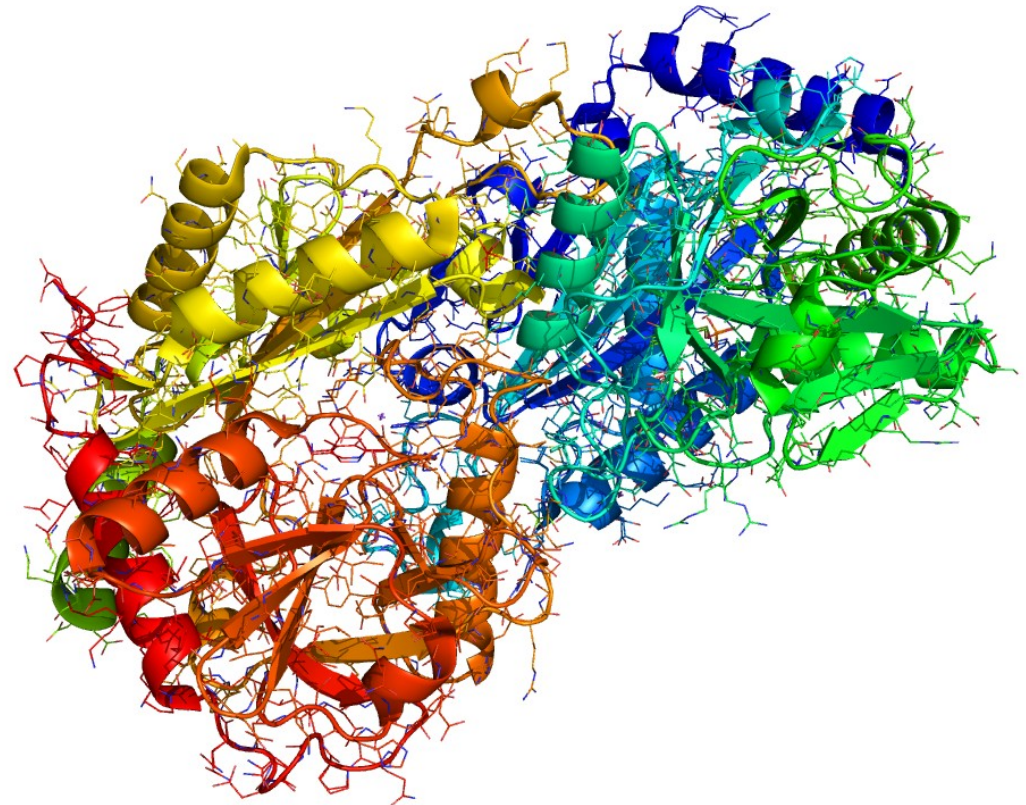
let's increase complexity further



RNA

ASP-tRNA
(PDB:1ASY)

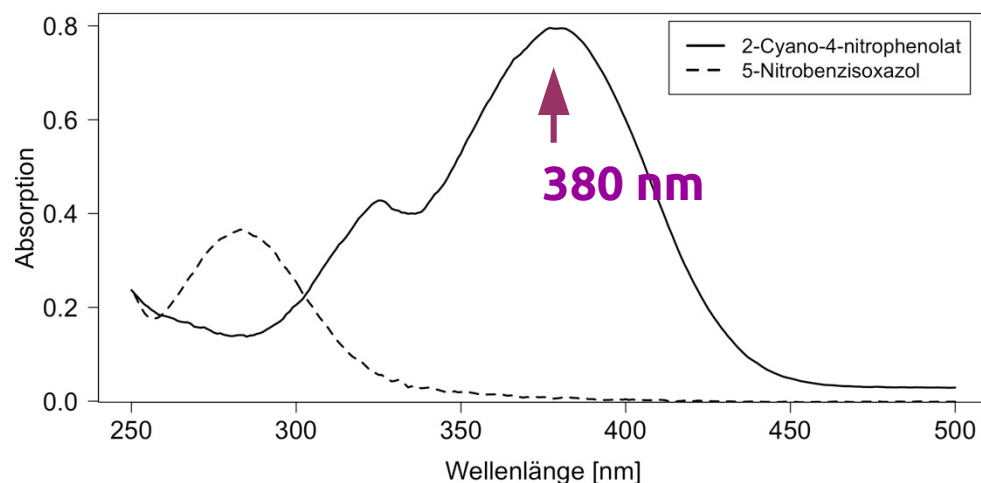
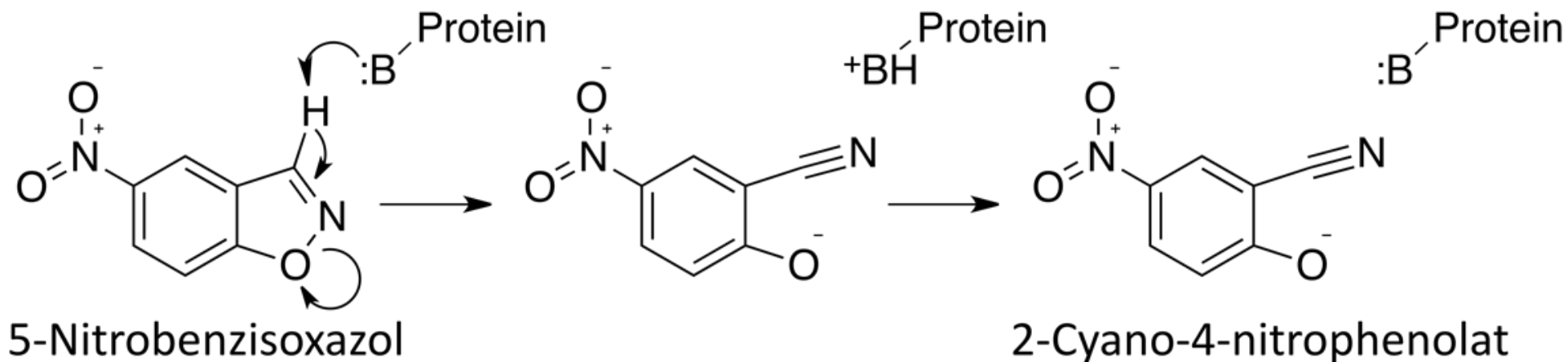
translation



Proteins

transaminase
(PDB:4CHI)

KEMP-eliminase reaction



challenges in protein design/engineering

- increased transformation rate of the substrate
- altered substrate spectrum (e.g. bigger/bulkier substrates)
- enhanced or altered stereo selectivity of the substrate/product

- educt / product tolerance

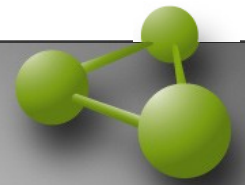
- usage cheaper cofactors

- higher stability to environmental conditions
- temperature tolerance
- pH tolerance
- organic solvents

- enzyme cascades / pathways to more advanced products
(related: regulation of
the protein expression level and or intermediate transformation rate)

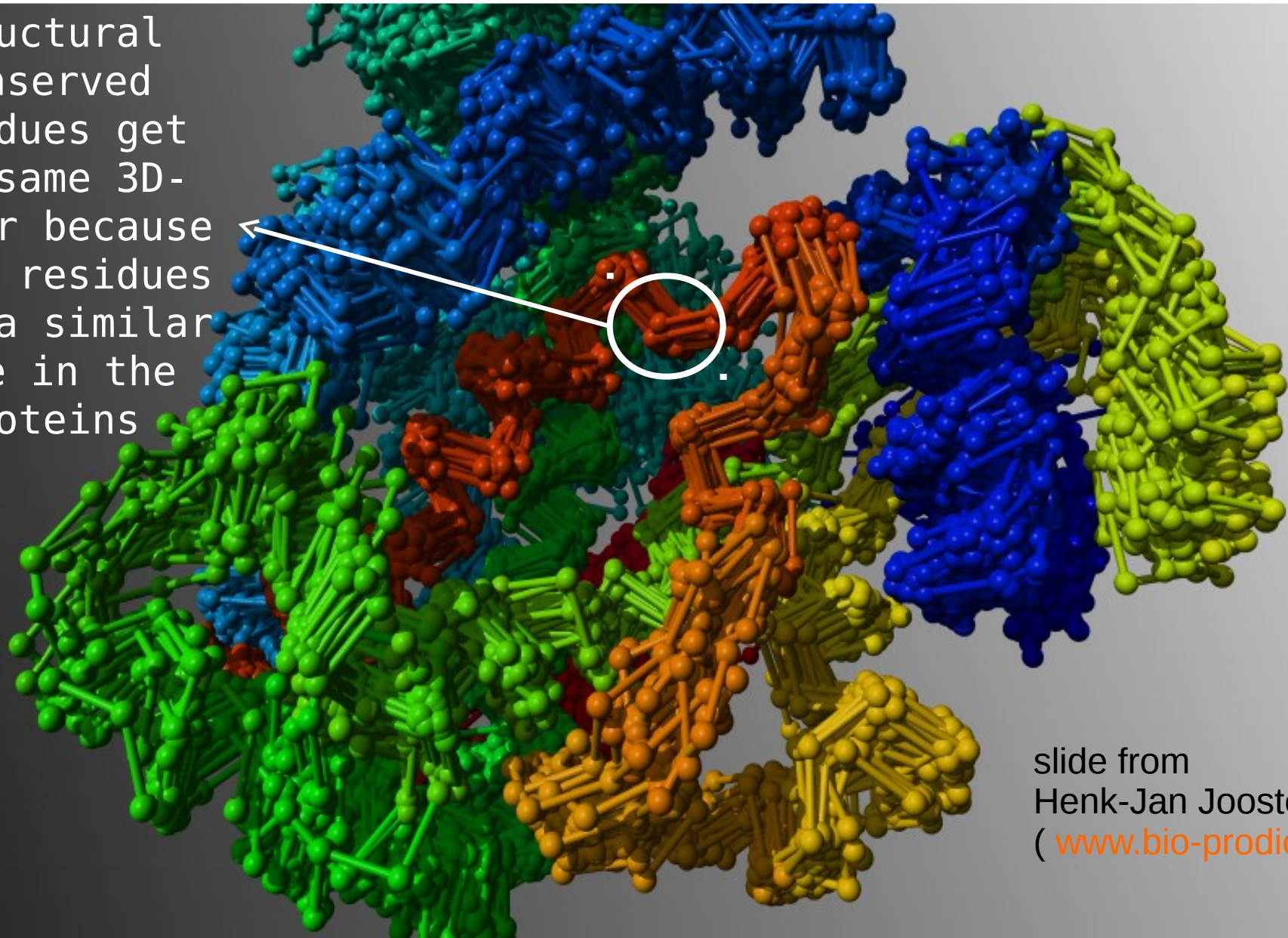
how to engineer ?

- rational engineering (if structure is known)
molecular modeling, 3D structure alignments
- (random) mutagenesis strategies
(error prone PCR, NNK libraries / CASTing)
- semi-rational approaches



Structure based alignments

Structural conserved residues get the same 3D-number because these residues have a similar role in the proteins

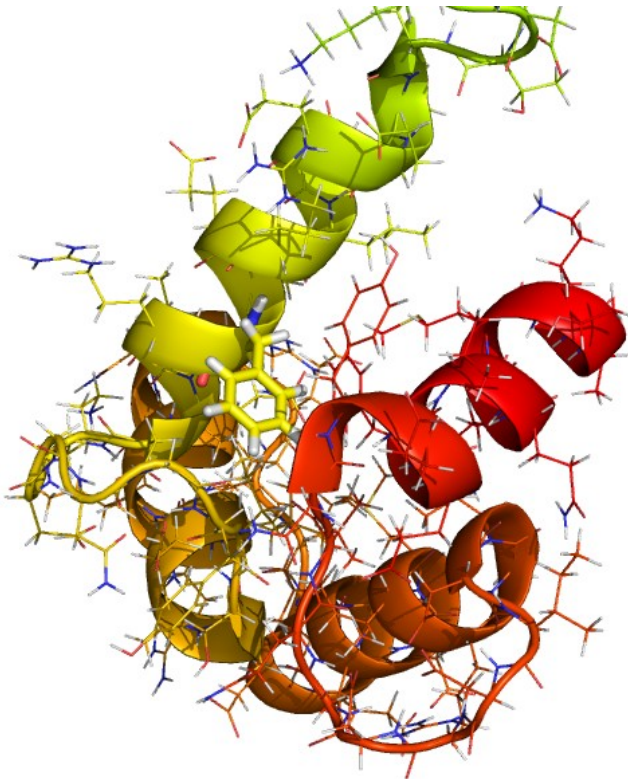


slide from
Henk-Jan Joosten
(www.bio-product.nl)

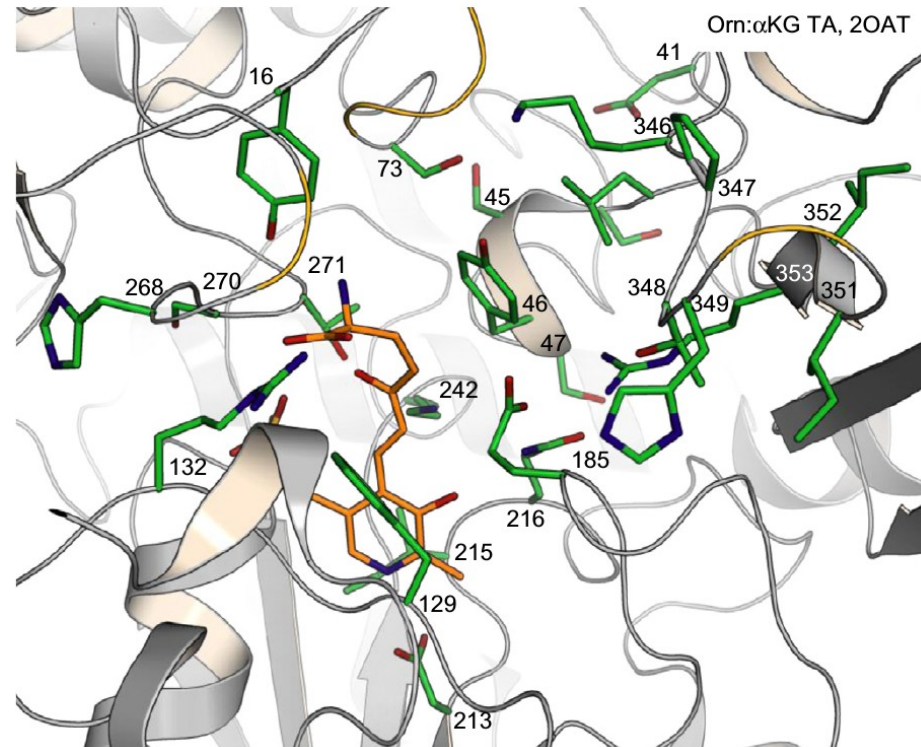
rational design

requirements:

- knowledge about the protein structure (NMR / X-ray)
- certain rigidity of the structure



“simple” active site
(AlleyCatK, PDB 1UPS)



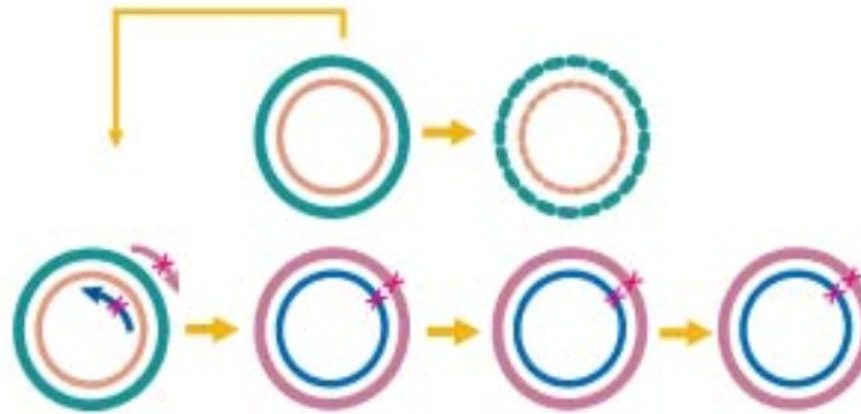
complex active site
(Orn:αKG TA (PDB: 2OAT)

active site modifications

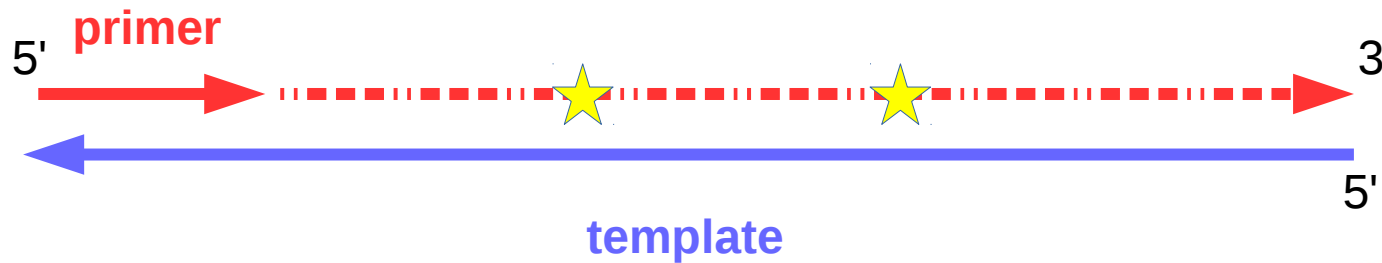
- changes in residue size (e.g. Phe → Ala)
- residue polarity (e.g. Glu → Gln)
- removing loops pointing into the active site
- exchanging loops inside the active site, or in outer spheres

(random) mutagenesis strategies

- QuikChange
(www.agilent.com)



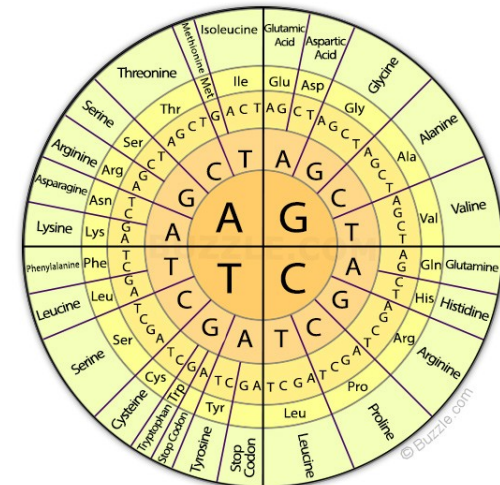
- error prone PCR



- degenerated codons, (e.g. NNK)
at a certain position in the gene
(where, e.g., is N = A/C/G/T and
K = G/T)



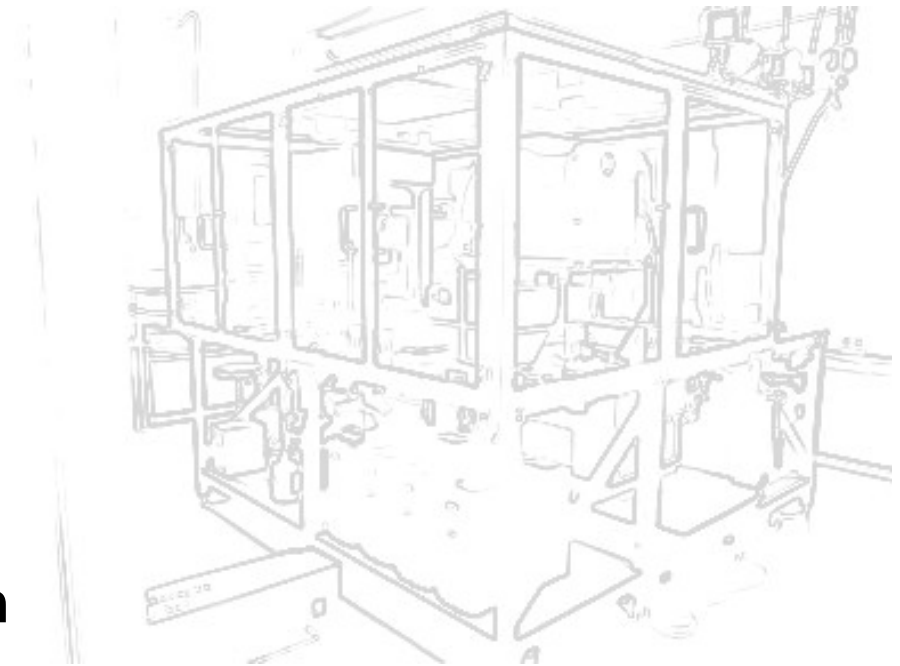
good coverage of
all 20 amino acids at a **single position**



how do we screen ?

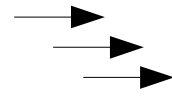
LARA robotic platform

Laboratory **A**utomation
Robotic **A**ssistant



the LARA movie





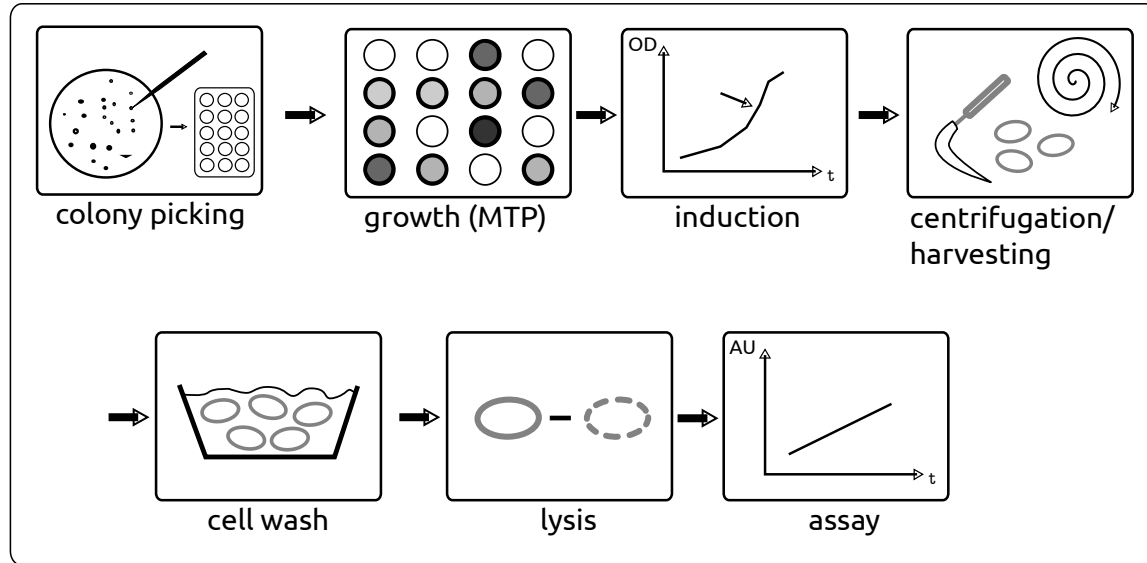
A

Protein design
 expression optimization
 lysis protocol
 assay development

B

LARA assisted
 process generation
 and database
 preparation

C Robotic process



D

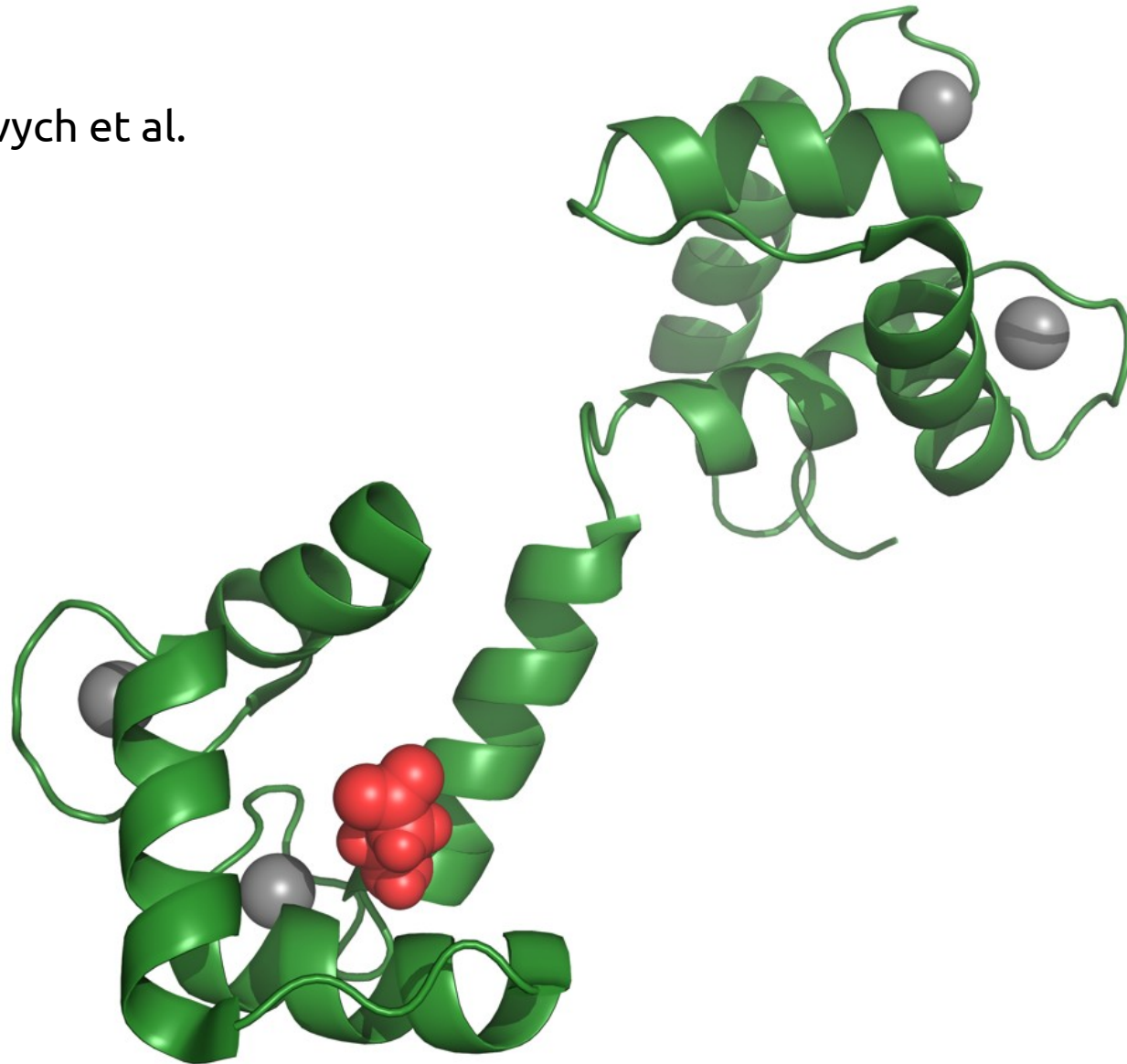
Data archivation
 data evaluation
 visualisation
 web presentation

E

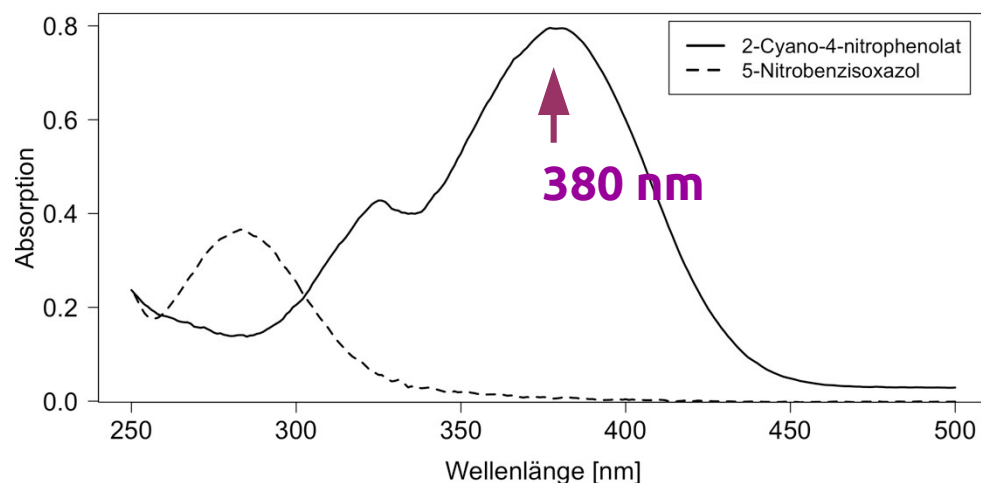
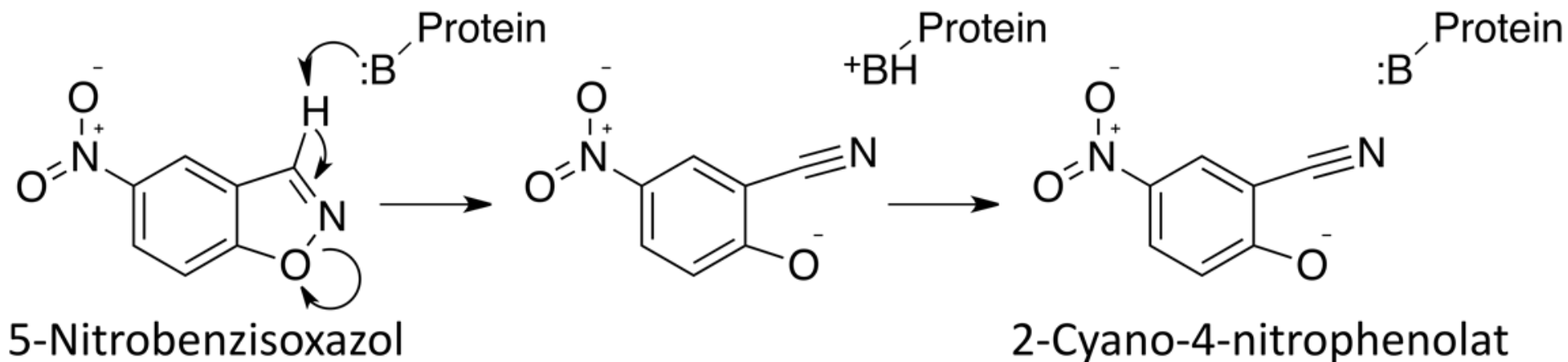
Our robotic process

evolution of the KEMP-eliminase

Ivan Korendovych et al.



KEMP-eliminase reaction



KEMP-eliminase after 7 rounds of evolution (Alleycat)

activity improvement $K_{\text{cat}}/K_{\text{m}}$

$6 \text{ M}^{-1}\text{s}^{-1} \rightarrow 814 \text{ M}^{-1}\text{s}^{-1}$

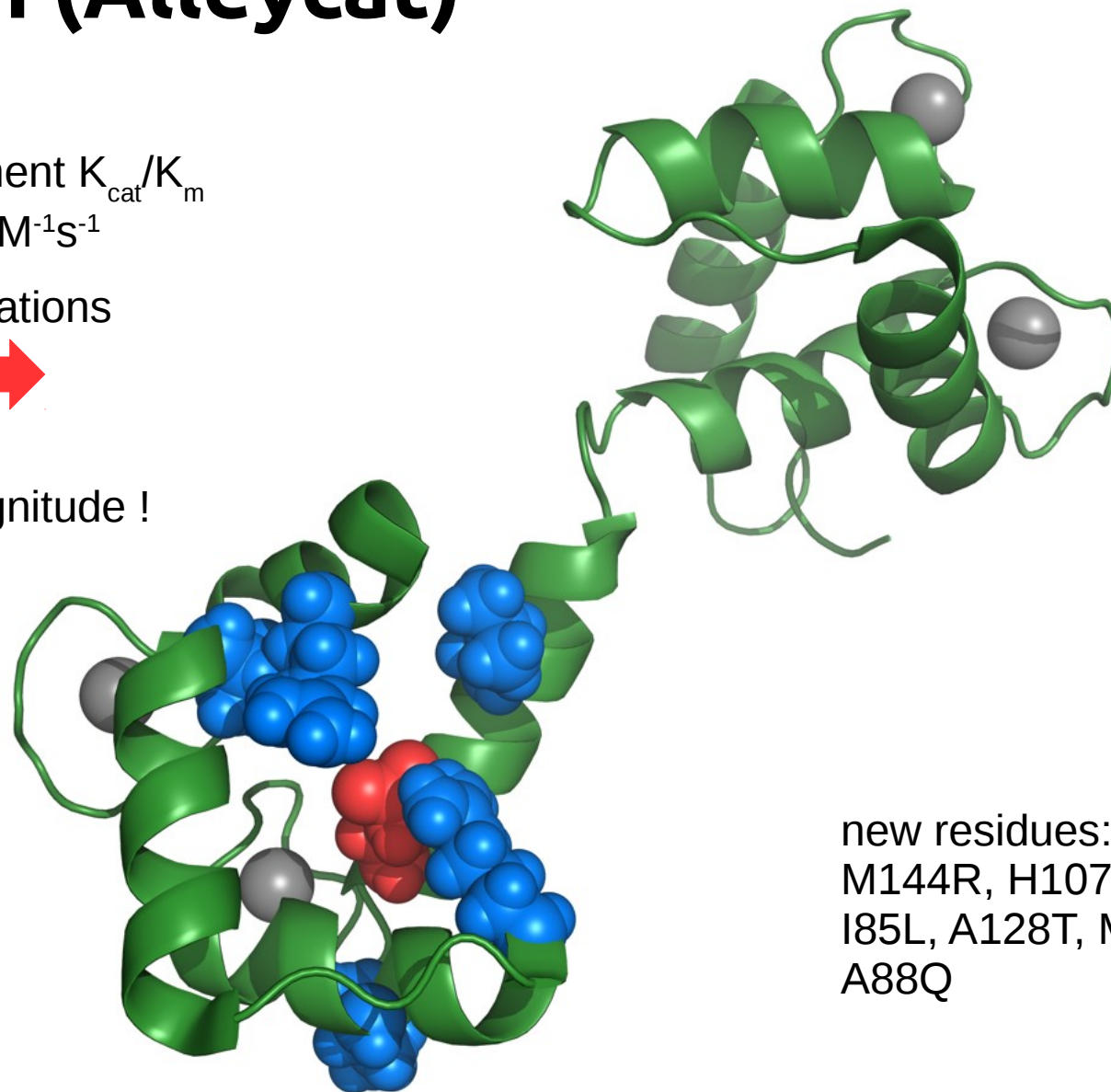
theroretical estimations

$10^6 \text{ M}^{-1}\text{s}^{-1}$



activity gap of ca.

2-3 orders of magnitude !



new residues:
M144R, H107I, L112R,
I85L, A128T, M124L,
A88Q

examples of questions for machine learning

- 1) beneficial mutations ?
- 2) correlated / interfering mutations ?
- 3) improvement of expression / folding ?
- 4) combination of two properties in one enzyme (e.g. selectivity and stability)

basis of current project:

BMC Biotechnology



Research article

Open Access

Engineering proteinase K using machine learning and synthetic genes

doi:10.1186/1472-6750-7-16

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Basic machine learning tools: linear regressions like:

- ridge regression least absolute shrinkage and selection operator (Lasso)
- partial least square regression (PLSR)
- support vector machine regression (SVMR)
- linear programming support vector machine regression (LPSVMR)
- linear programming boosting regression (LPBoostR)
- matching loss regression (MR)
- one-norm regularization matching-loss regression (ORMR)

explorable sequence space (limitations)

- microtiter plate based screening
10³ - 10⁴ variants per week
100 – 300 sequences
- μ -fluidics
ca. 10⁶ - 10⁸ per week, # sequences in the same range, but limited information on enzyme activity (a better yes-now answer)

future developments

μ -fluidics and chip based technologies
will allow to combine **100 000 000** activities
in the near future (ca. 3-5 years)
several concepts are under development



BIG DATA is awaiting you !

acknowledgements

RNA polymerization crew

Pierre-Alain Monnard (SDU Odense)
Philipp Löffler (SDU Odense)

machine Learning crew

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Marc Hellmuth (Uni Greifswald)
Stefan Born (TU Berlin)

de-novo protein crew

Ivan Korendovych (Syracuse, NY)
Moritz Voß (PhD student)
Caroline Nolten (Bachelor student)

group leader

Uwe Bornscheuer

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Thank you for your attention !

lara.uni-greifswald.de

tRNA and condon usage

- tRNA gene clustering
- tRNA concentration / abundance
- tRNA codon fidelity
- mRNA folding during translation
- tRNA modifications (“stress answer” ?)

nice review on that topic:

Novoa, E. M.; Ribas de Pouplana, L. Trends in Genetics **2012**, 28 (11), 574–581.

[dx.doi.org/10.1016/j.tig.2012.07.006](https://doi.org/10.1016/j.tig.2012.07.006)