Assessment of EMA in CASP14 (Evaluation of Model Accuracy)



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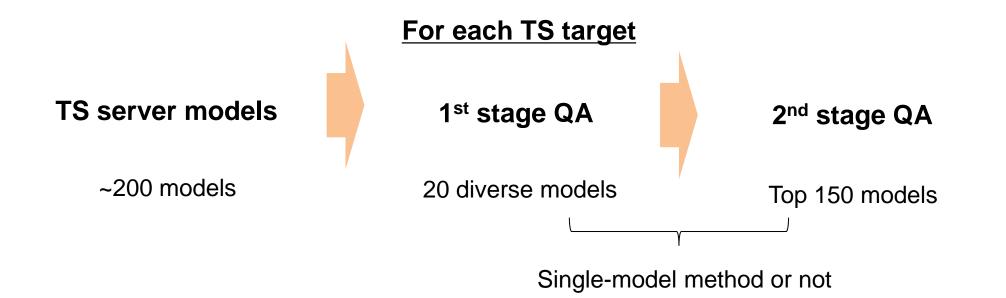
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CASP Organizers

What useful things can QA do after AlphaFold2?

QA participants did not have a chance to score AlphaFold2 models in CASP14. (except for a bit of post-analysis for CASP-COVID)

EMA/QA (Quality Assessment) of 3D models generated by TS servers



Global and Local QA:

- Global QA score (0~1) for each model (e.g. GDT-TS or LDDT)
- Local QA score (Å) for each residue of each model (distance deviation upon superposition)

Group Statistics

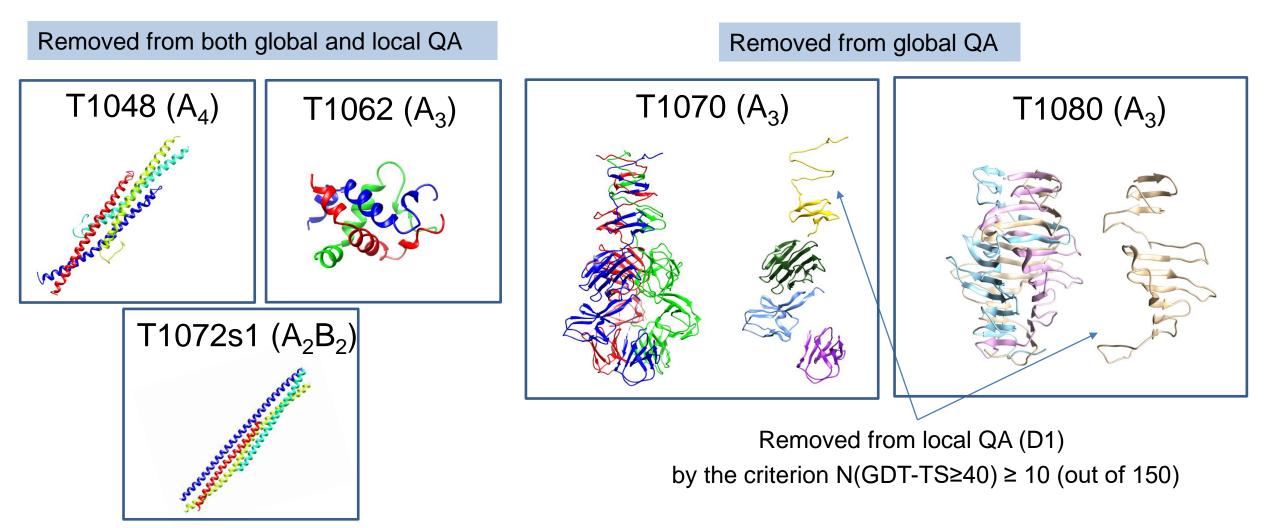
- Global QA
 - # groups = 73 (51 in CASP13)
 - g005, g044, g428: submitted only ~10% targets
 - g082: ~15%; g398: ~55%
- Local QA
 - # groups = 38 (29 in CASP13)
 - g082: ~15%

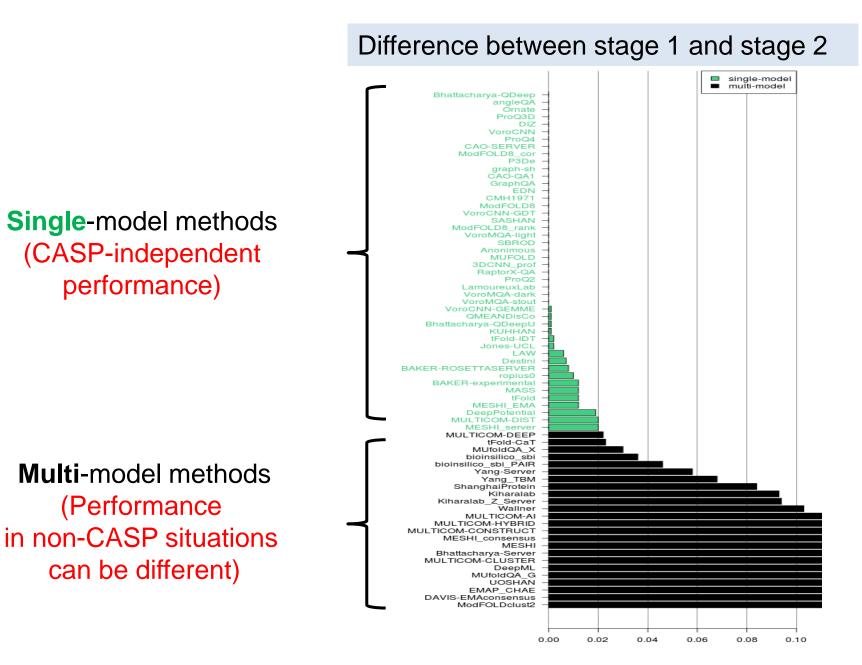
Target statistics

- Global QA targets (whole seq): 71 targets (79 in casp13)
 - N(GDT-TS≥40) ≥ 1 (out of 150): 58 targets
 - N(LDDT≥40) ≥ 1 (out of 150): 64 targets
 - (removed after manual inspection: T1048, T1062, T1072s1, T1070, T1080)
- Local QA targets (EU-wise): 94 EUs (108 in casp13)
 - N(GDT-TS≥40) ≥ 10 (out of 150): 90 EUs
 - (removed after manual inspection: T1070-D1, T1080-D1)

Removed targets after manual inspection

Oligomeric targets whose monomers show no core structures (QA of oligomeric targets → CAPRI QA)





Please contact me if you think that your method is misclassified.

How can QA contribute?

Scoring models after structure prediction

Global QA to select the best models Local QA to identify inaccurately/accurately modeled regions (with biomedical applications in mind)

Scoring models for better structure prediction

Global QA to guide conformational sampling during iterative structure prediction Local QA to detect inaccurately modeled regions to improve (e.g. by refinement)

Ranking global QA results (1/2)

Structure quality of top 1 model selected by QA

(Assessment for top 5 models resulted in very similar ranking.)

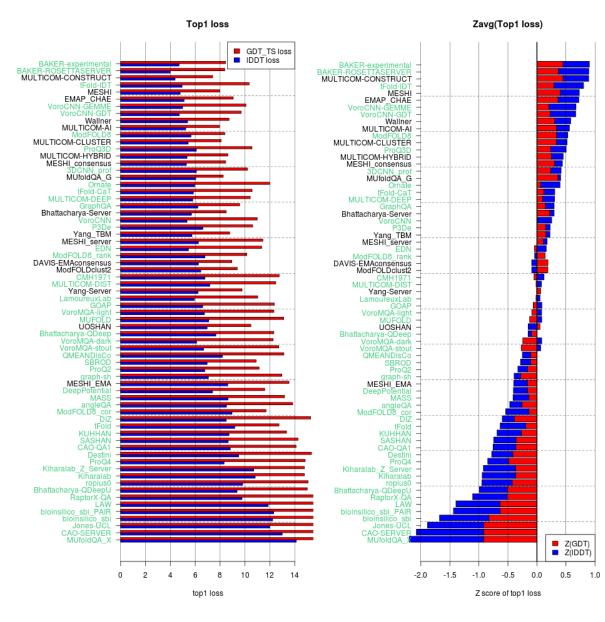
GDT-TS loss = |(GDT-TS of top 1 model) – (best GDT-TS)| LDDT loss = |(LDDT of top 1 model) – (best LDDT)|



Global QA ranking by sum of Z-scores for GDT-TS and LDDT

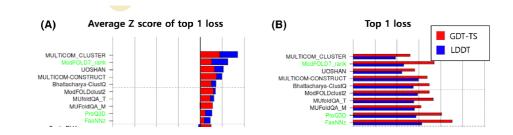
Z-score calculated by the standard CASP procedure with minimum z-score of -2. Penalty of -2 for un-submitted targets.

Global QA results (1/2): Ranking in Top1 loss



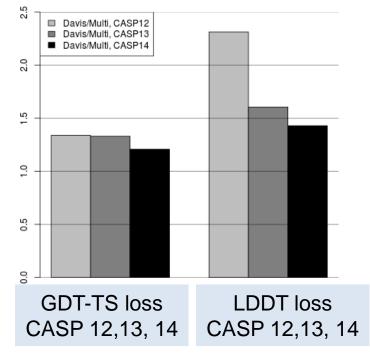
Best single-model methods: BAKER-ROSETTASERVER BAKER-experimental tFOLD-IDT

The best **multi**-model method performed worse than the best single-model method unlike in CASP13.



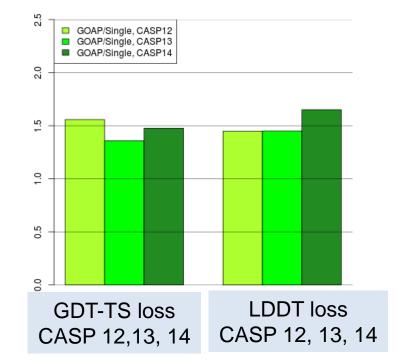
Progress over previous CASPs

Performance of the best **multi**-model method got worse when scaled by that of **DAVIS**



Davis-EMAconsensus $\operatorname{score}_{i} = \left\langle \frac{N_{\operatorname{res, model}}}{N_{\operatorname{res, target}}} (\operatorname{GDT-TS})_{i, \operatorname{model}} \right\rangle_{\operatorname{model}}$

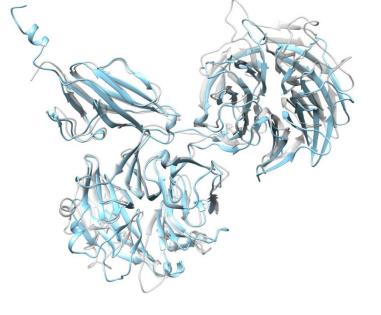
Performance of the best **single**-model method improved when scaled by that of **GOAP**

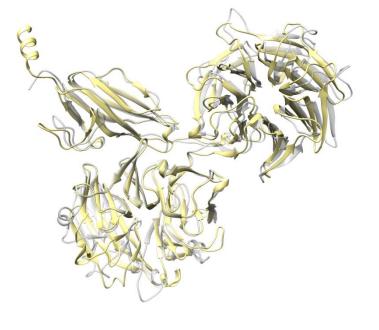


Similar LDDT, lower GDT-TS models were ranked higher (Example 1)

T1050



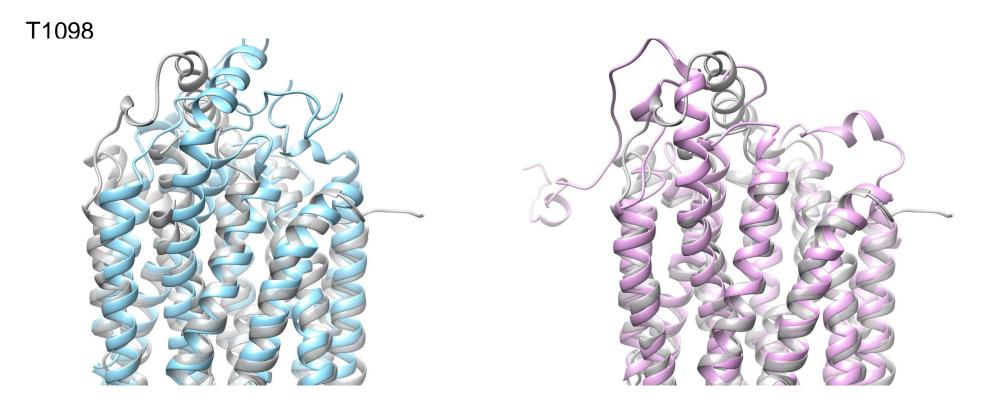




TS209_1

GDT-TS = 40 LDDT = 68 (Top 1 by 5 QA groups) TS487_1 GDT-TS = 56 LDDT = 67 (Top 1 by 13 QA groups) TS487_2 GDT-TS = 65LDDT = 67(not selected as top 1 by any QA)

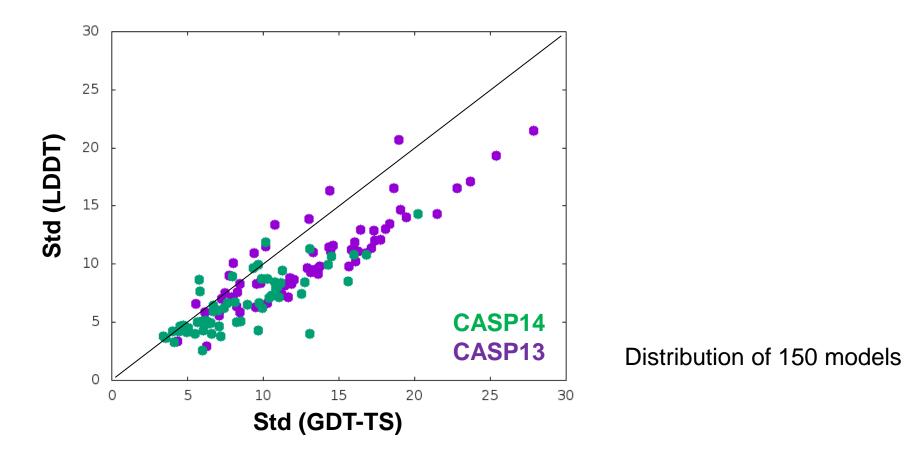
Similar LDDT, lower GDT-TS models were ranked higher (Example 2)



TS183_2 GDT-TS = 50 LDDT = 51 (Top 1 by QA247, QA325) TS075_4 GDT-TS = 57 LDDT = 52 (not selected as top 1 by any QA) Hard to find models with large variations in LDDT with similar GDT-TS unlike in CASP13.

Top server models are now more optimized in sidechains for given backbone structures in this CASP.

In addition, server models tend to be closer to each other in this CASP.



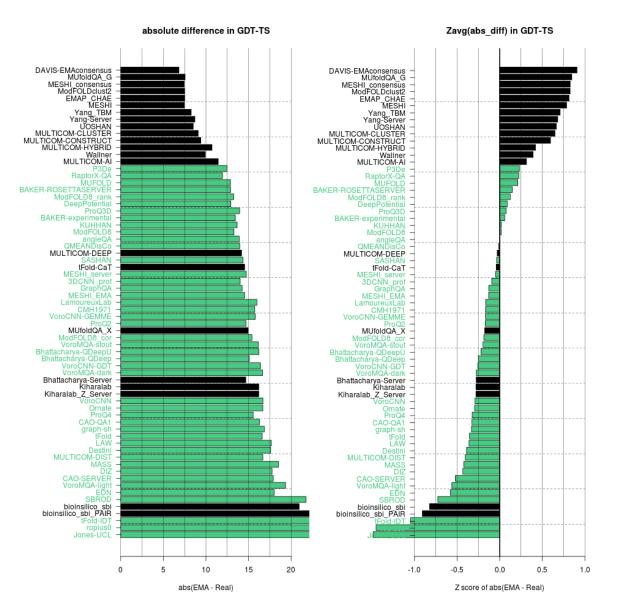
Ranking global QA results (2/2)

Absolute score

GDT-TS difference = |(QA score) – (GDT-TS of model)| LDDT difference = |(QA score) – (LDDT of model)|

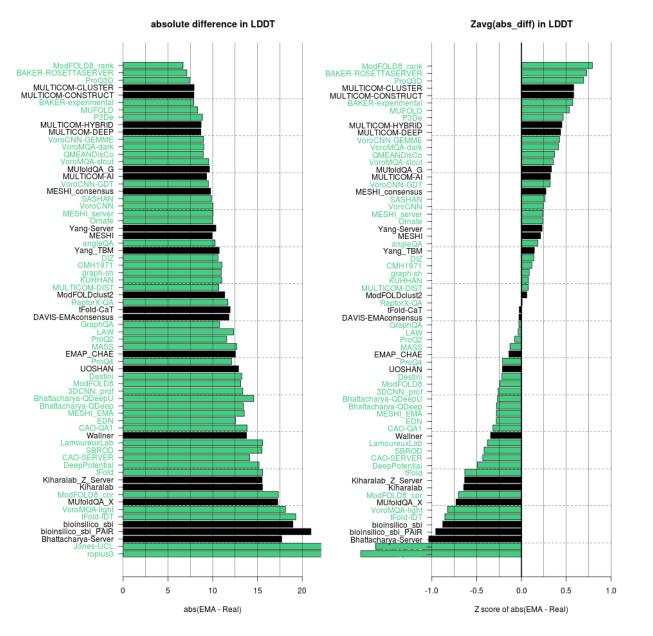
(per-model analysis)

Global QA results (2/2): Absolute GDT-TS difference



 Best absolute GDT-TS estimation by DAVIS with Δ=7.5 (6 in casp13)

Global QA results (2/2): Absolute LDDT difference



- Best absolute LDDT estimation by single-model methods with Δ=7 (6 in casp13)
- Best methods: ModFOLD8_rank, BAKER-ROSETTASERVER

Ranking local QA results

Z-score sum of three measures (ASE, AUC, & ULR-F1)

Model structures GDT-TS > 40 & Distance deviation calculated after EU-wise LGA superposition.

• ASE

Average residue-wise S-score difference

ASE =
$$\left(1 - \frac{1}{N} \sum_{i=1}^{N} |S(e_i) - S(d_i)|\right) \times 100$$

 $S(d) = \frac{1}{1 + (d/d_0)^2}$ $d_0 = 5$ Å

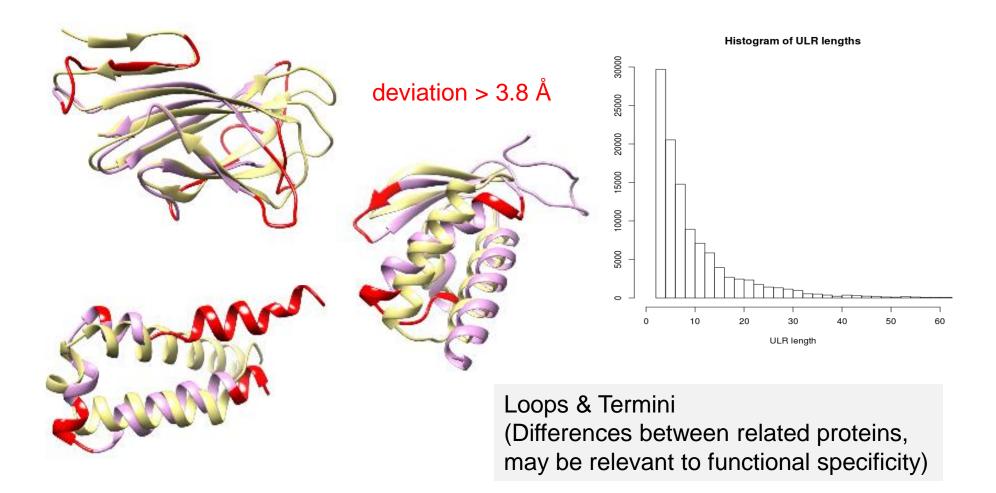
• AUC-ROC

Predictions for Inaccurately/accurately modeled residues (> 3.8 Å) by varying cutoff for each methods

• ULR-F1

Ability to detect inaccurately modeled regions

 ULR (unreliable local region): A region of sequential residues with distance deviation > 3.8 Å. (Single residues sandwiched between ULRs are united to neighboring ULRs, Minimum ULR length = 3)



 Assessing performance of ULR prediction F1 score with tolerance of +2 or -2 residues at each end of ULRs

 $F1 = 2 \frac{\text{accuracy} \times \text{coverage}}{\text{accuracy} + \text{coverage}}$

 $accuracy = \frac{\# \text{ correctly predicted ULR}}{\# \text{ predicted ULR}}$

 $coverage = \frac{\# correctly predicted ULR}{\# actual ULR}$

- The best score cutoff to maximize the F1 score was used for each group. (Several groups submitted scores in 0~1 scale)
- Naïve_Loop method (a reference method for local QA)
 Amino acid distance (Å) from the closest residue with secondary structure

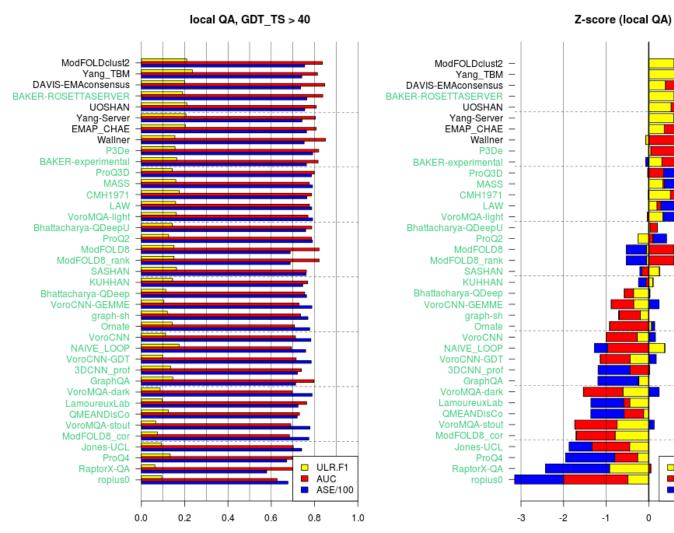
Local QA ranking

Z(ULR.F1)

Z(AUC)

Z(ASE)

Z-scores



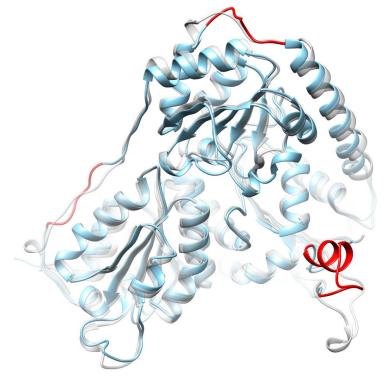
Only two **multi**-model methods did better than **DAVIS** (Best ULR-F1 of 0.24 by **Yang_TBM**)

Best **single**-model method: **BAKER-ROSETTASERVER** (ULR-F1 = 0.19)

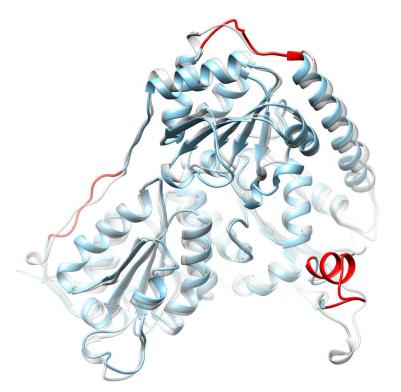
Naïve_Loop: ULR-F1 = 0.17ASE = 0.76AUC = 0.7

Higher performance for multi-model methods implies common structure prediction failures in certain regions (due to less structural or sequence information) for TS-servers.

Example 1: T1076-D1 (almost perfect ULR prediction)

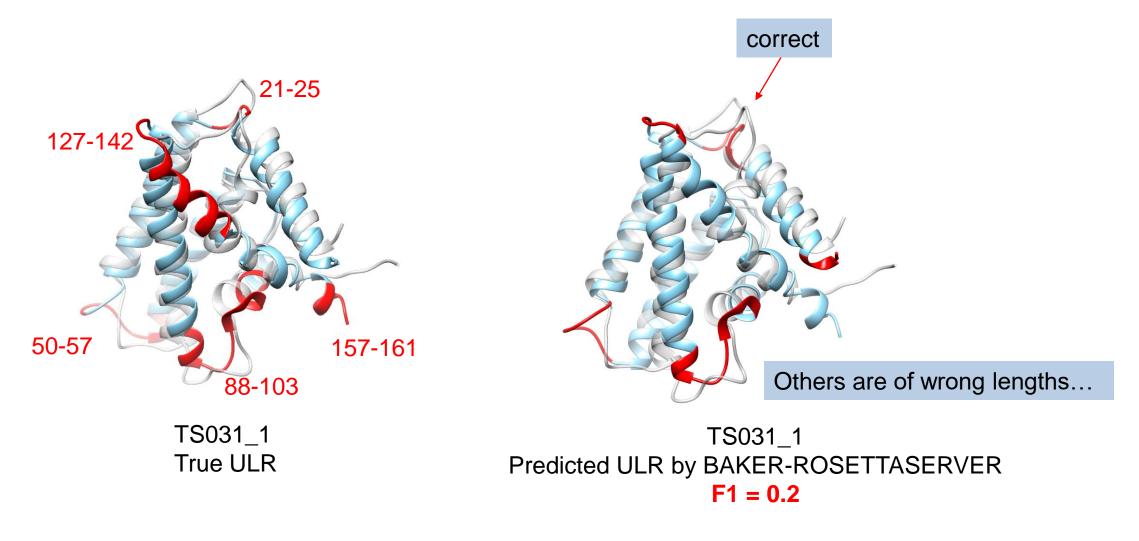


TS198_3 True ULR



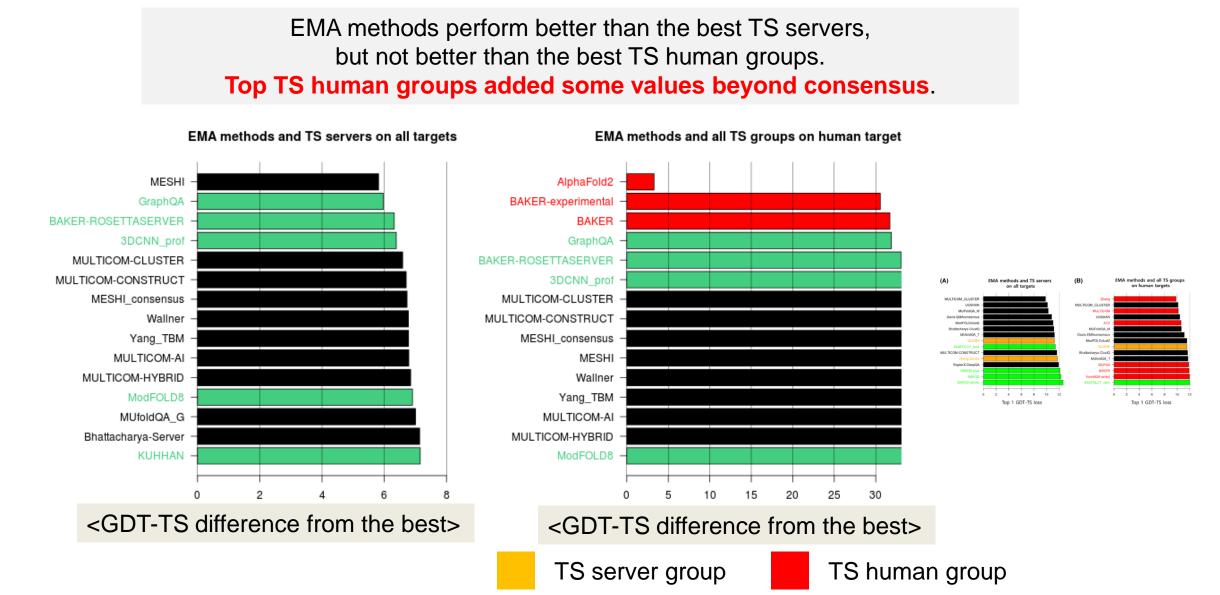
TS198_3 Predicted ULR by BAKER-ROSETTASERVER F1 = 1.0

Example 2: T1039-D1 (partial ULR prediction)



(More relaxed criterion \rightarrow increased F1, but no ranking change)

What if EMA methods participated in CASP14 as meta predictors? (CASP-specific performance)



Can QA help TS?: Best QA Methods for Top TS-servers

(Multi-model methods were not considered here.)

TS209 may be doing something optimal for it, which is different from QA209.	TS209	GDT loss	LDDT loss	TS324	GDT loss	LDI Ios
	TS209	0.73	0.52	TS324	1.79	0.9
	QA209	0.78	0.56	QA263	1.82	1.2
	QA167	0.74	0.67	QA209	2.30	0.9

TS ranked better than QA for

QA ranked better than TS for

TS031	GDT loss	LDDT loss	TS042	GDT loss	LDDT loss	TS226	GDT loss	LDDT loss
QA209	1.63	0.71	QA263	1.22	1.06	QA263	1.68	1.20
TS031	1.26	1.47	QA209	2.06	0.85	QA209	2.27	0.83
QA403	1.95	0.99	TS042	1.97	1.05	TS226	2.16	1.66

Round Table

5' presentation by each of the following groups:

Nao Hiranuma (Baker group) (BAKER-ROSETTASERVER, BAKER-experimental)

Liam McGuffin (ModFOLD8_rank)

Sheng Wang (tFOLD-IDT)

Lisha Ye (Yang group) (Yang_TBM)

Questions

How can QA do better in estimating GDT-TS? [Although low-GDT-TS/high-LDDT matters only for models of intermediate accuracy (50~70)]

How can local accuracy be estimated better?

<Future role of QA with near-perfect structure prediction>

Can QA do something useful for model structures of proteins involving conformational flexibilities or intrinsically disordered proteins?

How does your QA work differently for monomers and oligomers (if you have QA for oligomers)?

Can QA be extended to predict stabilities for monomers and binding affinities for oligomers?

Further visions regarding the role of QA?