CASP16 EMA

QMODE3

Alisia Fadini, Randy Read, Gabriel Studer

Choose top 5 models from the MassiveFold dataset

Large sampling of
AlphaFold2

```
PFRMAT QA
TARGET T0999
AUTHOR 1234-5678-9000
METHOD Description of methods used
MODEL 2
QMODE 3
ranked_0_unrelaxed_model_5_ptm_pred_82.pdb
ranked_13_unrelaxed_model_5_ptm_pred_196.pdb
ranked_28_unrelaxed_model_4_ptm_pred_30.pdb
ranked_32_unrelaxed_model_5_ptm_pred_2.pdb
ranked_4_unrelaxed_model_2_ptm_pred_179.pdb
END
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```

20 groups predicted
more than 60 targets

<u>Baselines</u>: iptm,
iptm+ptm, mean plddt
from MassiveFold

OpenStructure (OST) to score each MassiveFold model against experimental target

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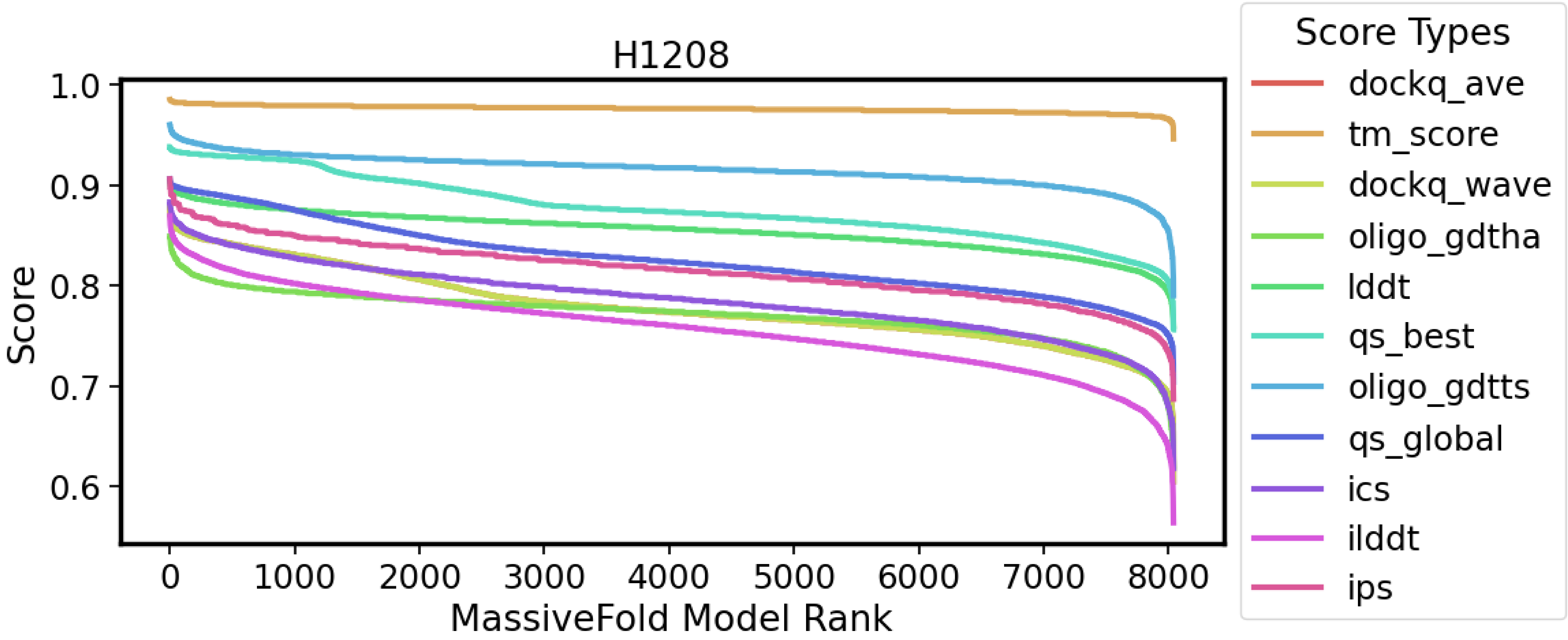

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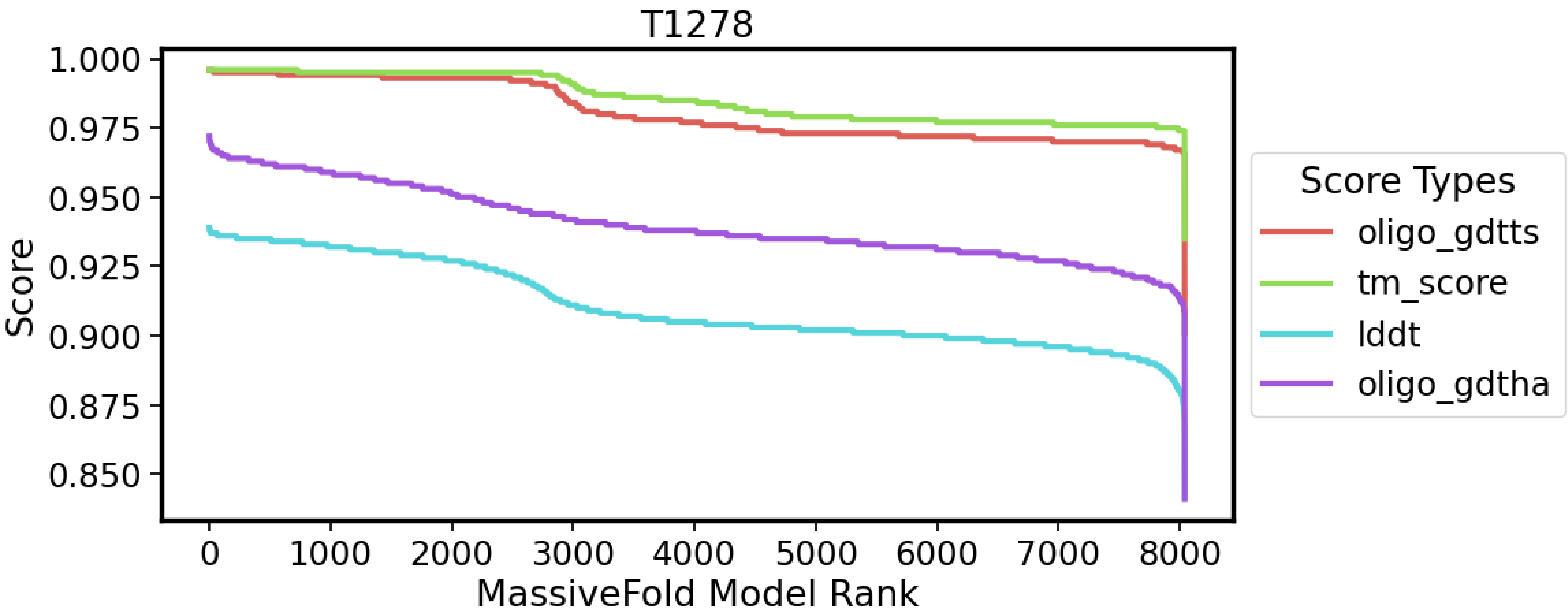

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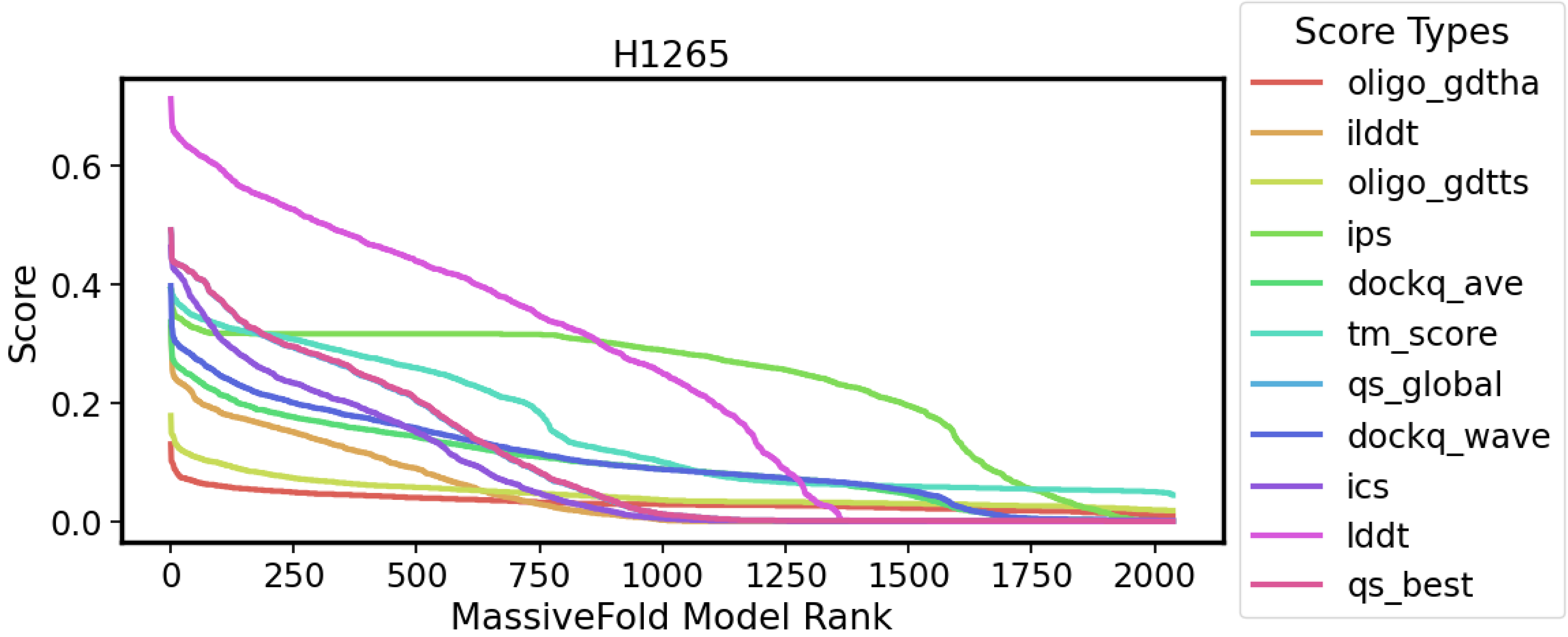

Assessing Group Predictions

Assign a penalty based on predicted ranking and true ranking

$$penalty = \sum_{i=1}^{5} (T_i - P_i)^2$$

T_i, score for i-th model in the true rankings

P_i, score for i-th model in the predicted rankings

Assessing Group Predictions

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OUTPUT FOR EACH PREDICTOR GROUP: **penalty matrix**

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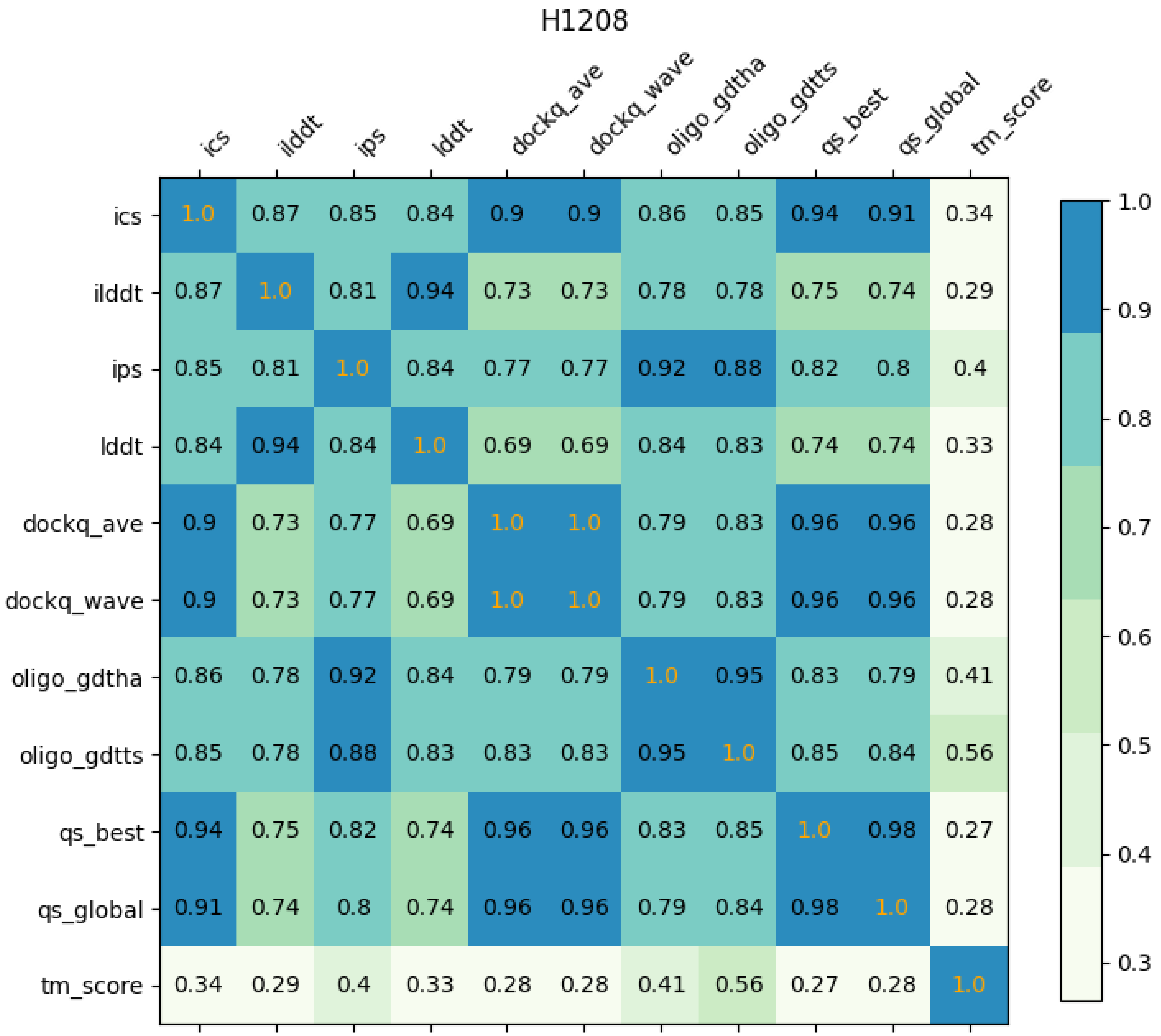
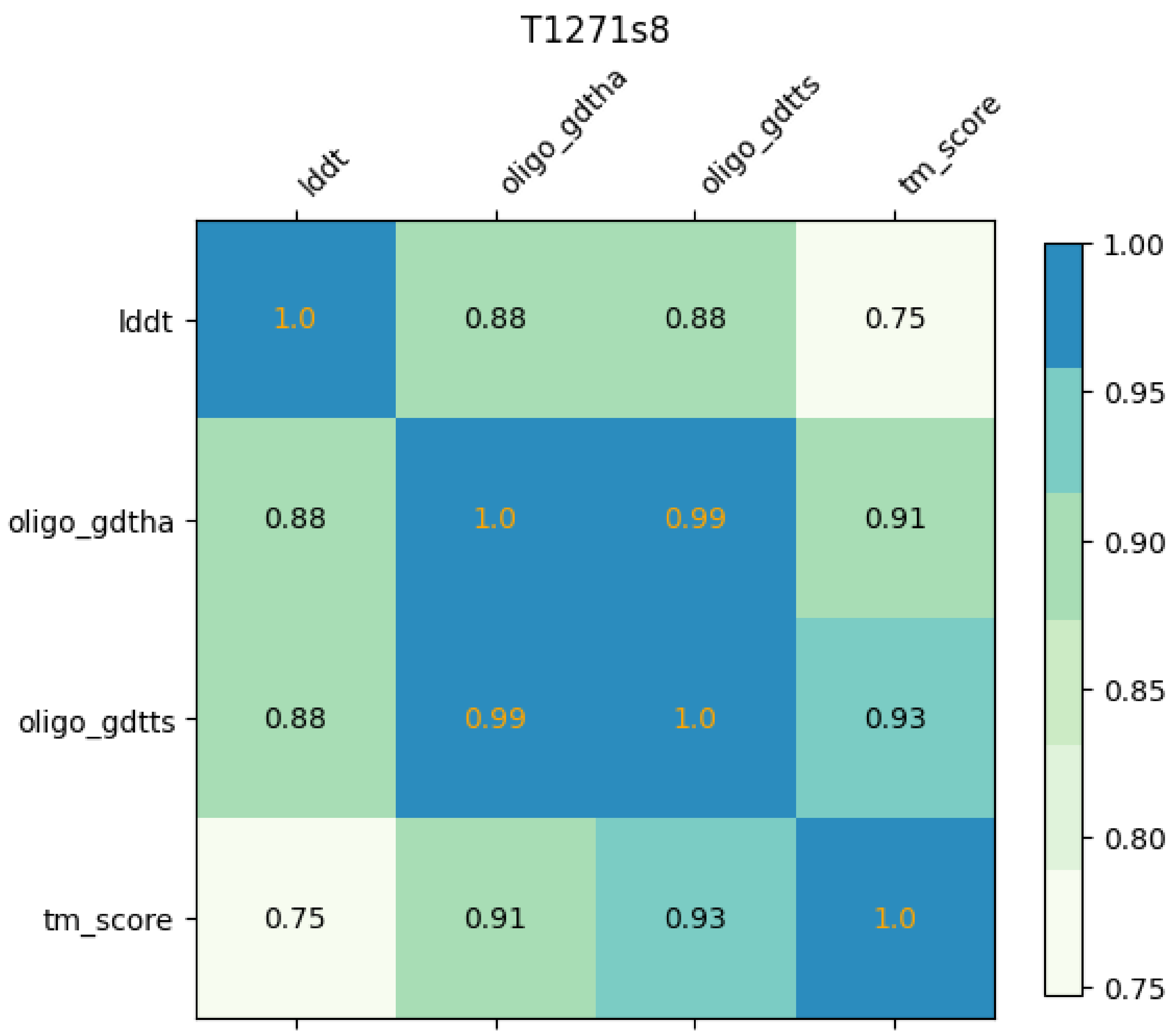
3 categories: monomers, homo-oligomers, hetero-oligomers

Correlation Matrix for Scores in MassiveFold Set



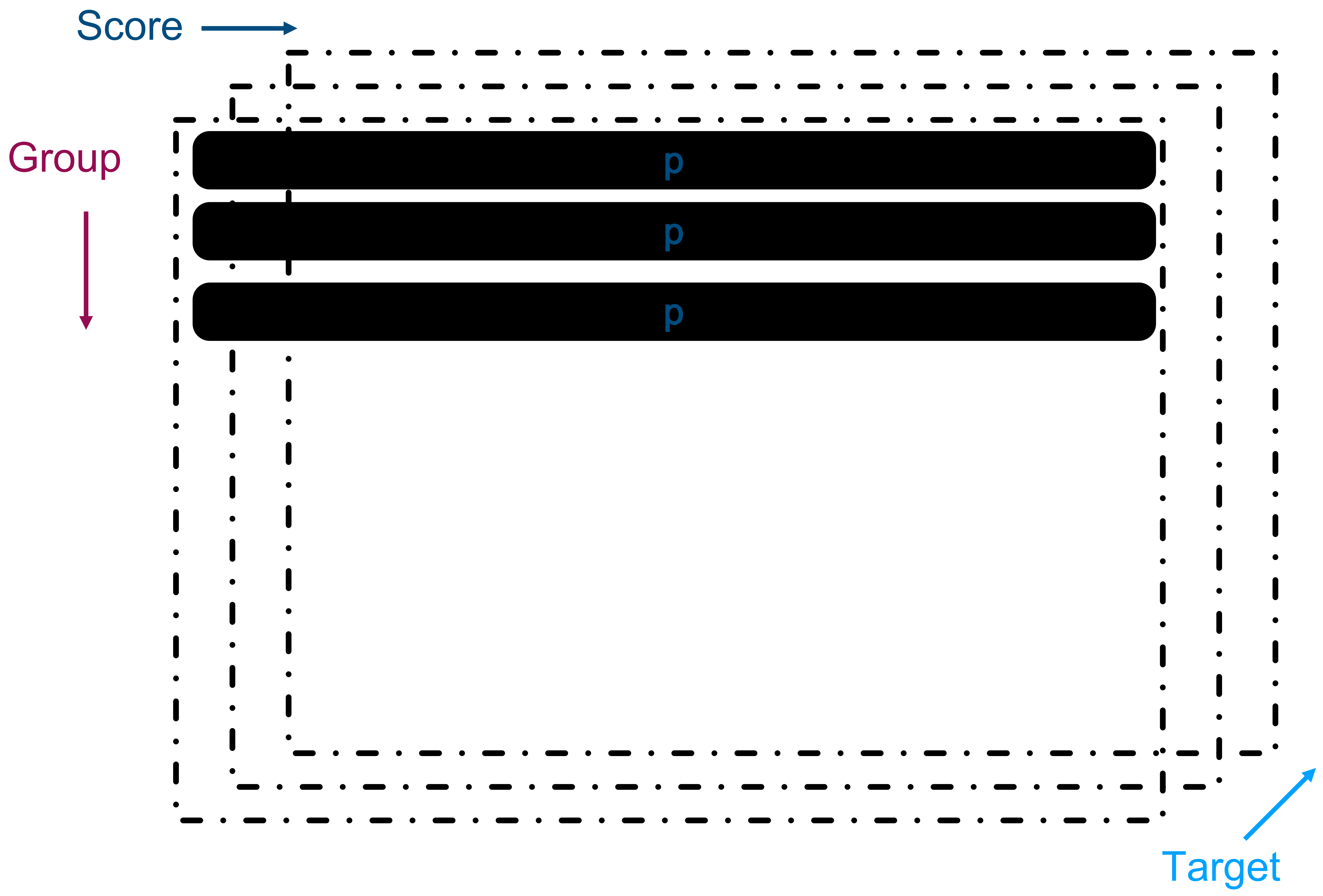
H* target example



T*s* target example

Predictor Group Rankings

weighted_penalty weights the penalties for each score type



weighted_penalty (w_p)

$$\sqrt{\mathbf{p}\Sigma^{-1}\mathbf{p}^{T}}$$

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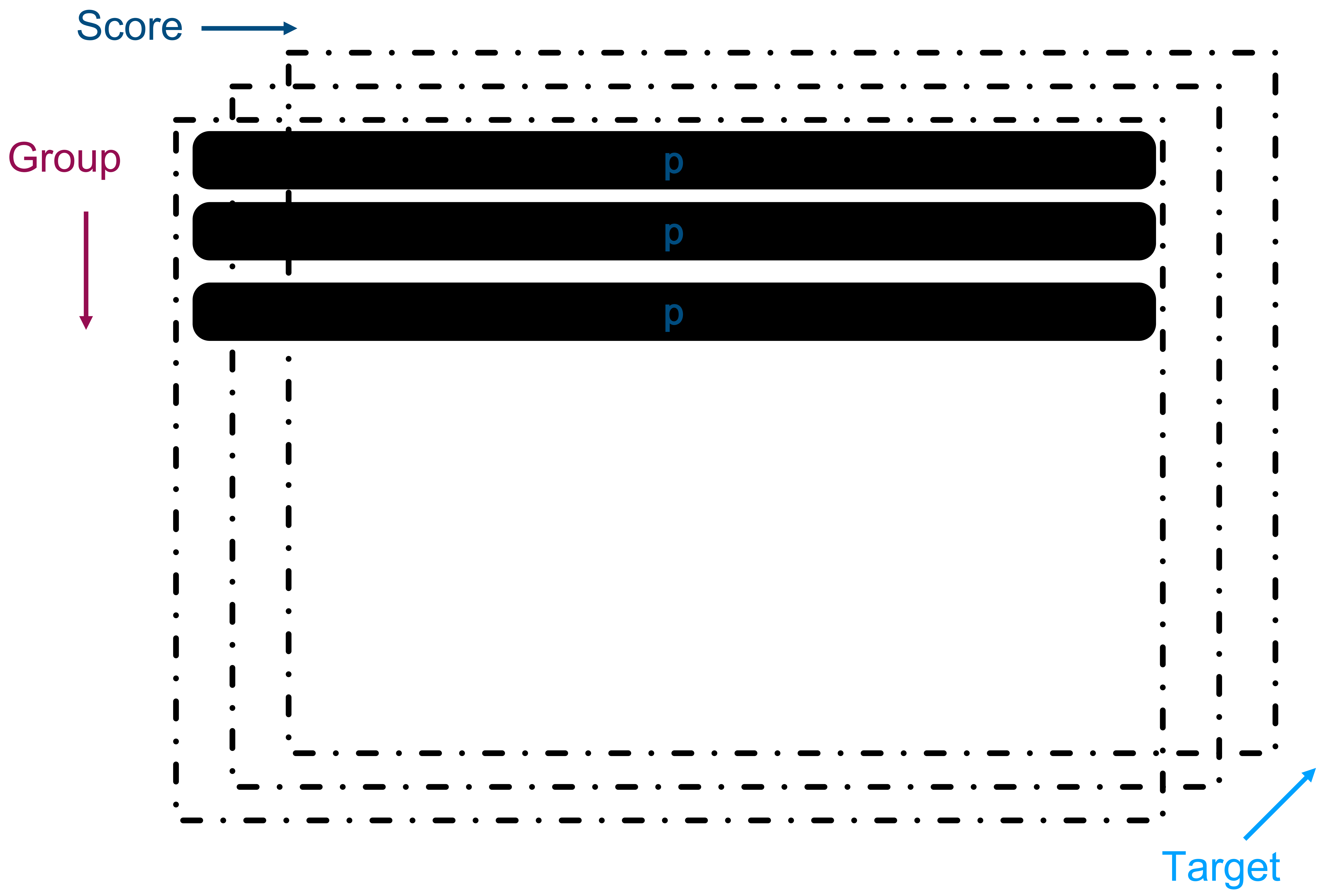

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Σ^{-1} is the covariance matrix of scores for MF models in that category

(also tested the covariance matrix of scores for MF dataset of that target)

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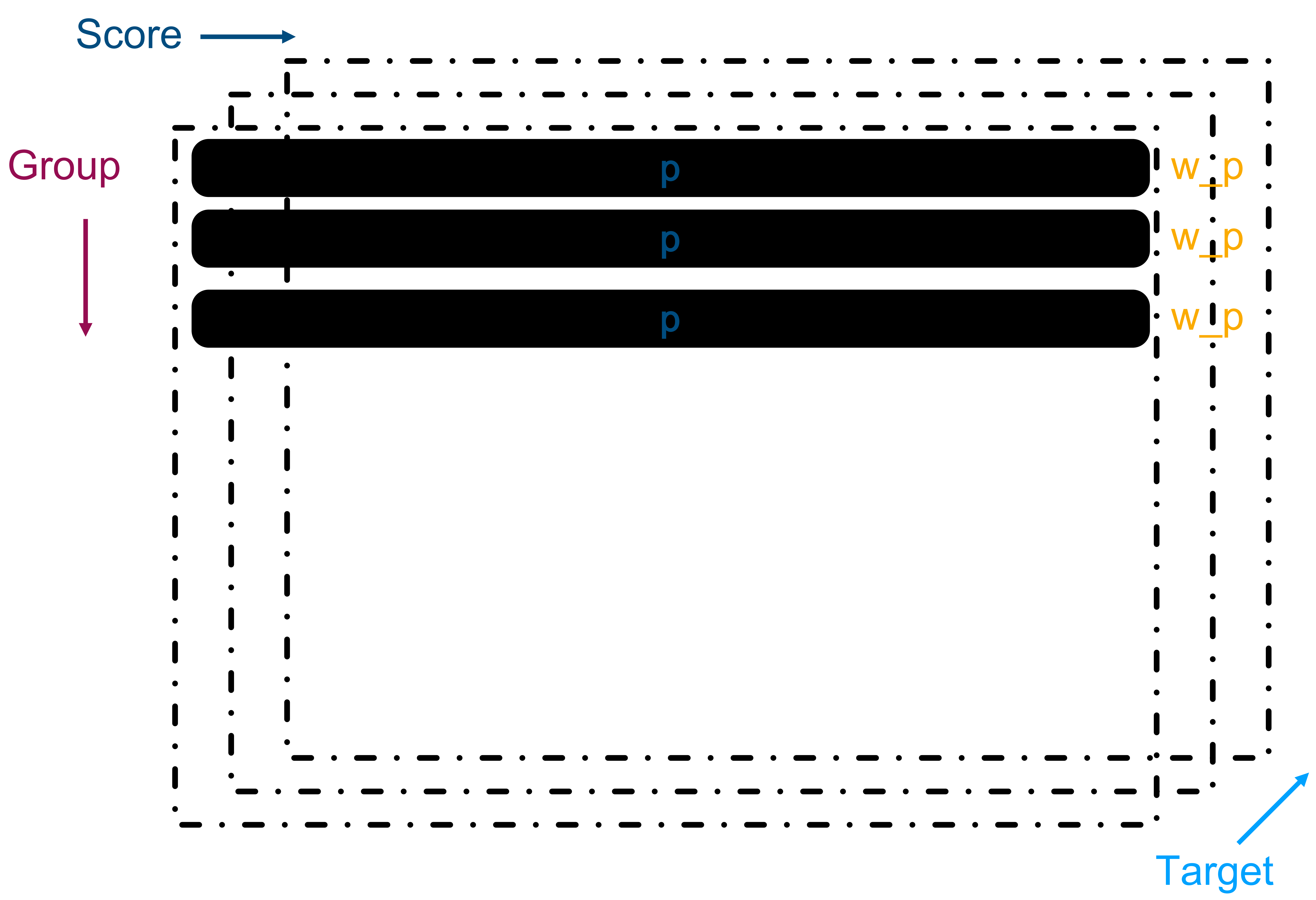

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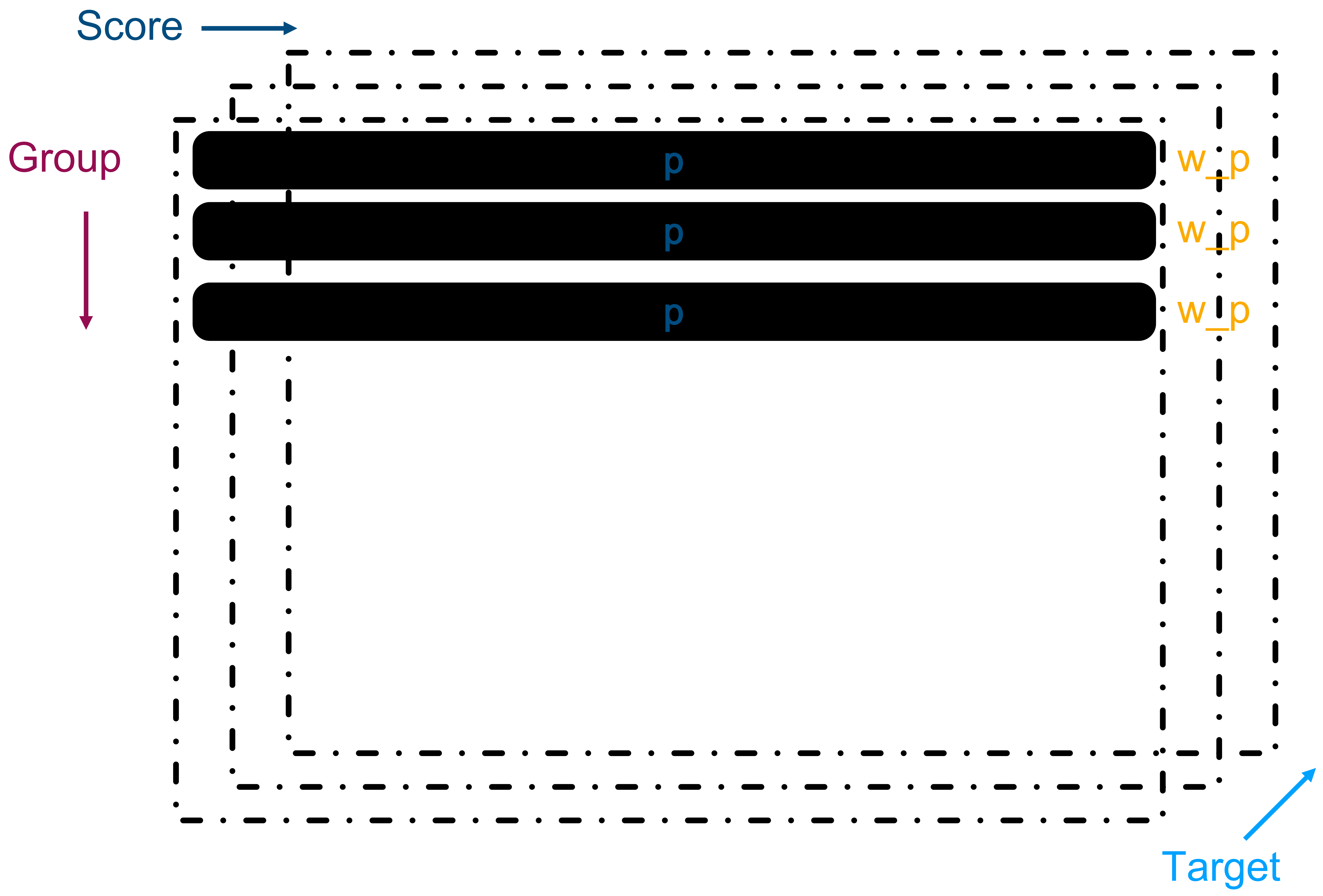

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For each group:

Mean of weighted_penalty over all targets

Predictor Group

Rankings

weighted_penalty, $\Sigma_{\cdot}^{-1}$ outlier rejection

Remove outlier “yarn ball” predictions

Mahalanobis Distance

measure of distance that accounts for correlations between variables and their variances

Useful:
identifying outliers
working with multivariate distributions

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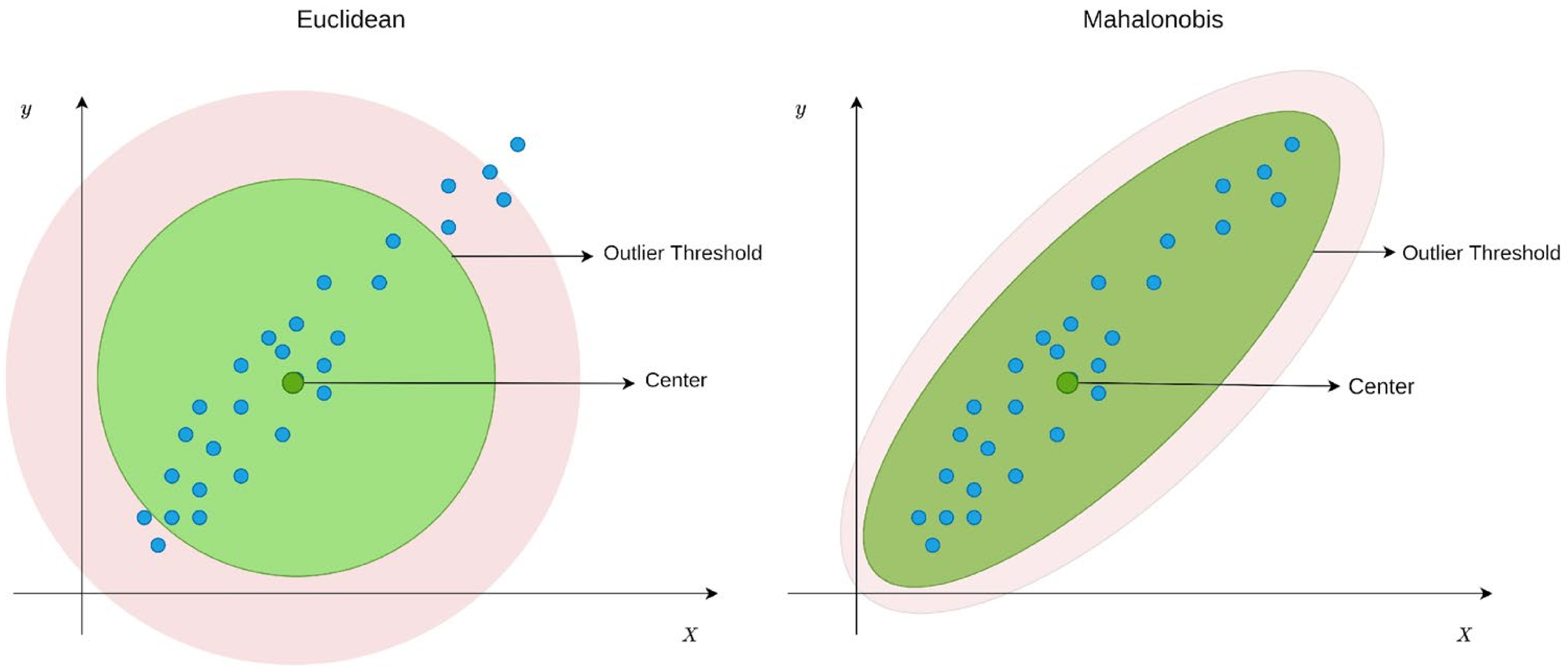
$$D_M(\mathbf{x}) = \sqrt{(\mathbf{x}-\mu)^\top \Sigma^{-1} (\mathbf{x}-\mu)}$$

$D_M(\mathbf{x})$: Mahalanobis distance of point $\mathbf{x}$

$\mathbf{x}$: Data point (vector)

μ: Mean vector of the distribution

Σ: Covariance matrix of the distribution



Plot by Sergen Cansiz, published in Towards Data Science

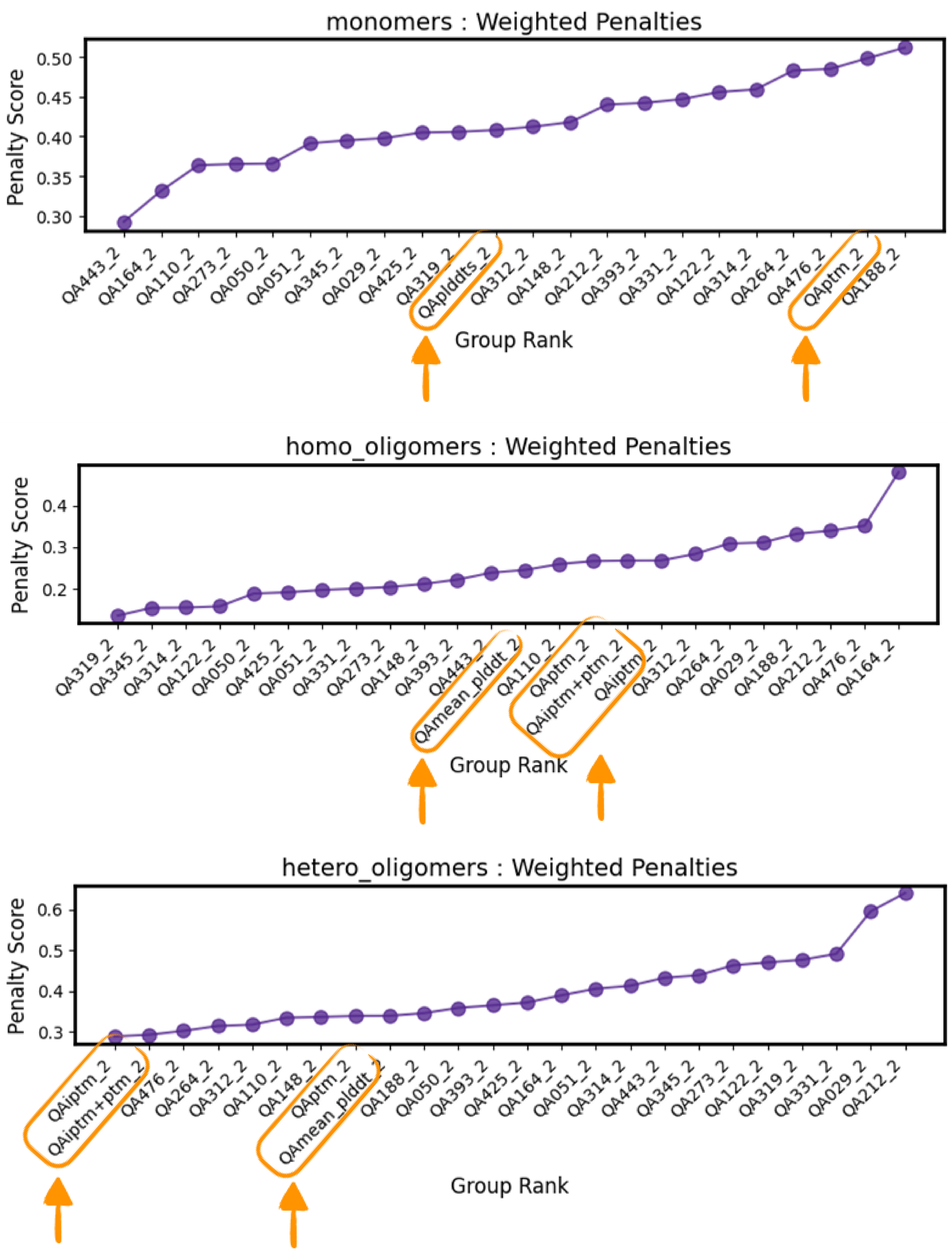
Predictor Group
Rankings
weighted_penalty, Σ^{-1} outlier rejection

Calculated Mahalanobis distance for each model from distribution of all models

Reject models with Mahalanobis distance larger than 3 standard deviations for Σ^{-1} computation

Remove outlier "yarn ball" predictions

Weighted Penalty-Based Rankings



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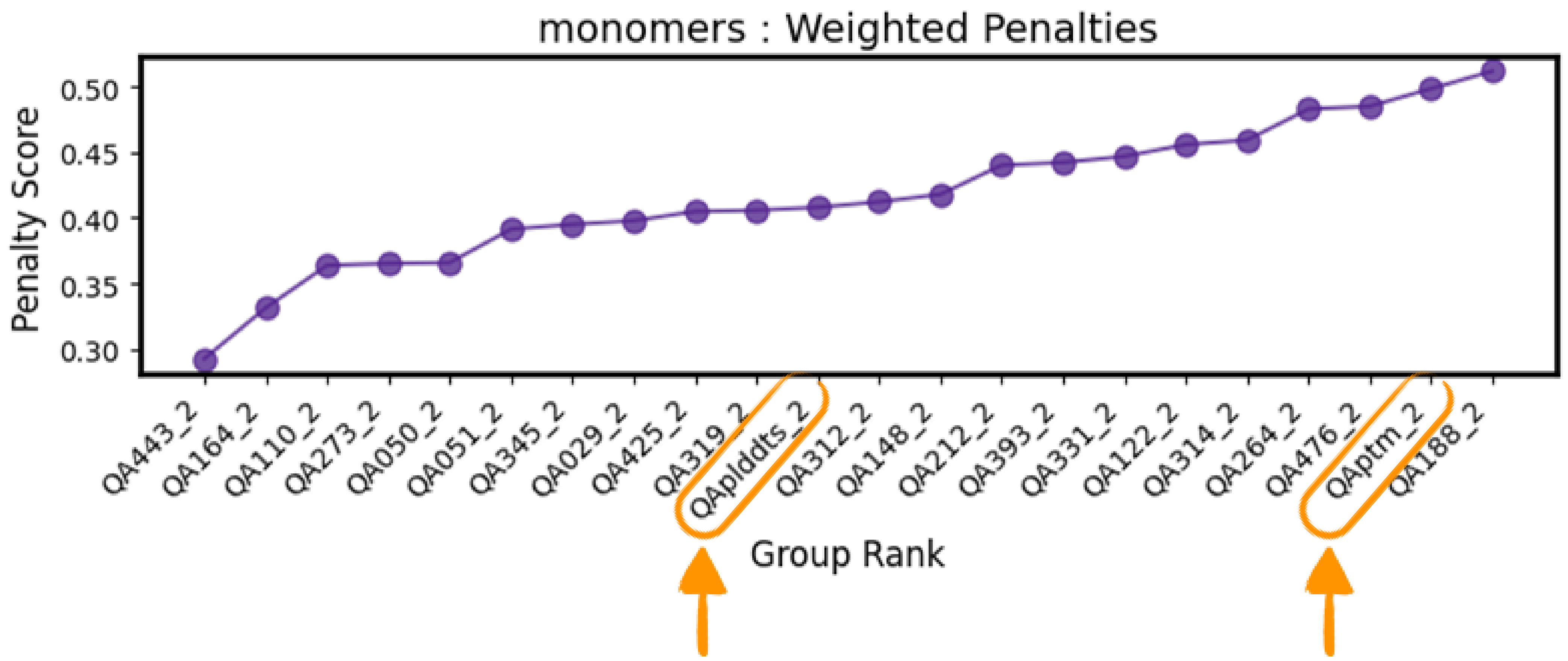
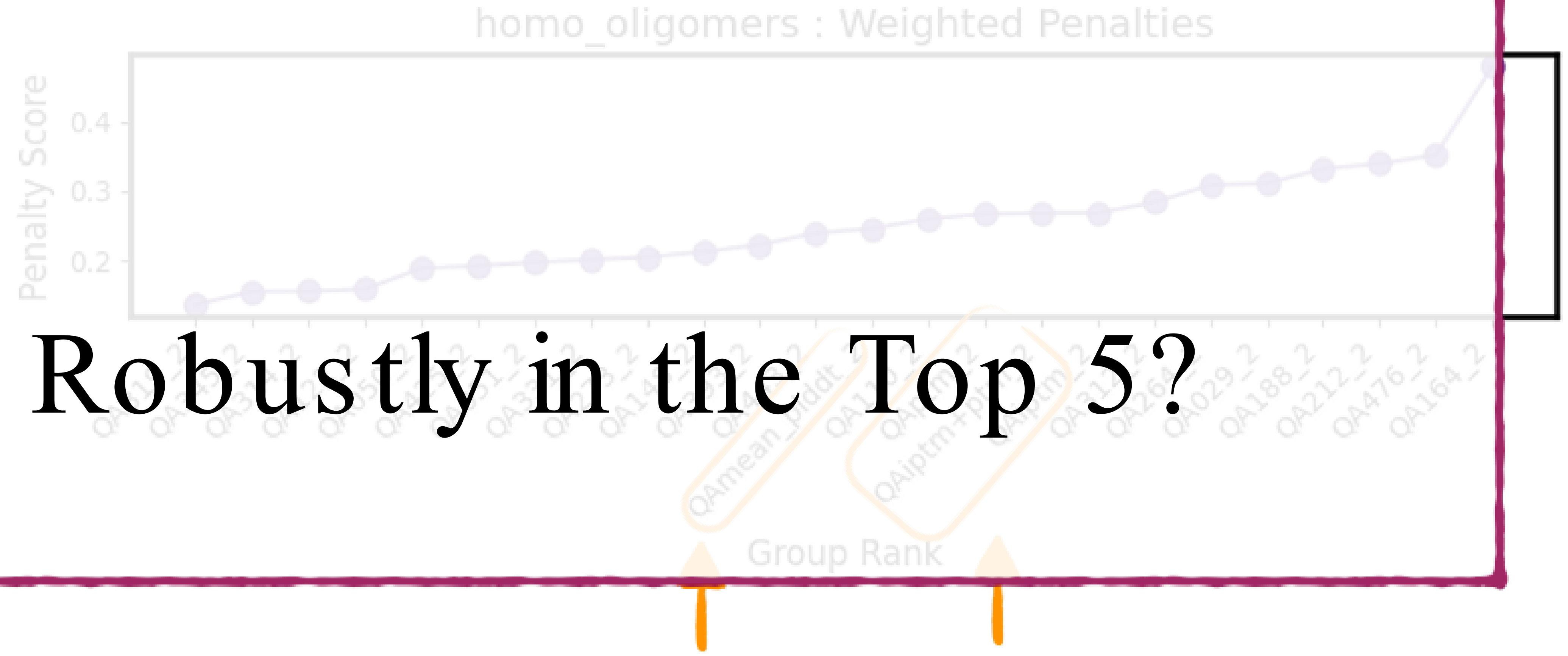
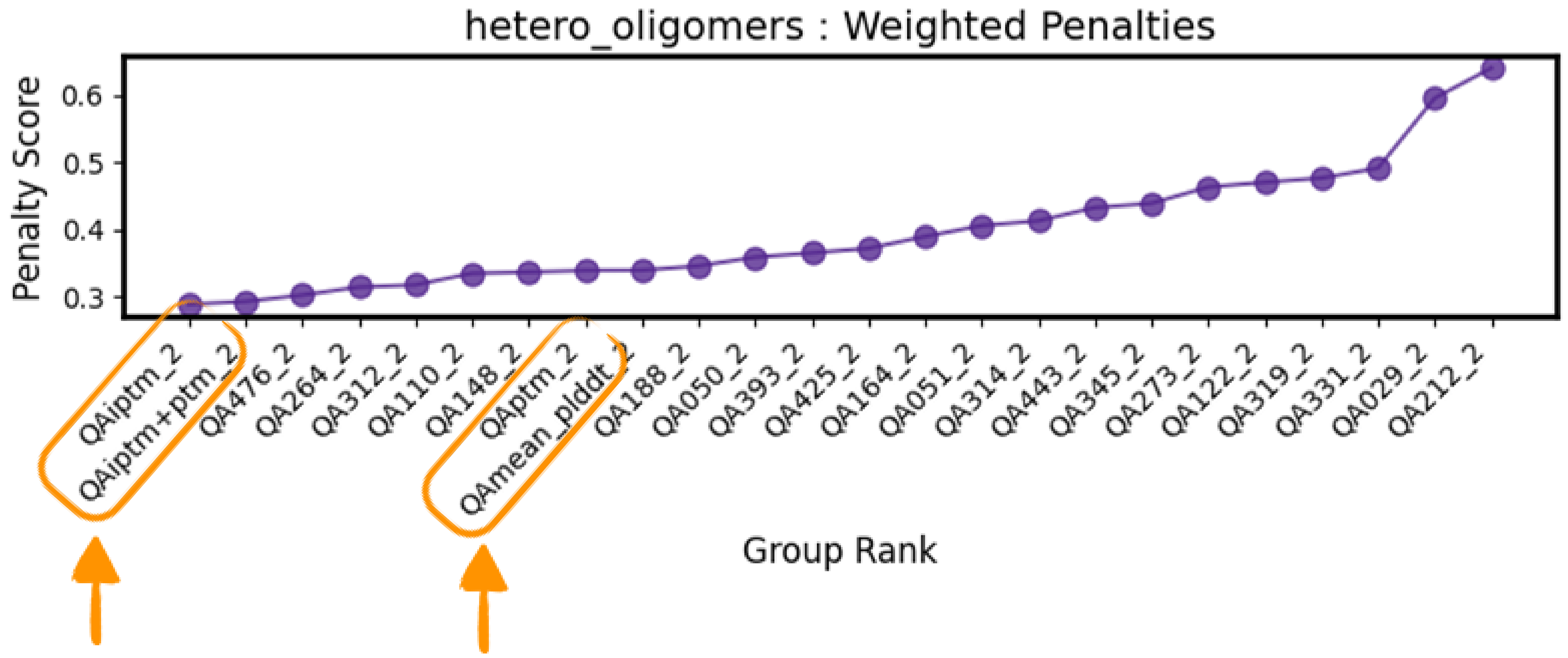
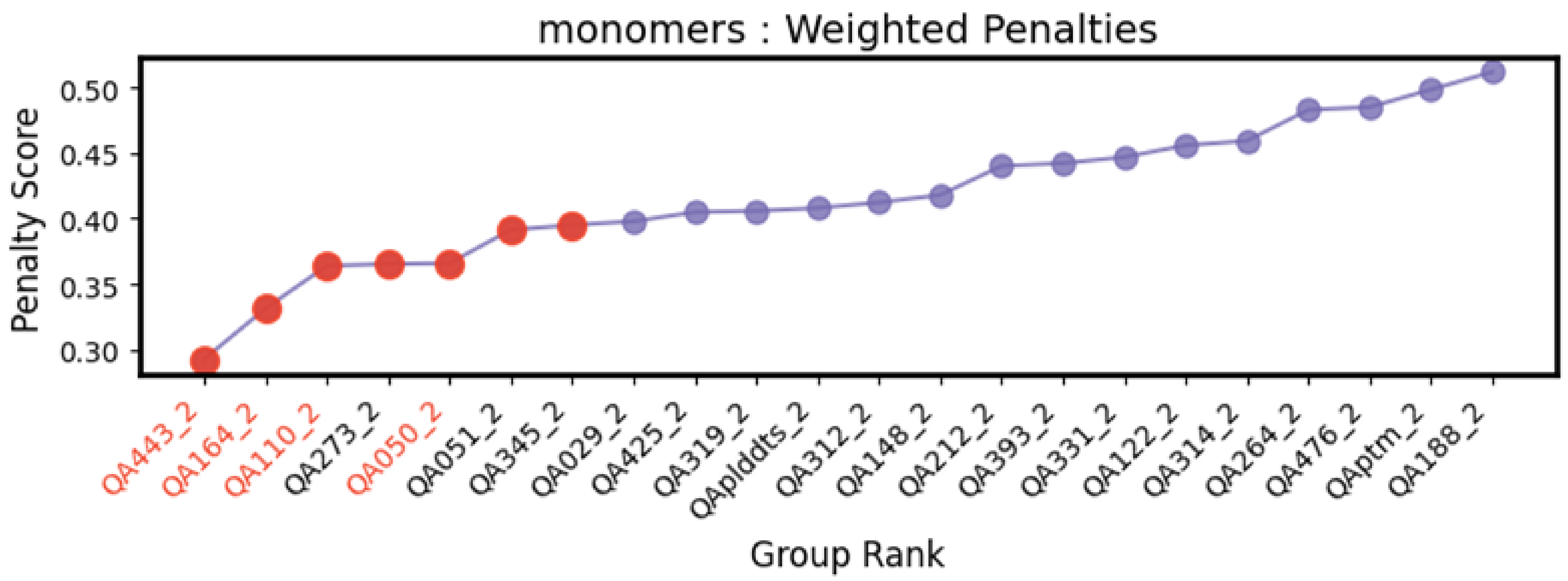


Groups Robustly in the Top 5?





Robust to ranking by Z-score and per-target covariance:



050 David Shortle – Human

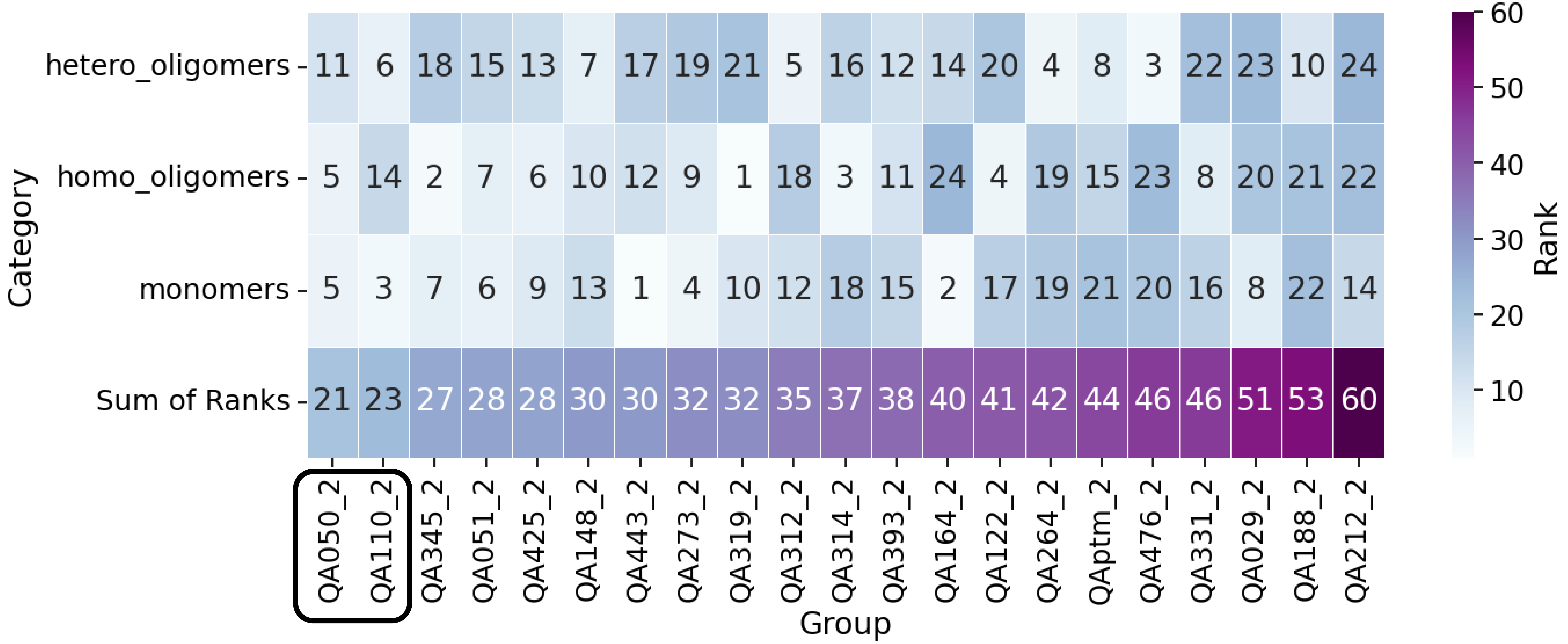
110 Wei Zheng – MIEnsembles-Server

164 Liam McGuffin – Human

Strong for Generality

050 David Shortle – Human

110 Wei Zheng – MIEnsembles-Server



050 David Shortle – Human
110 Wei Zheng – MIEnsembles-Server

050 David Shortle – Human

Method

- Scored models with a collection of statistical parameters and potentials.
- Compared model scores with the scores of 6000 high resolution PDBs.

Characteristics

- High resolution structure set was collection of single chain PDBs
- 3 sets of parameters combined and added with weights for a combination score

110 Wei Zheng – MIEnsembles-Server

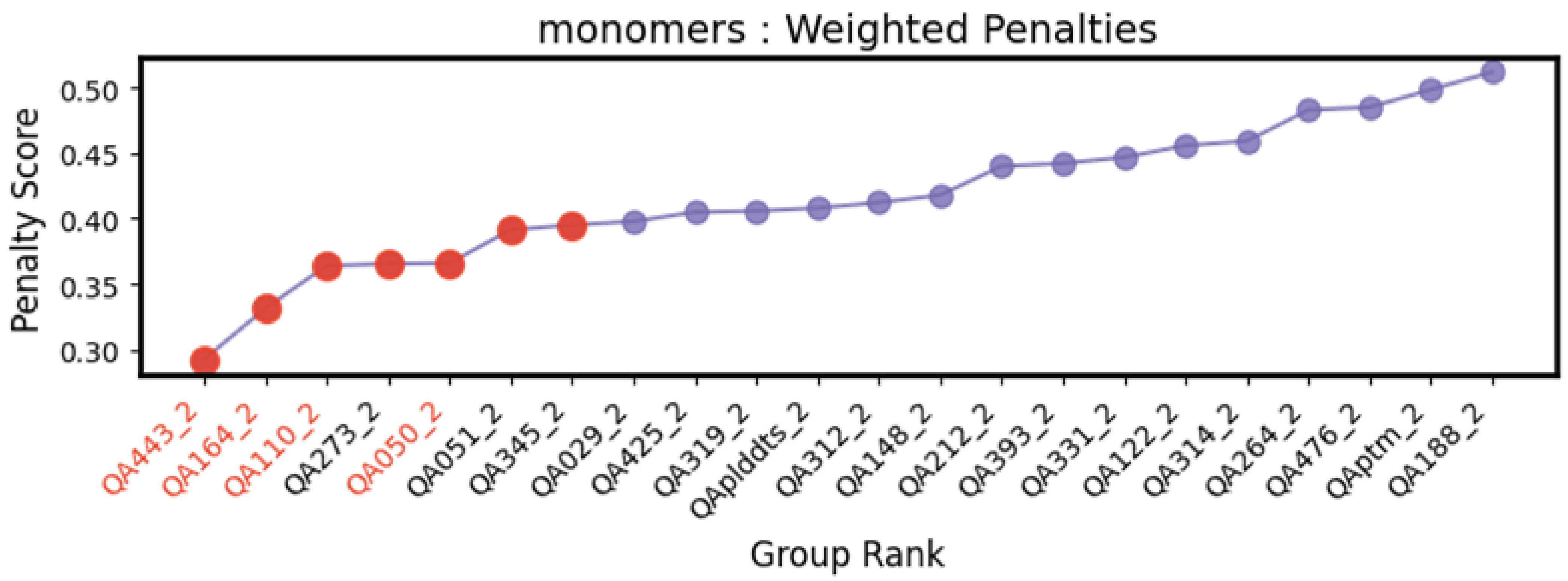
Method

- Use DMFold to construct high-quality MSAs for improved structure predictions.
- QA method integrates DMFold models to assess the quality of MassiveFold models

Characteristics

- Quality of the reference model influences the performance of the QA method
- For complexes: DMFold confidence (0.8ipTM+0.2pTM) is less sensitive in picking correct models than mean plddt for monomers

Robust to ranking by Z-score and per-target covariance:



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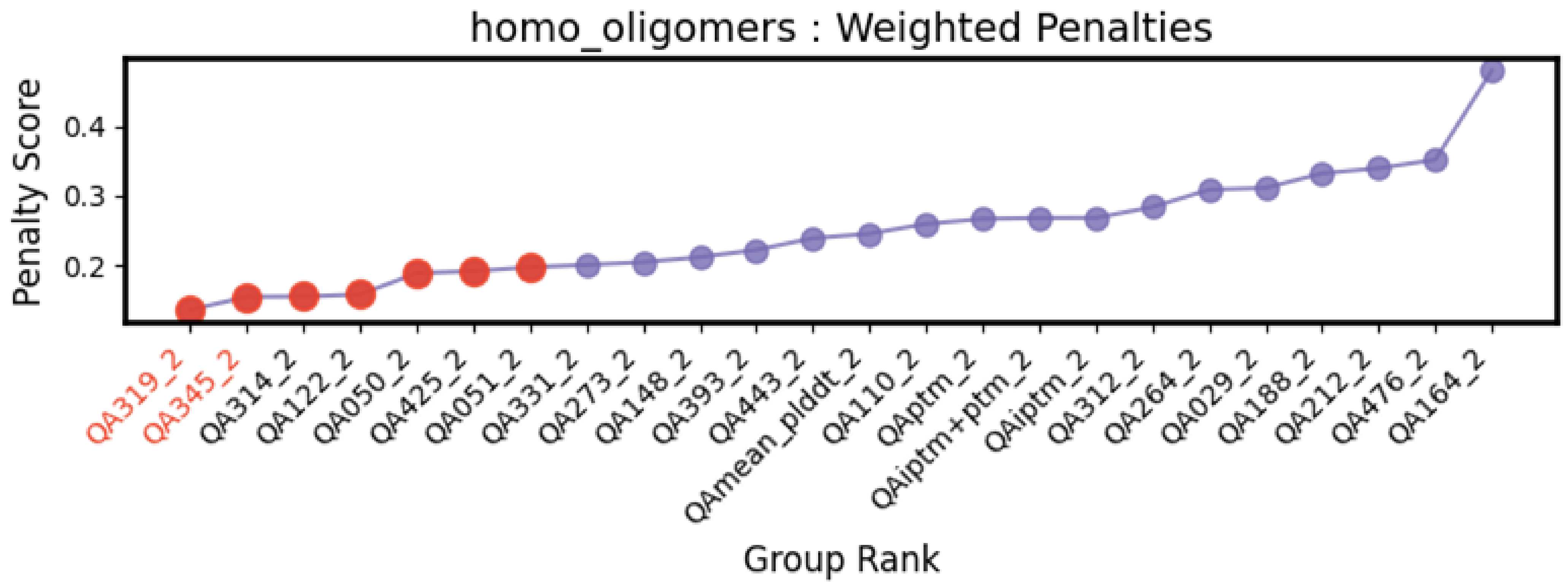

319 Jianlin Cheng – MULTICOM_LLM

345 Jianlin Cheng – MULTICOM_HUMAN

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319 Jianlin Cheng – MULTICOM_LLM

Method

- 200 MassiveFold models selected based on confidence scores
- MULTICOM QAs to select the top 5 models

Characteristics

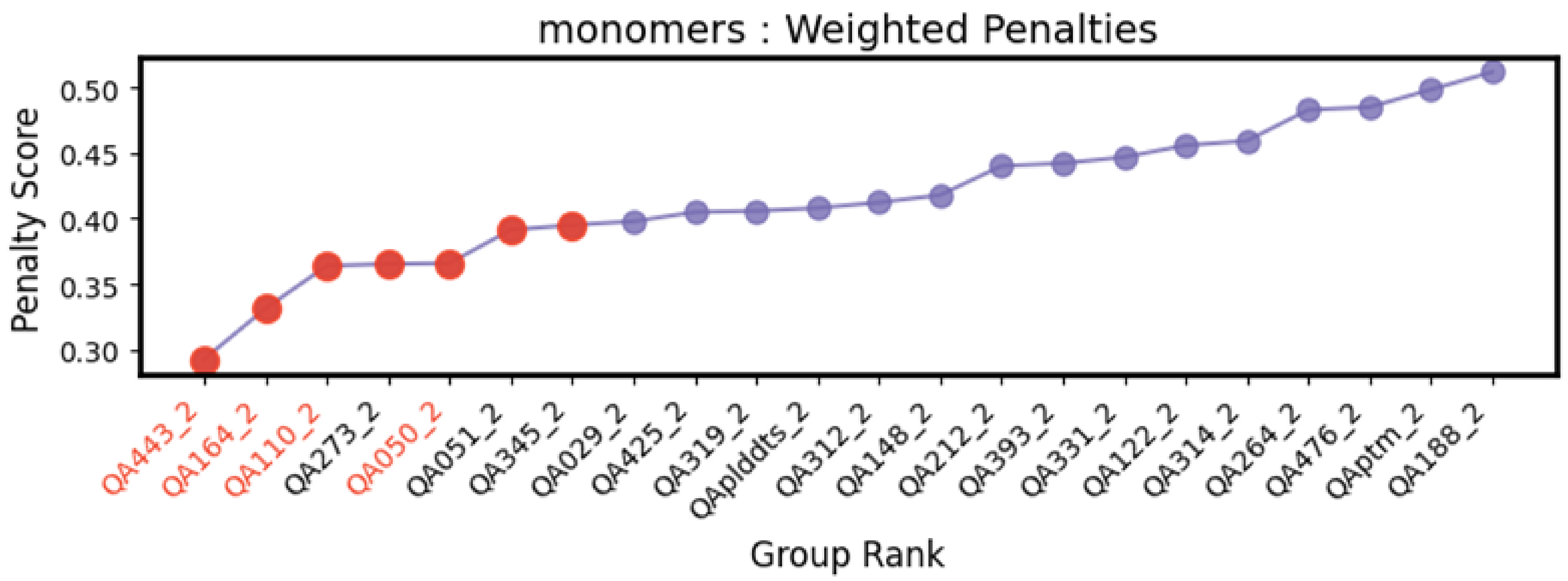
- Average pairwise similarity score to estimate the quality scores

345 Jianlin Cheng – MULTICOM_HUMAN

Method

- Also includes MULTICOM_GATE score
- Deep learning method that combines the pairwise similarity score and the single-model QAs to estimate the quality of the structures
- Model similarity graph

Robust to ranking by Z-score and per-target covariance:



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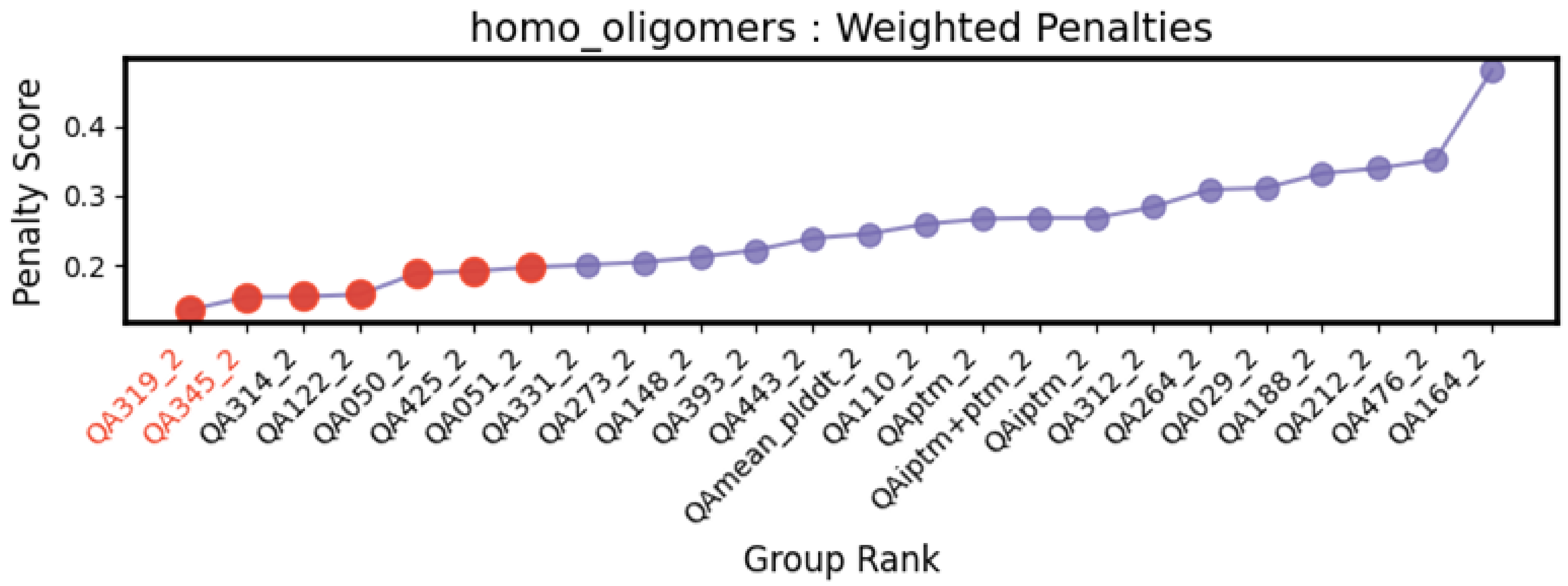

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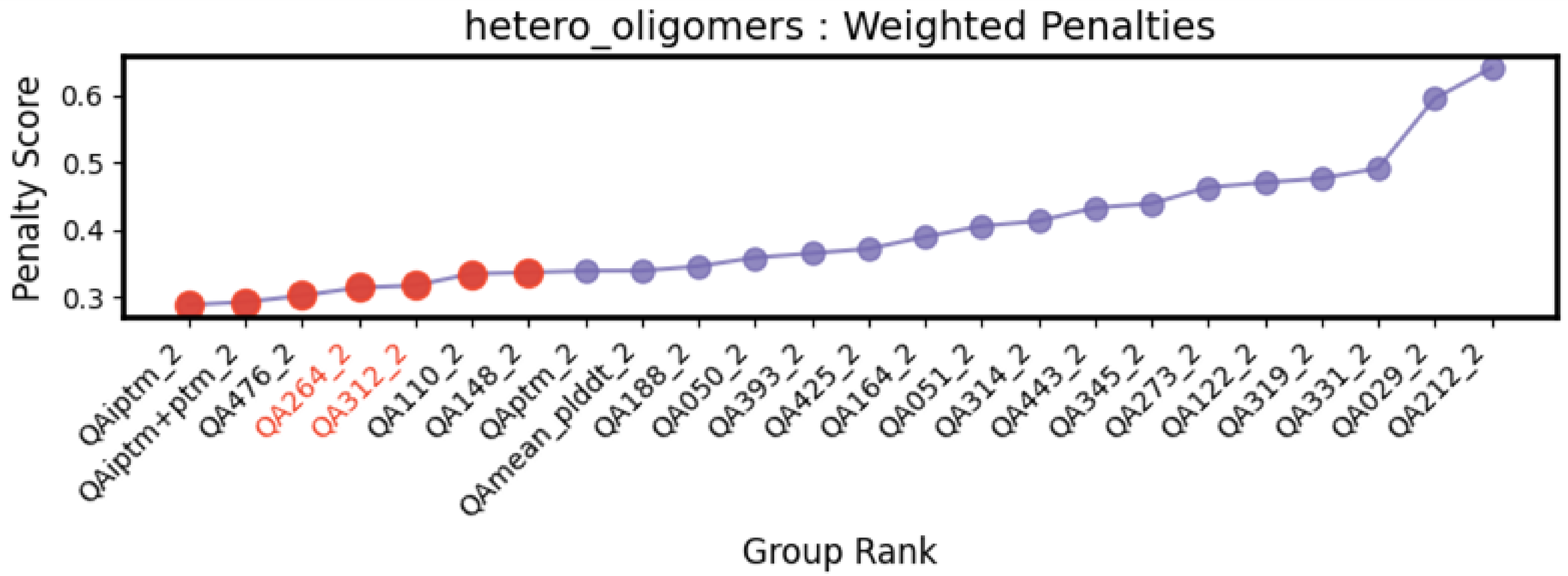

264 Guijun Zhang – GuijunLab-Human

312 Guijun Zhang – GuijunLab-Assembly

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312 Guijun Zhang – GuijunLab-Assembly

264 Guijun Zhang – GuijunLab-Human

Characteristics

- Did not use the ptm, iptm and plddt of MassiveFold

312 Guijun Zhang – GuijunLab-Assembly

Characteristics

- Used the confidence ranking score from MassiveFold for preliminary screening on 8040 structures.

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Final Thoughts

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Confidence Estimates and Experiment

- Finer-grained (atomic) estimates for confidence add value

Make this an explicit goal in CASP17?

- For practical uses of predicted models, confidence in relative domain orientations is essential

Should CASP17 evaluate PAE matrices? Or define something more general?

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QMODE1 and QMODE2

- Improvement in score distributions compared to CASP15

CASP16 EMA

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QMODE1 and QMODE2

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QMODE3

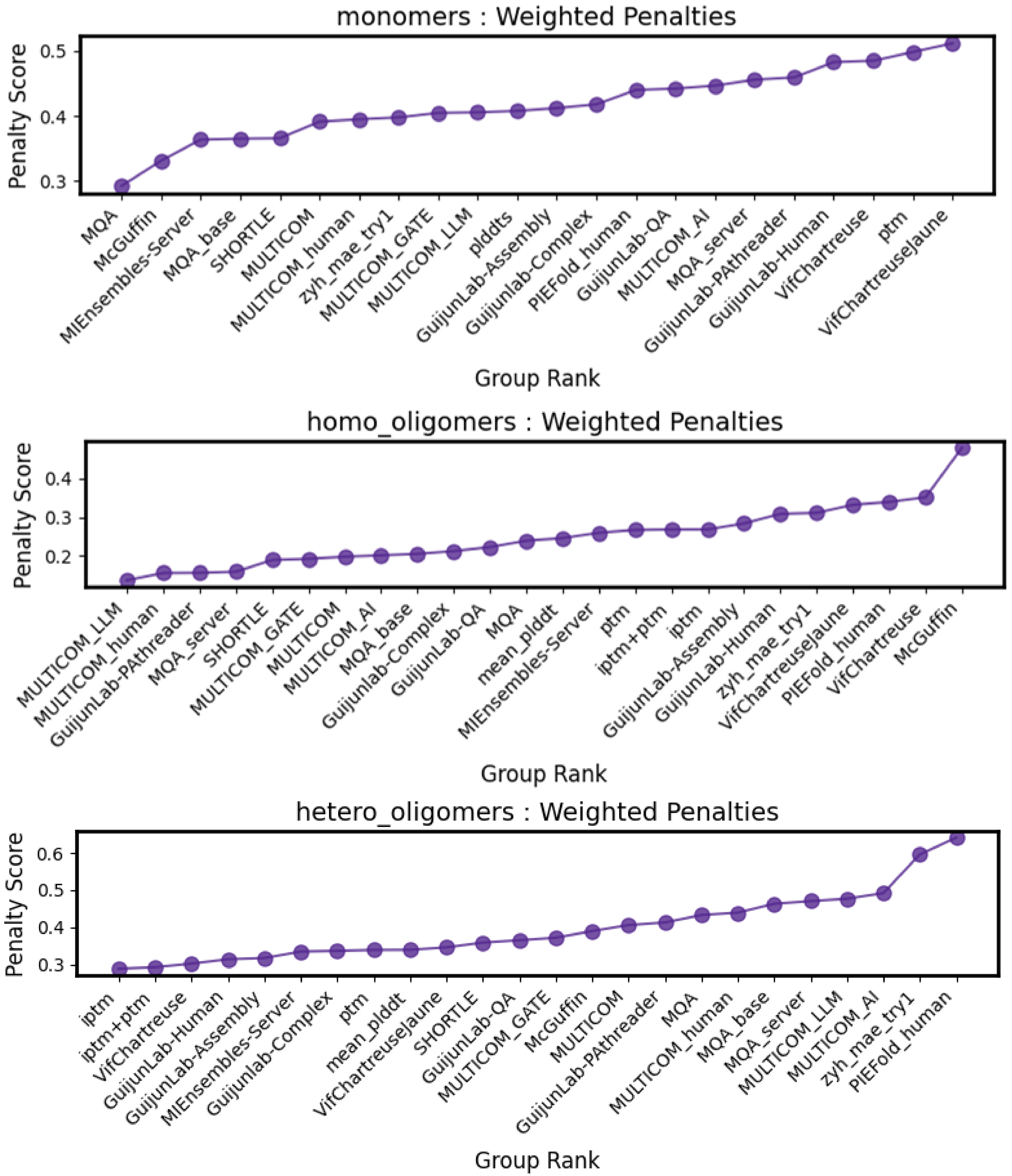
- Methods struggle to outperform AlphaFold2 iptm metric for evaluating hetero-oligomers

Informative future variant of QMODE3 could request ranking of all available models, instead of top 5

THANK YOU!

Questions?

Extra Slides


monomers : Weighted Penalties
Penalty Score
0.3
0.4
0.5
MQA
McGuffin
MIEnsembles-Server
MQA_base
SHORTLE
MULTICOM
MULTICOM_human
zyh_mae_try1
MULTICOM_GATE
MULTICOM_LLM
plddts
GuijunLab-Assembly
Guijunlab-Complex
PIEFold_human
GuijunLab-QA
MULTICOM_AI
MQA_server
GuijunLab-PAthreader
GuijunLab-Human
VifChartreuse
ptm
VifChartreuseJaune
Group Rank
homo_oligomers : Weighted Penalties
Penalty Score
0.2
0.3
0.4
MULTICOM_LLM
MULTICOM_human
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Group Rank
hetero_oligomers : Weighted Penalties
Penalty Score
0.3
0.4
0.5
0.6
iptm
iptm+ptm
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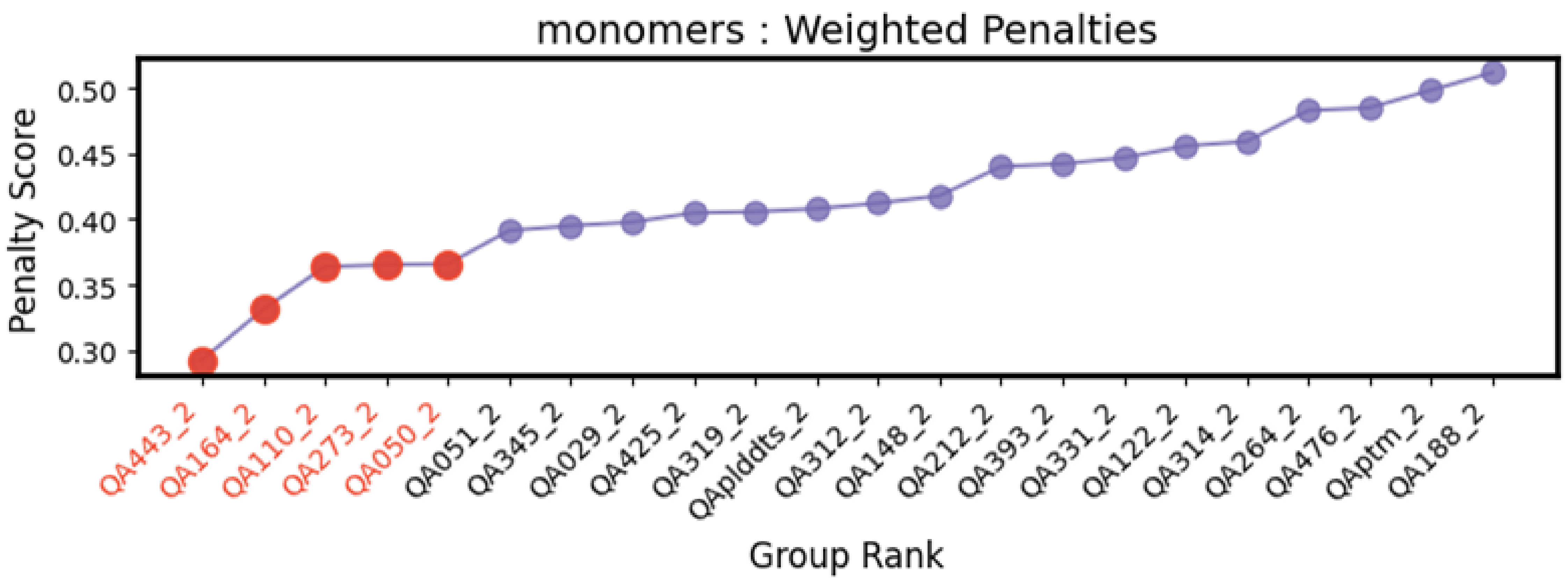
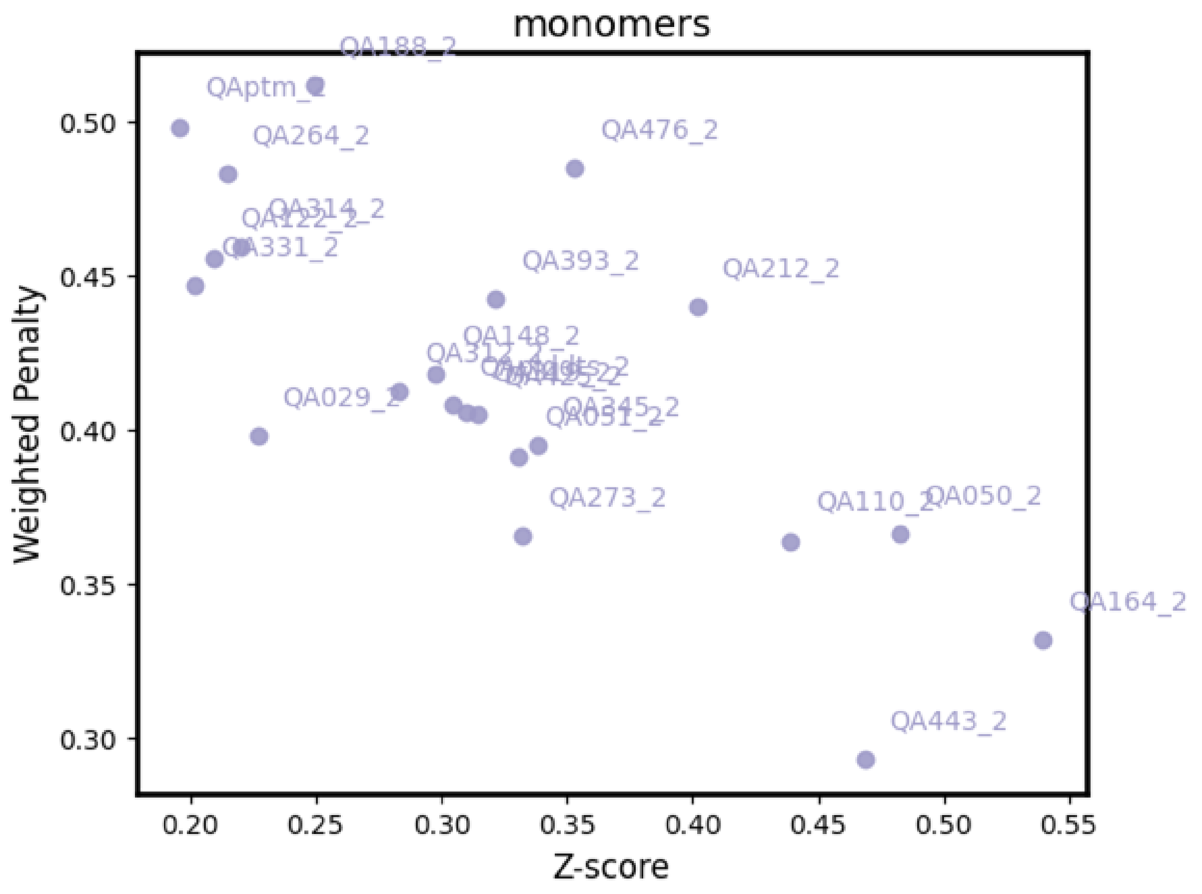
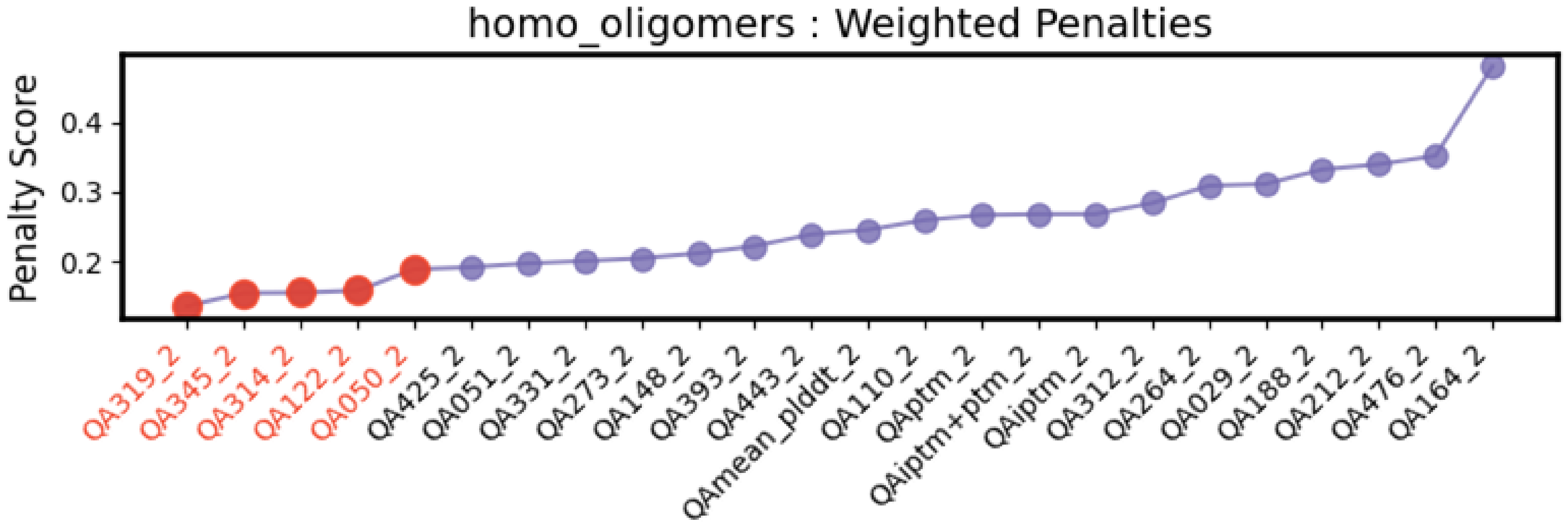
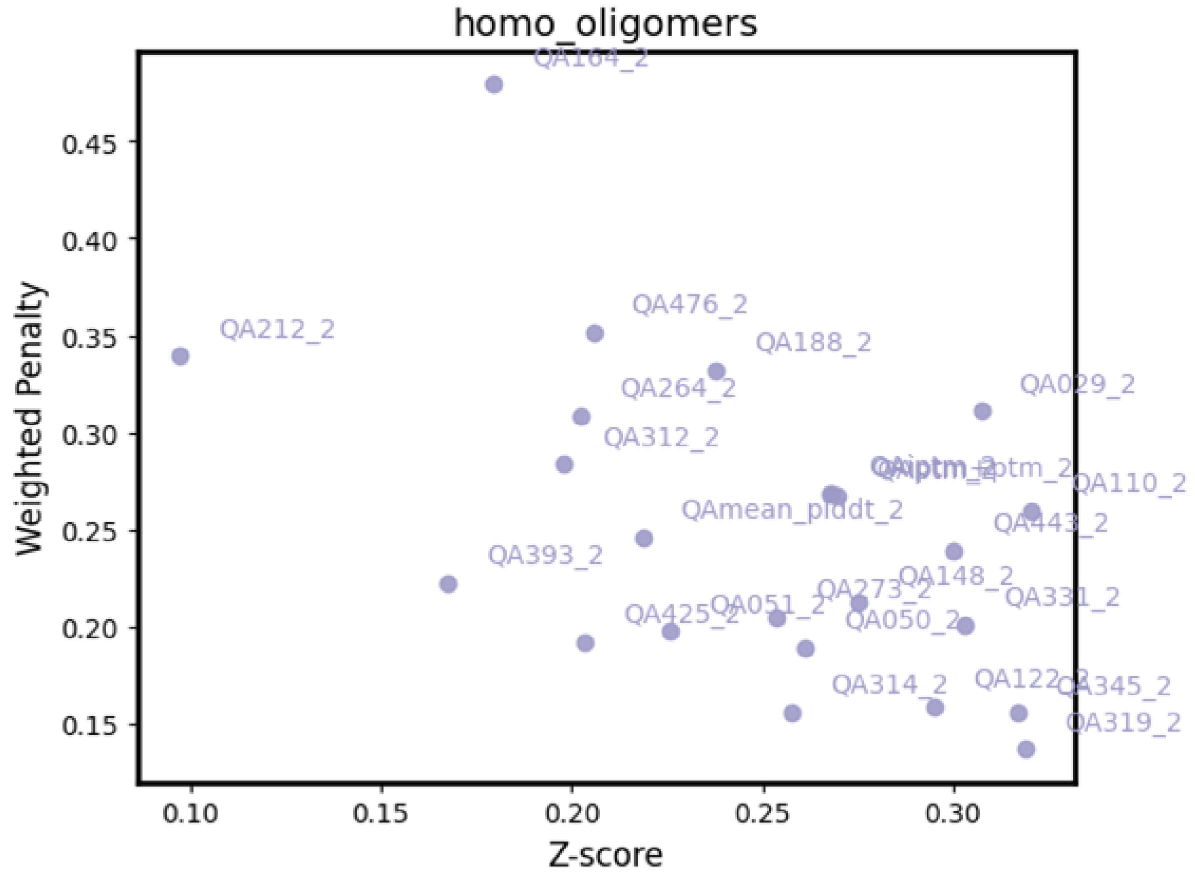
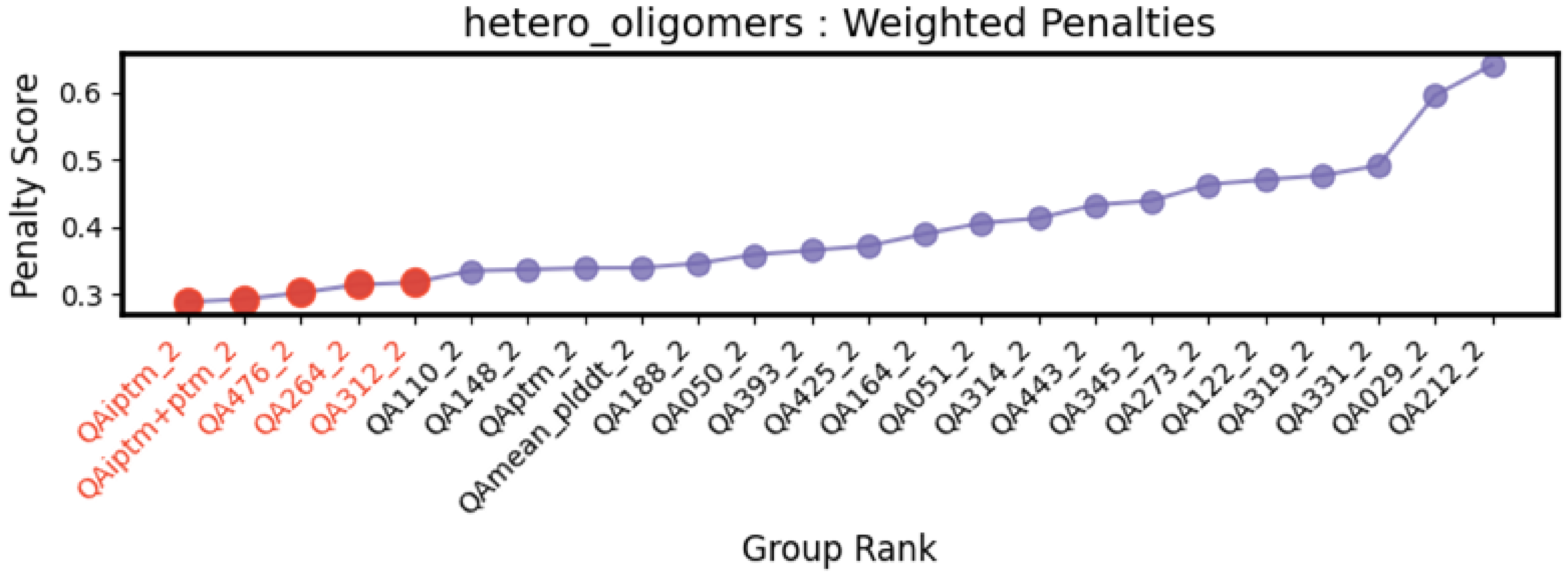
zyh_mae_try1
PIEFold_human
Group Rank

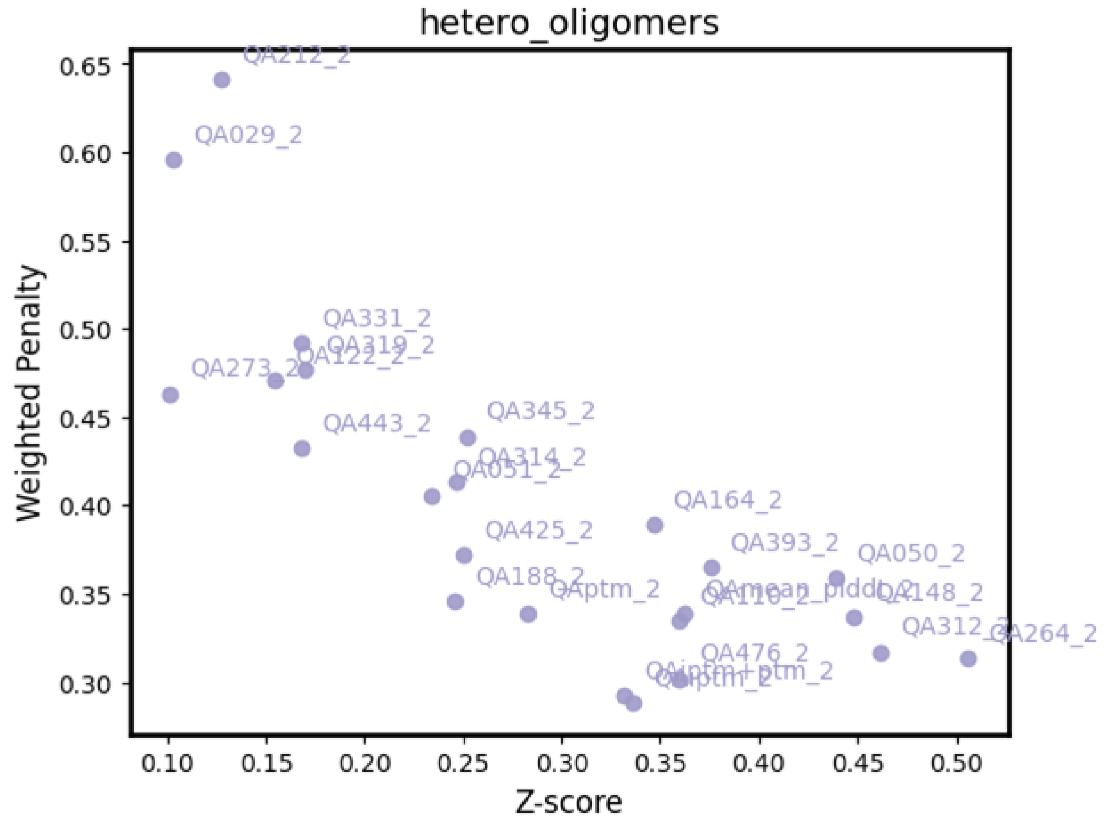

monomers : Weighted Penalties
Penalty Score
Group Rank
QA443_2
QA164_2
QA110_2
QA273_2
QA050_2
QA051_2
QA345_2
QA029_2
QA425_2
QA319_2
QAplddts_2
QA312_2
QA148_2
QA212_2
QA393_2
QA331_2
QA122_2
QA314_2
QA264_2
QA476_2
QAptm_2
QA188_2


monomers
Weighted Penalty
Z-score


homo_oligomers : Weighted Penalties
Penalty Score
QA319_2
QA345_2
QA314_2
QA122_2
QA050_2
QA425_2
QA051_2
QA331_2
QA273_2
QA148_2
QA393_2
QA443_2
QAmean_plddt_2
QA110_2
QAptm_2
QAiptm+ptm_2
QAiptm_2
QA312_2
QA264_2
QA029_2
QA188_2
QA212_2
QA476_2
QA164_2


homo_oligomers
Weighted Penalty
Z-score


hetero_oligomers : Weighted Penalties
Penalty Score
Group Rank
QAiptm_2
QAiptm+ptm_2
QA476_2
QA264_2
QA312_2
QA110_2
QA148_2
QAptm_2
QAmean_plddt_2
QA188_2
QA050_2
QA393_2
QA425_2
QA164_2
QA051_2
QA314_2
QA443_2
QA345_2
QA273_2
QA122_2
QA319_2
QA331_2
QA029_2
QA212_2

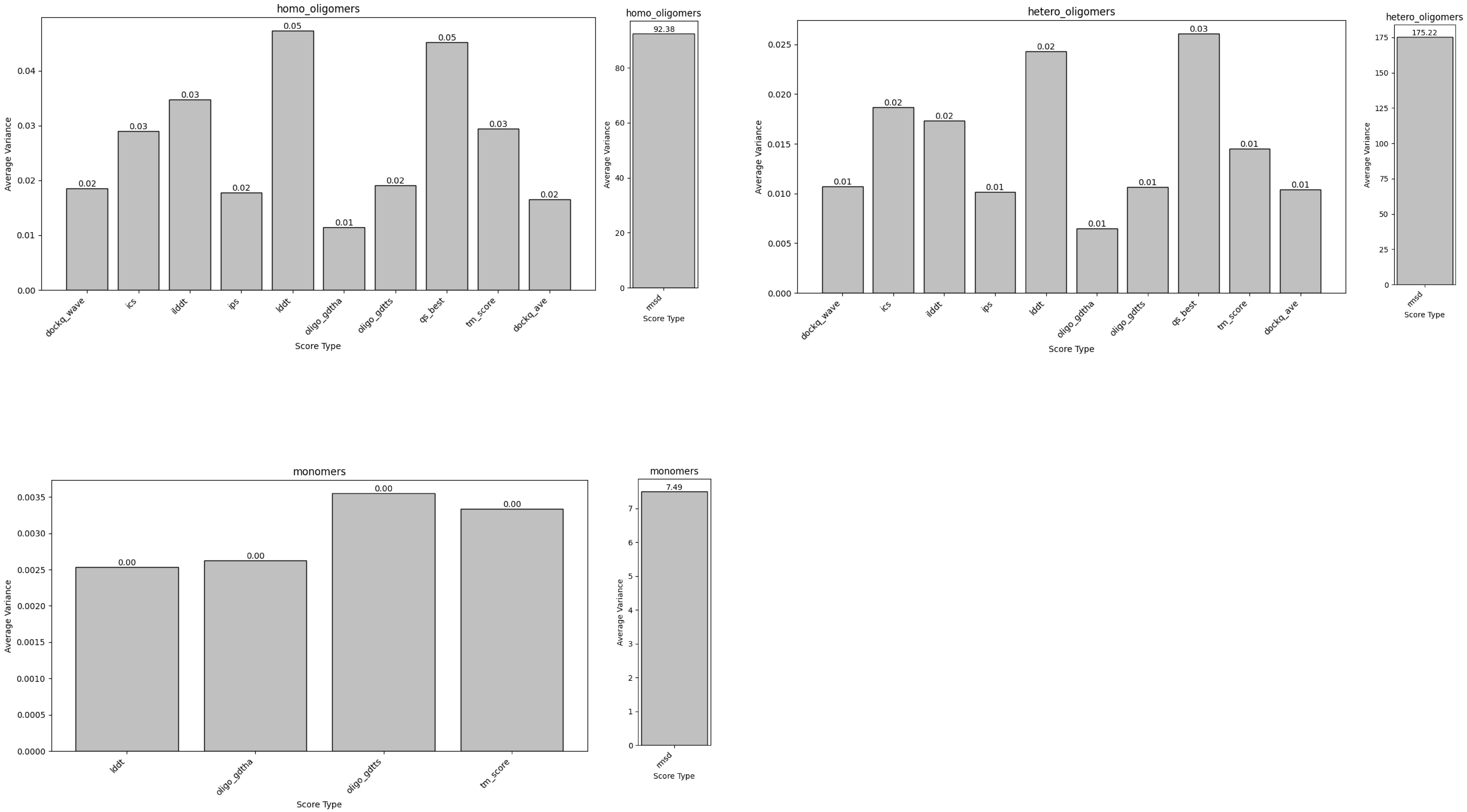

hetero_oligomers
Weighted Penalty
Z-score

Including MF baseline + min(Z)=0 + Z filter at -3

Targets missing:

H1272: 9 components, too big and complicated to be done in MassiveFold

T1247: structure was released early and target was cancelled


homo_oligomers
Average Variance
Score Type
dockq_wave
ics
ilddt
ips
lddt
oligo_gdtha
oligo_gdtts
qs_best
tm_score
dockq_ave
0.02
0.03
0.03
0.02
0.05
0.01
0.02
0.05
0.03
0.02
homo_oligomers
rmsd
92.38
hetero_oligomers
Average Variance
Score Type
dockq_wave
ics
ilddt
ips
lddt
oligo_gdtha
oligo_gdtts
qs_best
tm_score
dockq_ave
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0.02
0.02
0.01
0.02
0.01
0.01
0.03
0.01
0.01
hetero_oligomers
rmsd
175.22
monomers
Average Variance
Score Type
lddt
oligo_gdtha
oligo_gdtts
tm_score
0.00
0.00
0.00
0.00
monomers
rmsd
7.49