



# From Scores to Trust: A Quality Engine for Diving Judges

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# Agenda

- 1 Introduction**
- 2 Engine**
- 3 Live Demo**
- 4 Results**
- 5 Q & A**
- 6 Appendix**



## How Diving Is Scored

**In competitive diving, even one point can change everything.**

A judge's score directly impacts:

- Rankings
- Advancement
- Recognition
- Athlete opportunities

How scoring works:

- Judges award 0-10 points per dive.
- Highest and lowest scores are removed (if 5+ judges)
- Remaining scores are summed x Degree of Difficulty (DD)

## App Today: What It Already Does Well?



### Strong on Data Capture

- Register judges and divers
- Record scores and compute results
- Store and replay competition videos


# What's Missing: No View of Judge Quality

## What We See

Individual scores from each judge for every dive performance

## What's Hidden

Long-term behavioral patterns and consistency metrics over time

DIVER			TEAM			COACH			AGE	25		Final   1   370.90				
DATE	March, 18, 2022		EVENT	Men's 1M - Finals		DIVE ORDER	8									
MEET	2022 NCAA Division III (Unofficial)		LOCATION	IU Natatorium, 901 West New York Street, Indianapolis,												
V/O	Rnd	Dive#	Dive Description	DD	J1	J2	J3	J4	J5	J6	J7	Net Total	Award	Running Total	Rnd Place	
o	1	405C	Inw 2.5 Som - Tuck	3.1	8.0	8.0	8.0	7.0	7.5	8.0	8.0	24.0	74.40	74.40	1	
o	2	107C	Fwd 3.5 Som - Tuck	3.0	8.0	6.5	6.5	6.5	6.5	7.0	7.0	7.0	20.5	61.50	135.90	1
o	3	205C	Back 2.5 Som - Tuck	3.0	5.5	5.5	6.0	5.5	5.0	5.0	5.5	16.5	49.50	185.40	5	
o	4	305C	Rev 2.5 Som - Tuck	3.0	6.0	7.0	6.5	6.0	6.0	6.0	6.5	18.5	55.50	240.90	5	
o	5	5152B	Fwd 2.5 Som 1 Tw - Pike	3.2	7.5	6.5	6.5	7.0	6.5	6.5	7.0	20.0	64.00	304.90	1	
o	6	5335D	Rev 1.5 Som 2.5 Tw - Free	3.0	7.0	7.5	7.5	7.0	7.0	7.5	9.0	22.0	66.00	370.90	1	
DD Totals: Vol: 0 Opt: 18.3 All: 18.3 Rank: Vol: Opt: Avg score: Vol: Opt: 6.79 All: 6.79 Avg counted score: Vol: Opt: 6.75 All: 6.75														FINAL TOTAL	370.90	

## What's Missing: No View of Judge Quality

### **The Gap**

No structured feedback system to help judges identify and improve their scoring patterns

## From “Feeling” to Data

Subjective, unconscious preferences are inevitable in any judging system.  
Today, people judge judges by “*feeling*” rather than objective measures.

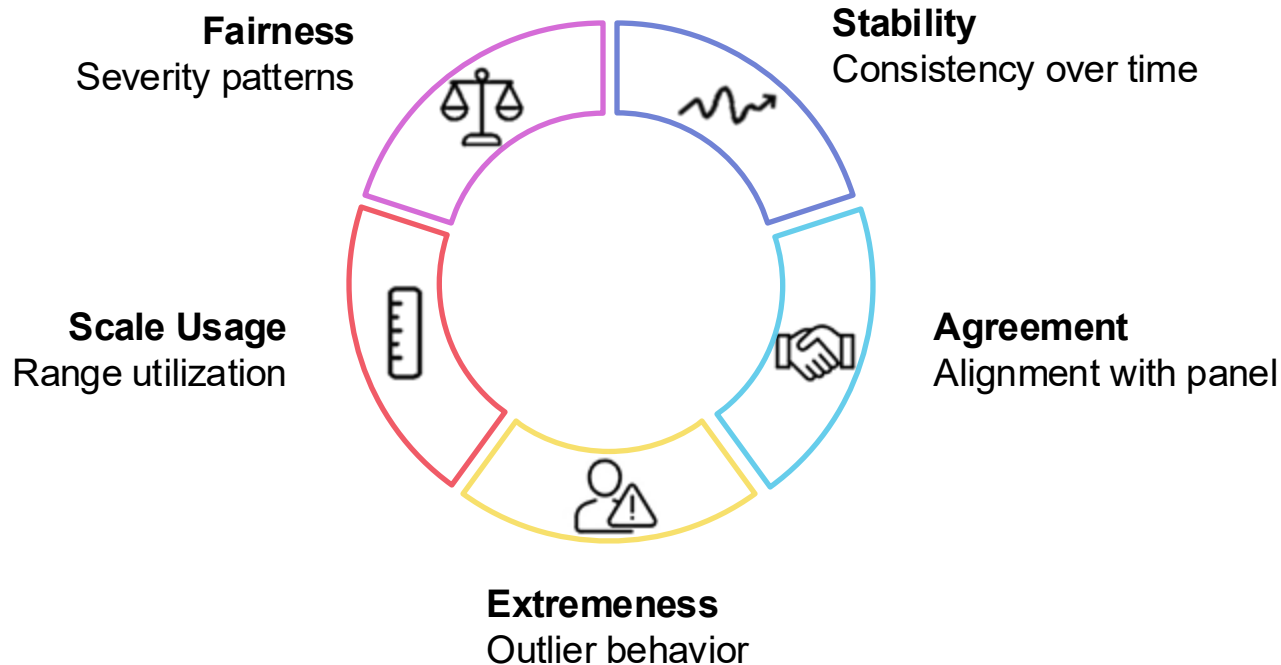
The goal: move to a clear, data-based view of fairness

100%

Data-Driven  
Objective assessment

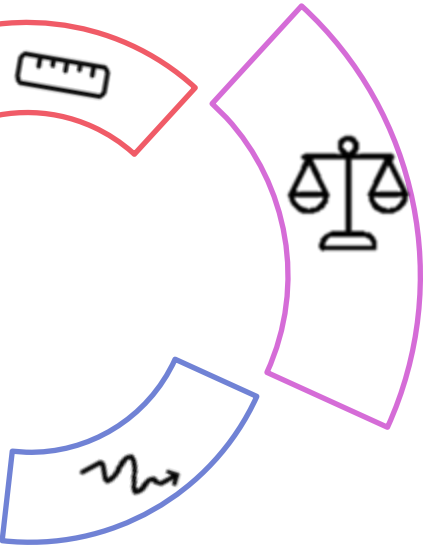
## What Makes a Good Judge?

Defining quality in five intuitive dimensions





# Fairness – Are They Systematically High or Low?



Compare each judge to the **panel consensus baseline**

Above Baseline → Lenient  
Below Baseline → Severe

## A Fair Baseline for Each Dive

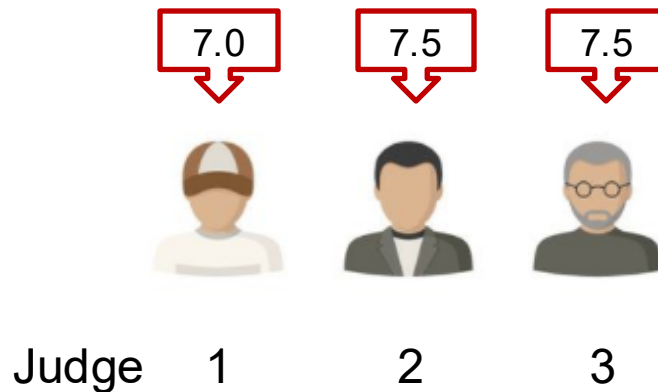
2 Judges Panel



Baseline Score = Flagged / NA

## A Fair Baseline for Each Dive

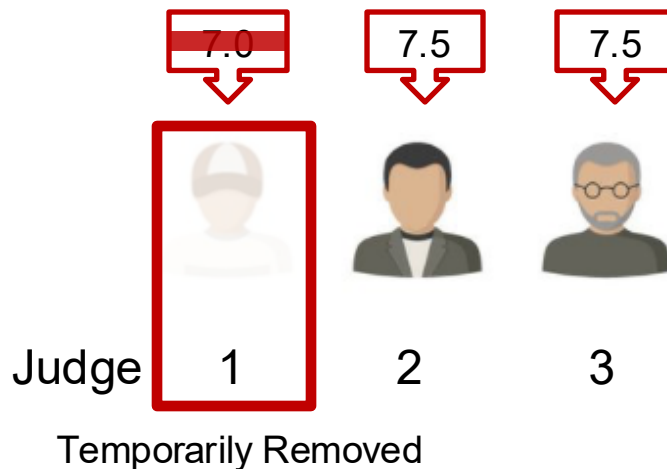
3 Judges Panel



## A Fair Baseline for Each Dive

Step 1 – Leave Judge X Out

3 Judges Panel

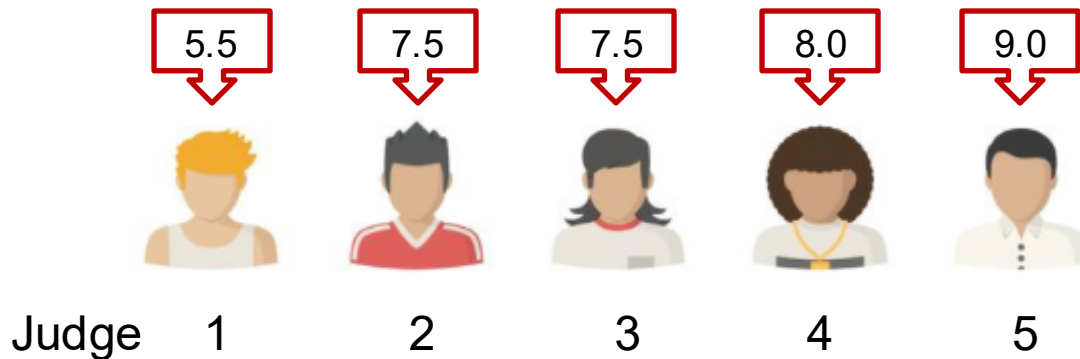


Step 2 – Take the Average ➡ Baseline Score

Baseline Score for Judge 1 = Mean Score of 2 and 3 = 7.5

## A Fair Baseline for Each Dive

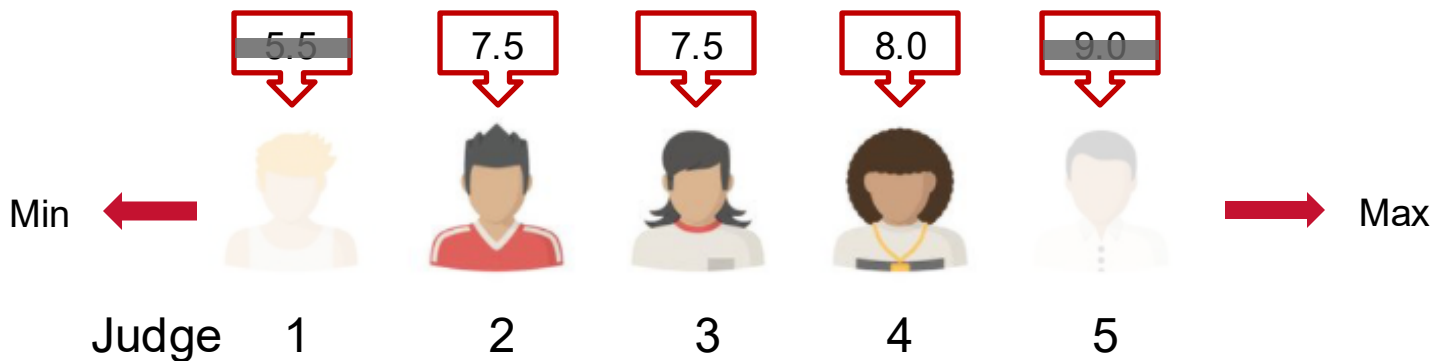
5 Judges Panel



# A Fair Baseline for Each Dive

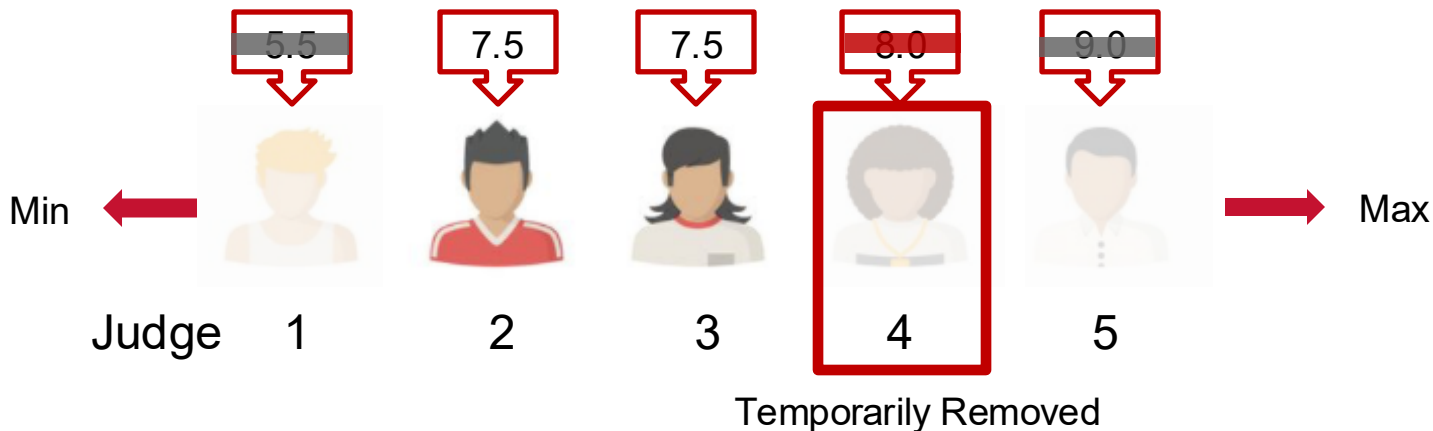
Step 1 – Remove the Most Extreme Scores

5 Judges Panel



## A Fair Baseline for Each Dive

Step 2 – Leave Judge X Out

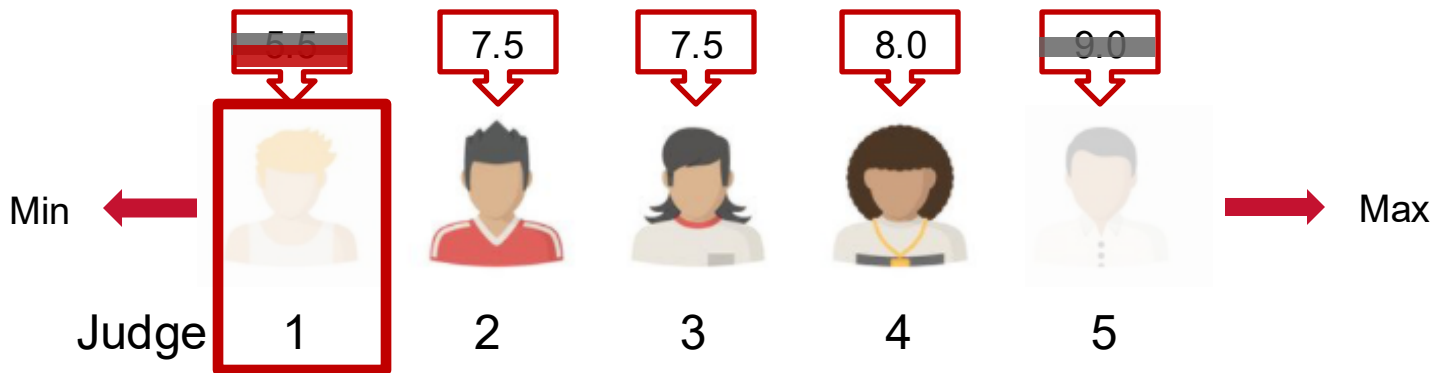


Step 3 – Take the Average ➡ Baseline Score

Baseline score for Judge 4 = mean score of 2 and 3 = 7.5

## A Fair Baseline for Each Dive

Step 2 – Leave Judge X Out



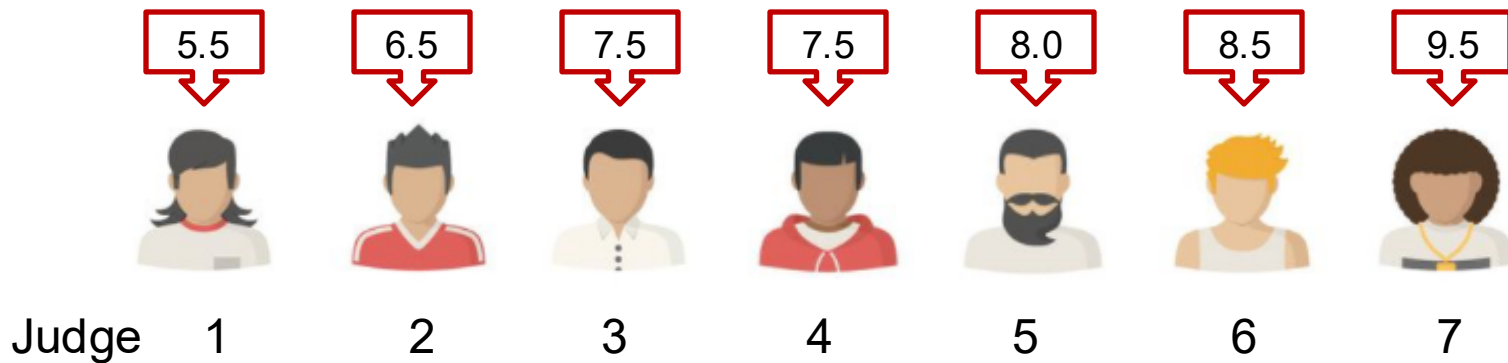
Step 3 – Take the Average ➡ Baseline Score

Baseline Score for Judge 1 = Mean Score of 2, 3 and 4 = 7.67



## A Fair Baseline for Each Dive

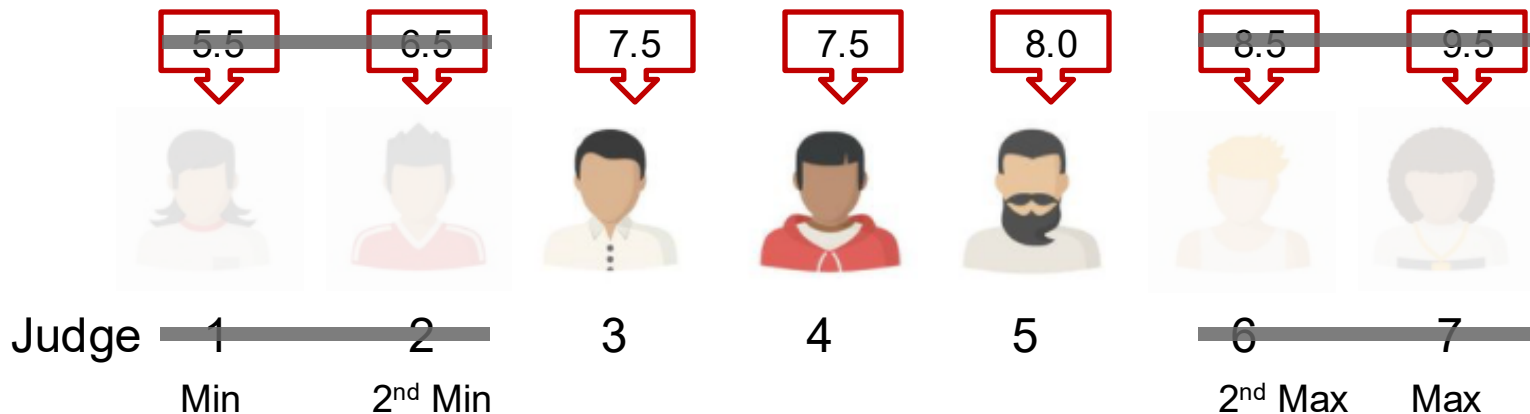
7 Judges Panel



## A Fair Baseline for Each Dive

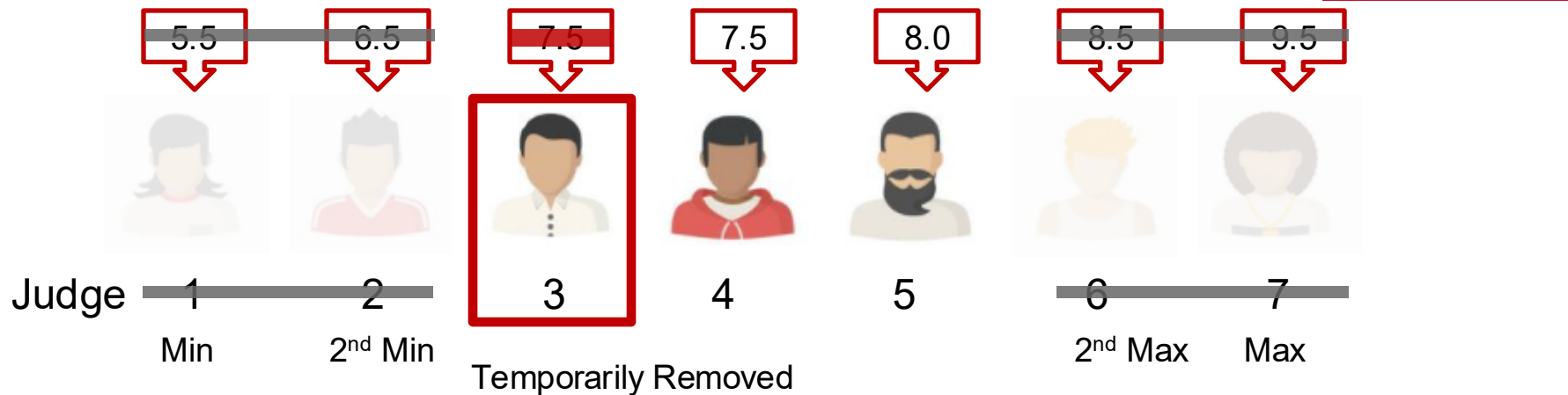
Step 1 – Remove the most extreme scores

7 Judges Panel



## A Fair Baseline for Each Dive

Step 2 – Leave Judge X Out



Step 3 – Take the Average ➡ Baseline score

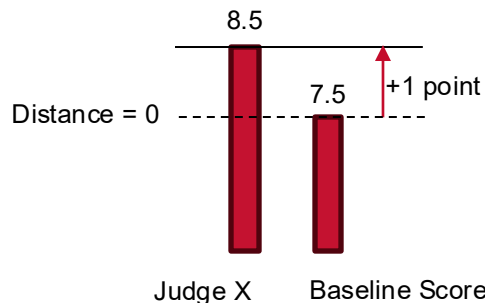
Baseline Score for Judge 3 = Mean Score of 4 and 5 = 7.75

# Fairness – Are They Systematically High or Low?

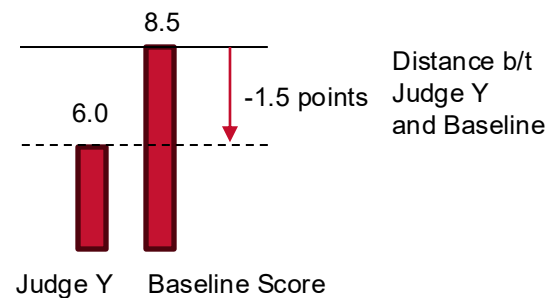


Severity = Average (Judge score – Baseline)

For One Dive



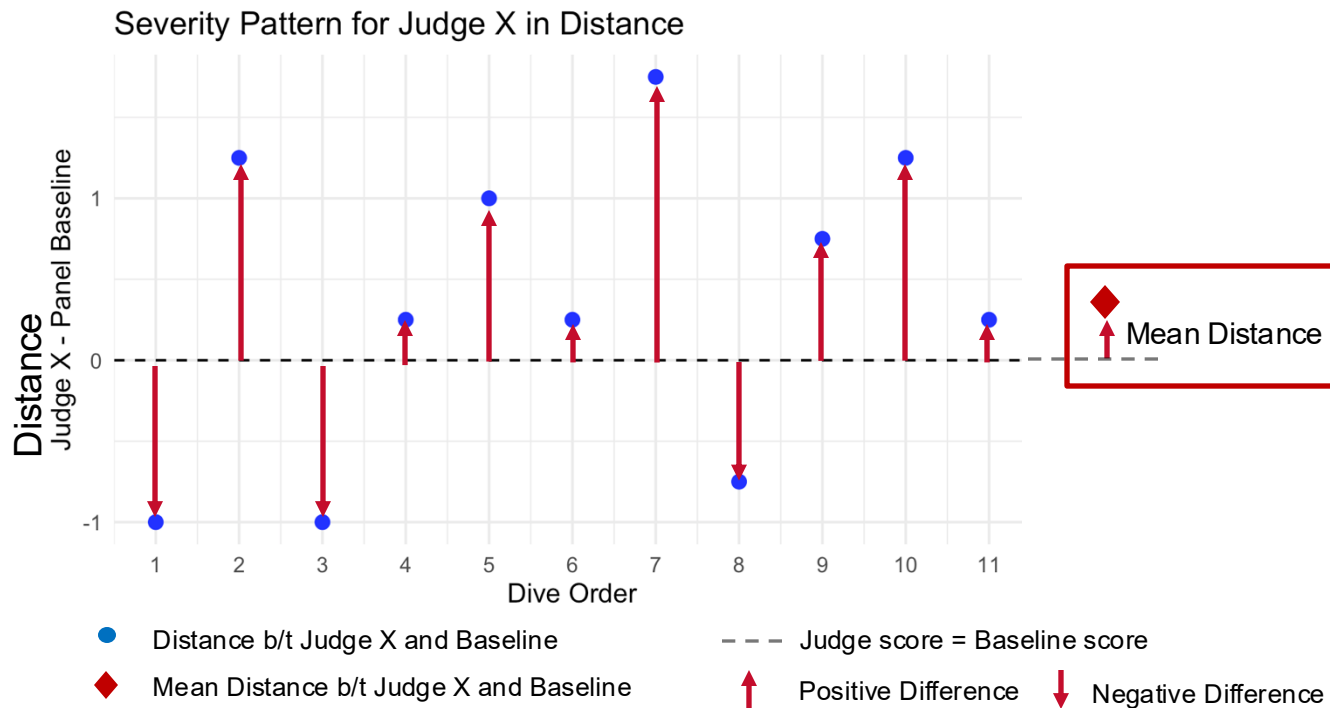
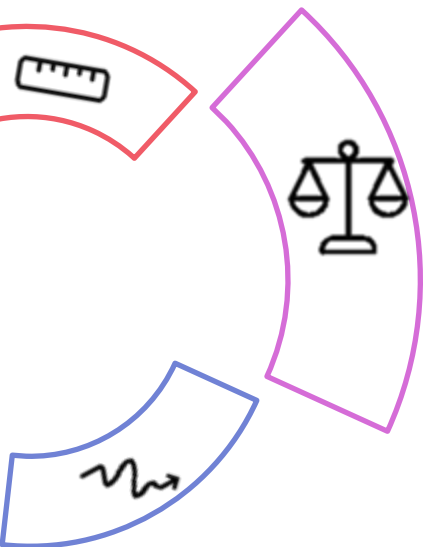
Distance b/t  
Judge X  
and Baseline



+ ➡ Leniency

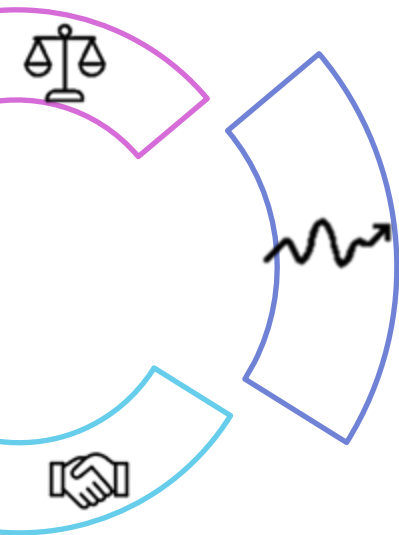
- ➡ Severity

## Fairness – Are They Systematically High or Low?



Slight Leniency within Reasonable Bounds

## Stability – Do They Bounce Around?

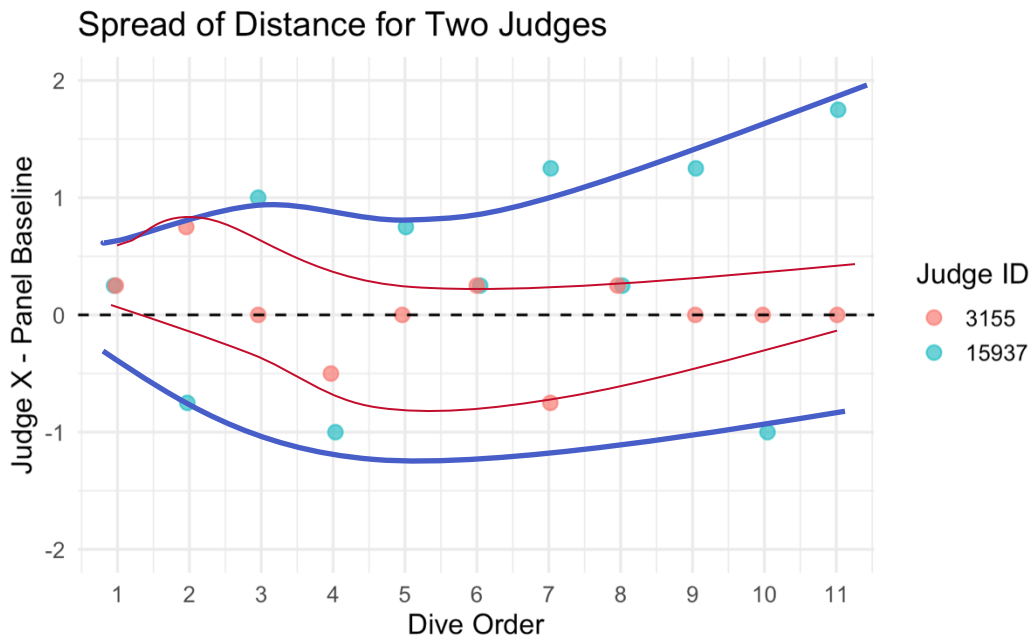
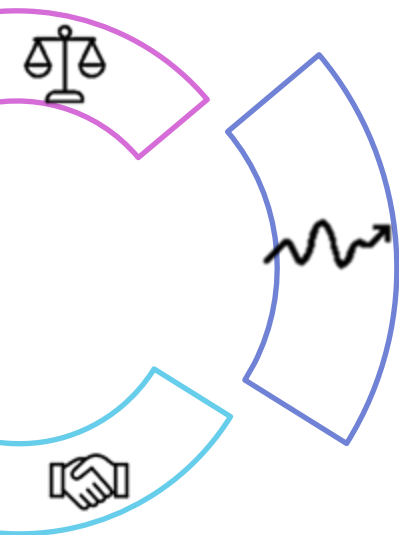


Inconsistency = Spread of (Judge score – Baseline)  
*(How spread out these differences are)*

Small Spread → Stable and Predictable

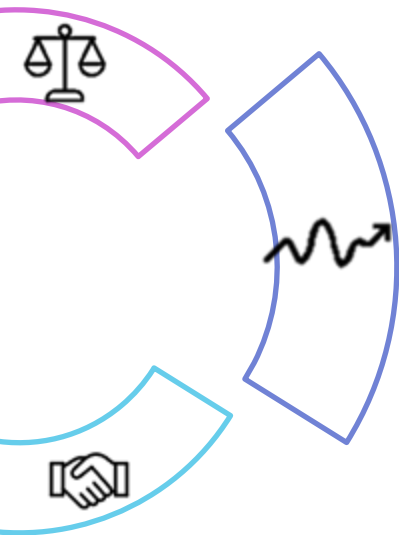
Large Spread → Noisy and Inconsistent

## Stability – Do They Bounce Around?



Dots Stay Close to 0	➡	Small Spread	➡	More Consistent
Dots Move Up and Down	➡	Large Spread	➡	Less Consistent

# Stability – Do They Bounce Around?



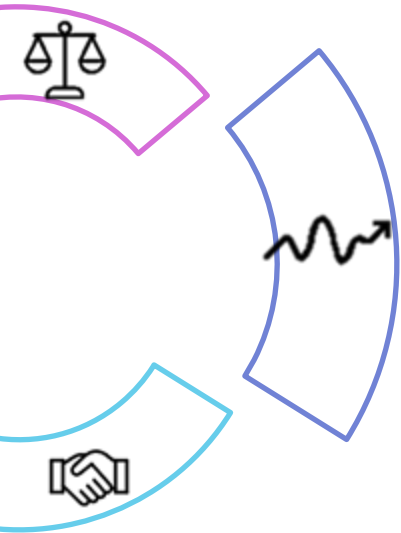
Summary Statistics for Judge Inconsistency (2024&2025)

Min	25 %ile	Median	75 %ile	Max
0.249	0.492	0.559	0.599	1.404

- Tier A – Highly Consistent  
 $0 \leq \text{Inconsistency} < 0.492$  (25 %ile)
- Tier B – Typical Consistency  
 $0.492$  (25 %ile)  $\leq \text{Inconsistency} \leq 0.599$  (75 %ile)
- Tier C – Needs Review for Consistency  
 $\text{Inconsistency} > 0.599$  (75 %ile)



# Stability – Do They Bounce Around?



## Summary for selected judge

Judge ID	Judge	Dives	Score range	Severity	Inconsistency	Agreement	Extremeness	Range use	Overall rank
		558	8.00	0.05	0.47	0.86	0.60	3.04	31

Highly Consistent (Stable and Predictable)

## Agreement – Do They Rank Dives Like the Panel?



Agreement = Correlation (Judge ranking, Baseline ranking)

*(Whether the judge's rank-ordering of dives aligns with the panel's.  
Agreement ranges from -1 to 1)*

- Close to 1 → Strong Agreement in Ranking Dives
- Close to 0 → Poor Agreement in Ranking Dives
- Close to -1 → Actively Reversed Ranking

## Agreement – Do They Rank Dives Like the Panel?



### Summary for selected judge

Judge ID	Judge	Dives	Score range	Severity	Inconsistency	Agreement	Extremeness	Range use	Overall rank
		558	8.00	0.05	0.47	0.86	0.60	3.04	31

Strong Agreement with the Panel

# Extremeness – Are They Often the Lone Outlier?



- Step 1 – On Each Dive  
Check uniquely highest or uniquely lowest
- Step 2 – Count How Often  
“Extreme dives” = dives where they are the lone outlier  
Extremeness frequency = % of dives where they are the lone outlier
- Step 3 – Measure How Far  
For those dives, measure the gap to the nearest judge  
Extremeness intensity = average gap on those dives

## Extremeness – Are They Often the Lone Outlier?



### Summary for selected judge

Judge ID	Judge	Dives	Score range	Severity	Inconsistency	Agreement	Extremeness	Range use	Overall rank
		558	8.00	0.05	0.47	0.86	0.60	3.04	31

Average Gap is 0.60 Points from the Nearest Judge

## Scale Usage – Do They Use the Full Range?



Range ratio = Judge Spread  $\div$  Panel Average Spread

*(How wide their scores spread across dives)*

- Range Ratio  $\approx 1$   $\rightarrow$  The judge uses the scale similarly to the panel
- Range Ratio  $< 1$   $\rightarrow$  The judge uses a narrower range (stays in the middle)
- Range Ratio  $> 1$   $\rightarrow$  The judge uses a wider range (more extremes)

## Scale Usage – Do They Use the Full Range?



### Summary for selected judge

Judge ID	Judge	Dives	Score range	Severity	Inconsistency	Agreement	Extremeness	Range use	Overall rank
		558	8.00	0.05	0.47	0.86	0.60	3.04	31

This judge uses a 3 times wider range than the panel average.

## From Metrics to Penalties and Overall Rank

Fairness penalty	Grows with the absolute size of Severity
Inconsistency penalty	Grows with Inconsistency
Agreement penalty	Higher when Agreement is low
Extremeness penalty	Higher when the judge is extreme frequently and by a large margin
Range-use penalty	Small when range ratio $\approx 1$ Large when much smaller or larger than 1

Note: Each penalty is a non-negative score, where 0 represents ideal behavior and larger values indicate greater deviation from the panel consensus.

- Rank judges on each penalty  
(Rank 1 = best)
- Add the five ranks to get an overall score

Overall rank:

Overall Score = Sum of 5 Penalty Ranks  
(Lower is Better)





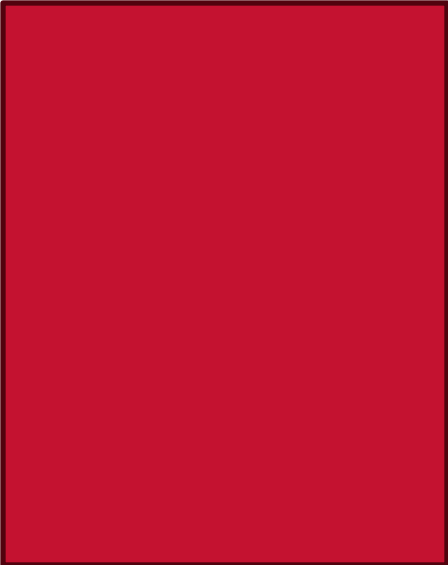
From Metrics to Penalties and Overall Rank

Summary for selected judge

Row	Judge ID	Judge	Dives	Severity	Inconsistency	Agreement	Extremeness	Range use	Overall rank
Value			558	0.047	0.468	0.859	0.597	3.038	31
Rank (1 = best; of all judges)				31 / 100	18 / 100	78 / 100	40 / 100	37 / 100	31 / 100

## Judge Leaderboard – Who Is Most Reliable (2024-2025 FL)?

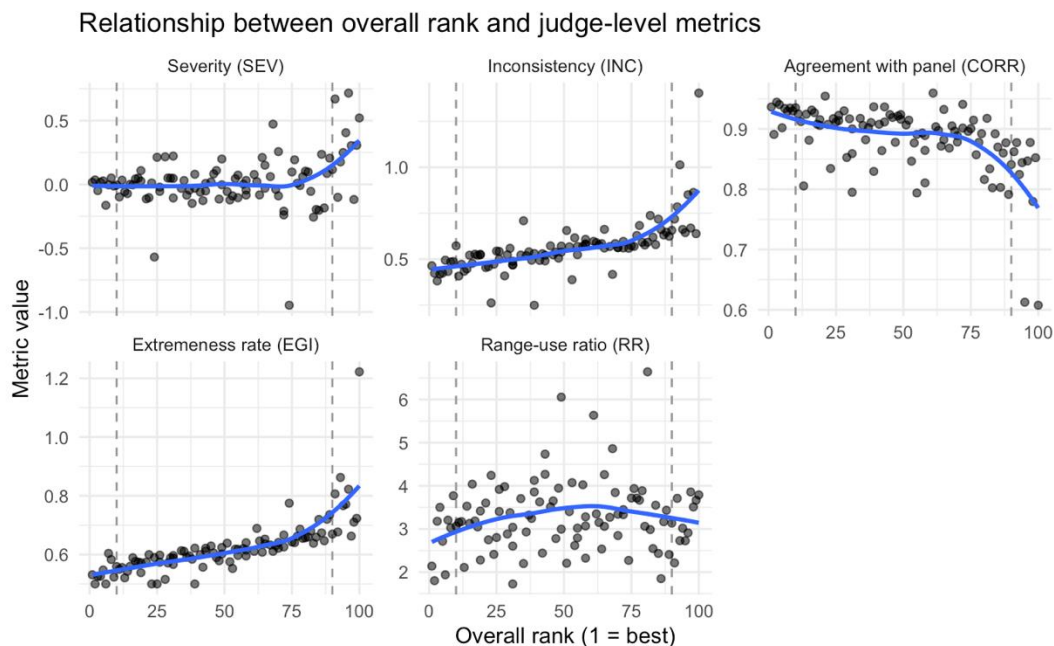
Top 10 judges by composite performance score

Judge ID	Judge	Number of dives	Severity	Inconsistency	Agreement with panel	Extremeness	Range-use ratio	Overall rank
		274	0.016	0.463	0.937	0.531	2.139	1
		132	0.035	0.423	0.891	0.500	1.801	2
		221	-0.049	0.381	0.945	0.526	3.179	3
		209	0.017	0.418	0.941	0.526	3.501	4
		456	0.028	0.424	0.902	0.548	2.716	5
		154	-0.164	0.494	0.934	0.500	1.937	6
		1257	-0.004	0.432	0.929	0.604	3.205	7
		55	0.050	0.484	0.935	0.583	3.025	8
		209	-0.013	0.487	0.930	0.523	3.771	9
		506	-0.005	0.572	0.935	0.560	3.065	10

## Judge Assessment Card – Example

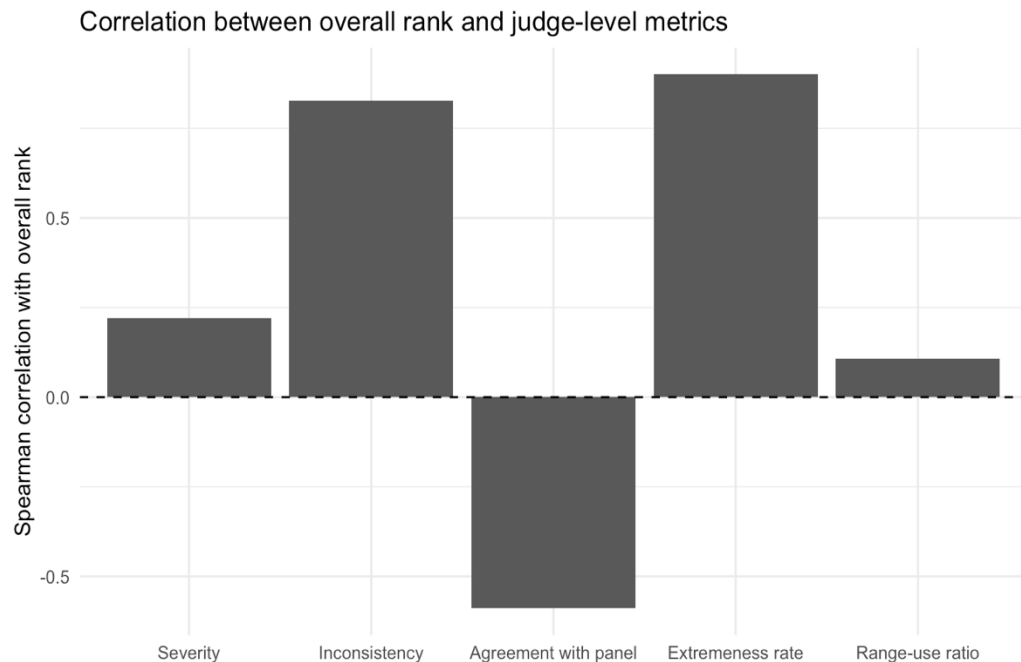
**Live Demo:** [Choose a Judge ID, See Their Profile](#)

## Relationship between overall rank and judge-level metrics



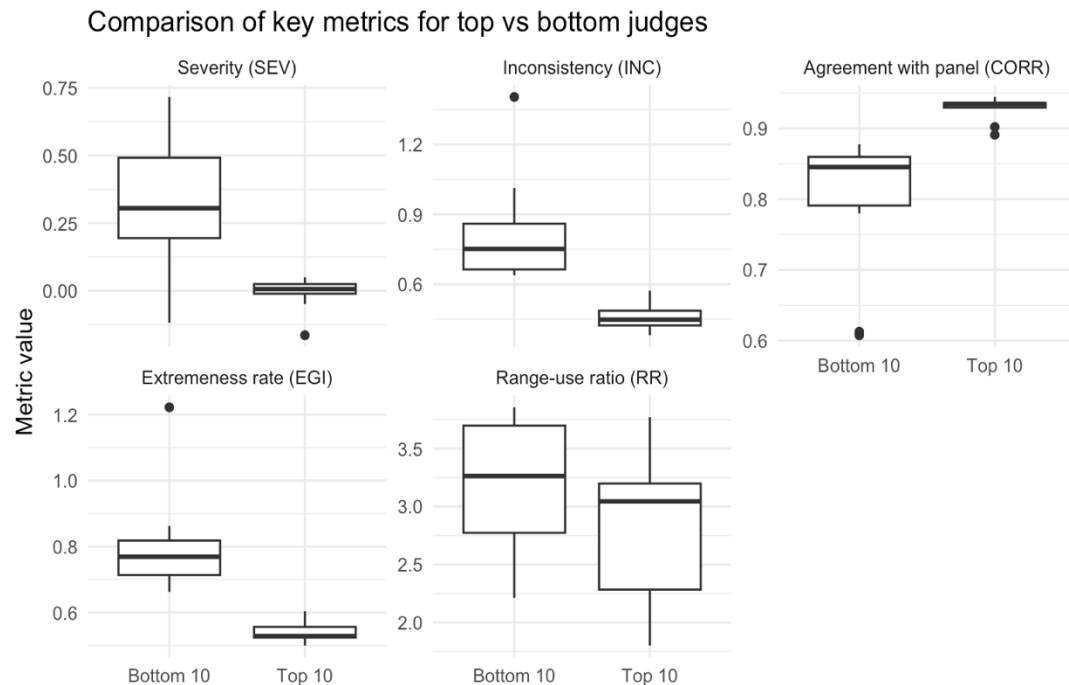
- **SEV:** Severity stays near zero, then turns clearly positive for the lowest-ranked judges (consistent high scorers).
- **INC:** Inconsistency rises steadily with worse rank and spikes for the bottom judges.
- **CORR:** Agreement with the panel declines with rank and drops sharply in the worst decile.
- **EGI:** Extremeness intensity stays modest until it rises noticeably near the worst ranks.
- **RR:** Range-use ratio is slightly higher in the middle ranks but does not clearly separate the extremes.

## Correlation between overall rank and judge-level metrics



- Overall rank is most strongly and positively associated with inconsistency (INC) and most strongly and negatively associated with agreement with the panel (CORR).
- Severity (SEV) shows only a modest association with rank, and the range-use ratio (RR) is only weakly related.

## Comparison of key metrics for top vs bottom judges



- **INC & SEV:** Bottom 10 have higher inconsistency and more positive severity; top 10 have low INC and SEV  $\approx 0$ .
- **CORR level:** Agreement is much stronger for the top judges.
- **CORR spread:** Top group has tight, high CORR; bottom group shows lower medians and wider spread.
- **EGI:** EGI is clearly higher and more variable among the bottom judges
- **RR:** Bottom judges tend to use slightly more of the scale (higher RR)



**Questions?**

# Reference

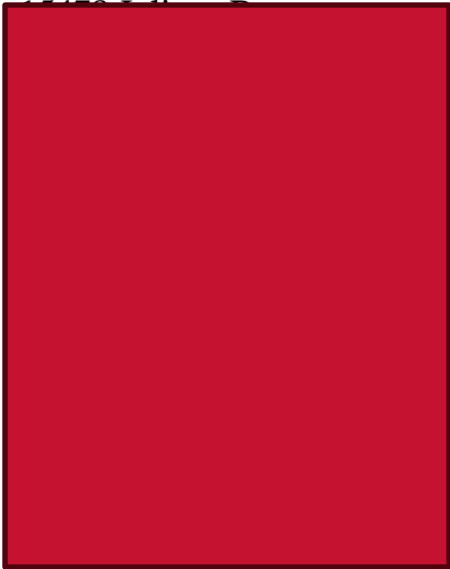
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Judge Leaderboard – Who Is Least Reliable (2024-2025 FL)?

Bottom 10 judges by composite performance score

Judge ID	Judge	Number of dives	Severity	Inconsistency	Agreement with panel	Extremeness	Range-use ratio	Overall rank
		176	0.670	0.718	0.862	0.806	2.212	91
		506	-0.101	0.785	0.877	0.677	3.709	92
		156	0.176	1.013	0.825	0.863	2.728	93
		77	0.250	0.661	0.844	0.767	3.017	94
		66	0.405	0.644	0.613	0.771	2.725	95
		310	0.716	0.851	0.847	0.822	2.909	96
		132	0.304	0.669	0.878	0.663	3.856	97
		36	-0.118	0.863	0.780	0.711	3.509	98
		88	0.307	0.638	0.852	0.723	3.666	99
		12	0.521	1.404	0.608	1.222	3.789	100

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**Thank you!**

