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GOOD JUDGMENT PROJECT AND THE CONTRIBUTION WEIGHTED MODEL

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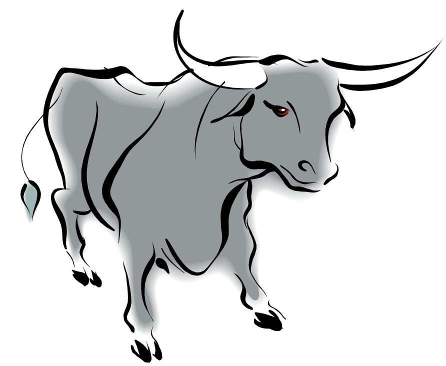
Harnessing the wisdom of the crowd to forecast world events

- IARPA created the ACE Program to dramatically enhance the accuracy, precision, and timeliness of intelligence forecasts
- Development of advanced techniques that elicit, weight, and combine judgments
- Five university-based teams enter the 2011-2015 tournament (GJP eliminated the other 4 teams after the second year)
- Each team submitted forecasts each day for each question, using methods of its choice
- IARPA has posed over 500 questions for the last 4 years:

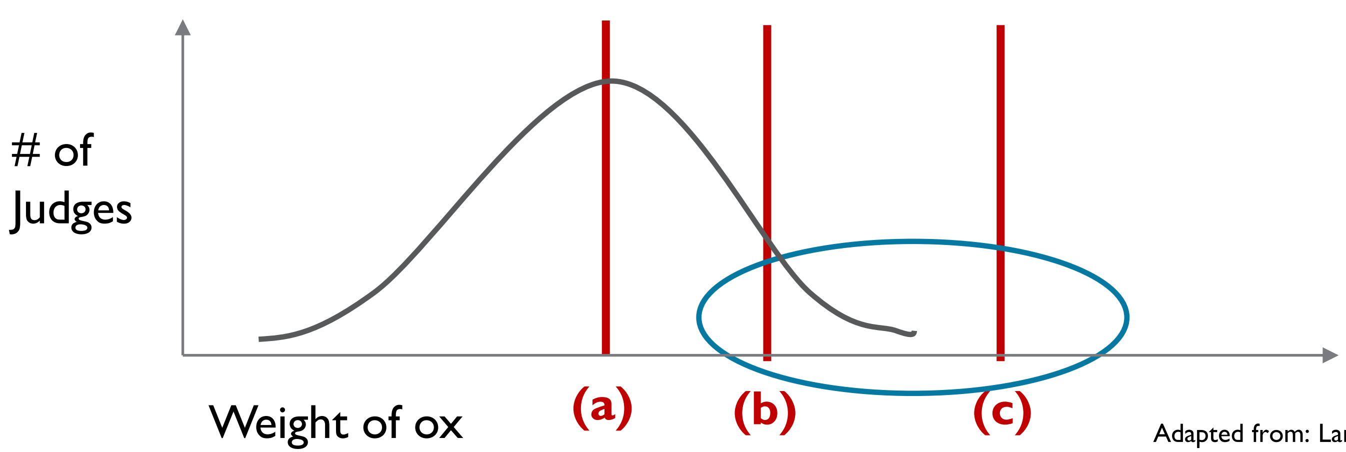
Wisdom of the crowd

Collective intelligence

- Average responses
- Diminish individual errors
- Knowledgeable and diverse
- Better than or equal to:
  - Average individual
  - Randomly selected individual



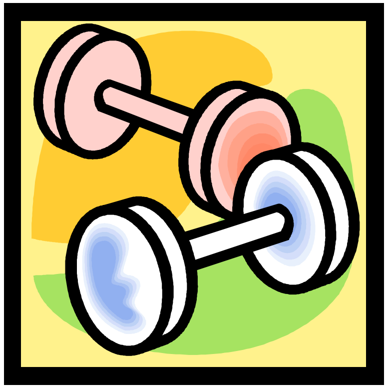
Sir Francis Galton's ox



Adapted from: Larrick, Mannes and Soll (2012)

Aggregation of judgment

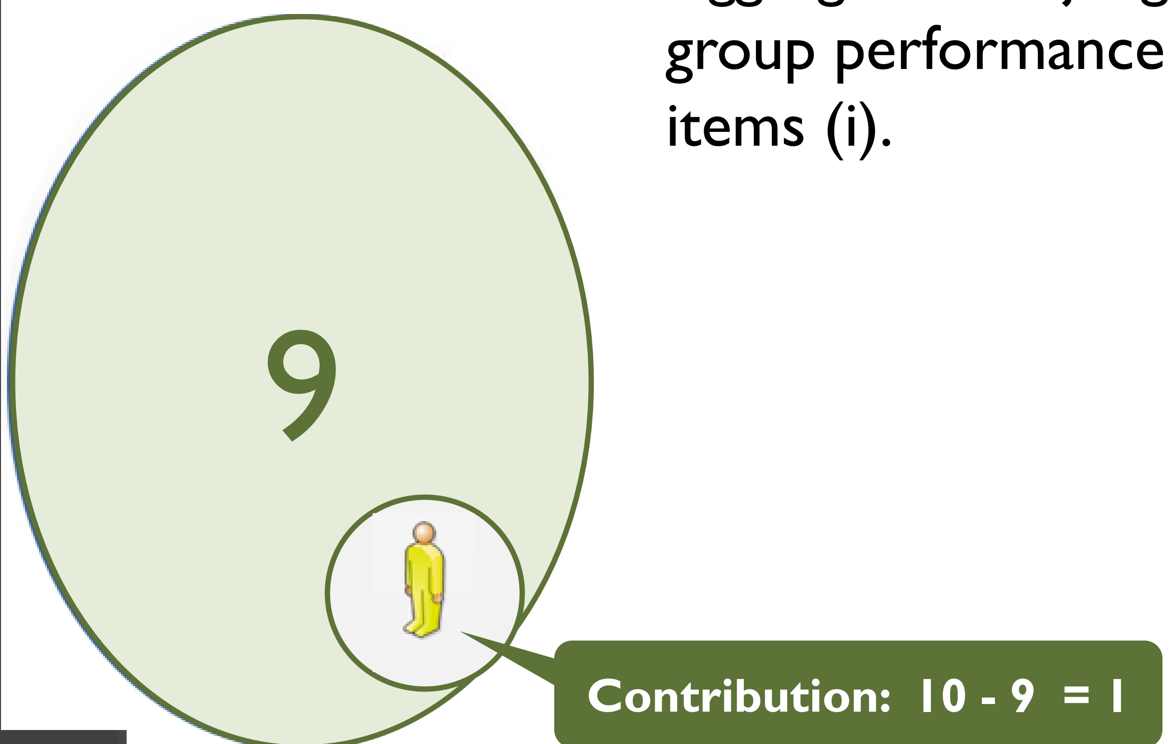
- Methods for aggregation
  - Behavioral (e.g., jury and committee)
  - Markets (e.g., prediction markets)
  - Mathematical
    - Bayesian models
    - Weighting models
- Bases for weights
  - Past performance
  - Test performance (Cooke)



Identifying experts

Contribution:

- Measure the expertise that the judge brings to the group.
- Aggregation of judge's impact on the group performance (Score) across all items (i).



The Aggregation Model

Group's aggregate forecast: $\mathbf{P_{Git} = A\ (P_{jit})}$ Forecast of judge (j) for event (i) at time (t)

Aggregation function

Re-calculate the group's forecast, excluding j: $\mathbf{P_{(G\,-\,j)it}}$

Merit score of the group : $\mathbf{S_{Git} = f\ (P_{Git})}$ **Merit function (e.g. Brier score)**

Judge's contribution to the group **item i at time t**: $\mathbf{C_{jit} = S_{Git} - S_{(G\,-\,j)it}}$

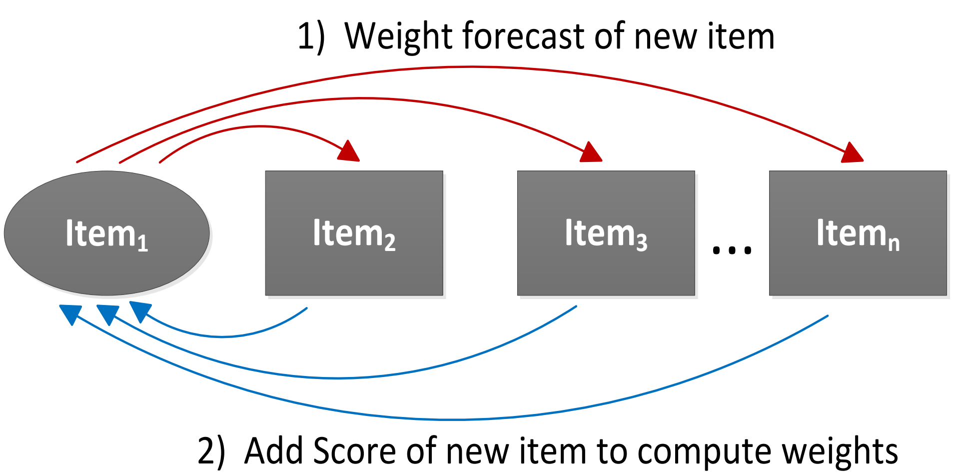
Judge's average contribution : $\mathbf{C_{jt} = \Sigma\ C_{ijt}\ /\ I_j}$ **All I_j items j answers at t**

$\mathbf{C_{jt,}}$

- **reflect the relative expertise of the various judges *in the context of the group***
- **can be positive, negative or 0**
- **can vary over time as more items are being forecasted**

Contribution Weighted Model

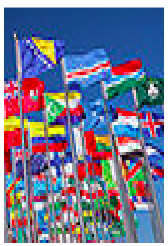
- Budescu and Chen (2015) proposed using a weighted aggregate of all positive contributors.
  - w_{jt}, are scaled such that all $w_{jt} \geq 0$, and $\Sigma\, w_{jt} = 1$.
  - $P_{Gi(t+1)} = A(w_{jt}, P_{ji(t+1)})$ for item i at time (t+1)
- CWM model:
  - weights are proportional to the contribution scores
  - only judges with positive contributions are used.
  - $w_{jt} = 0$ if $C_{jt} \leq 0$, and $w_{jt} = (C_{jt} / \Sigma C_{jt})$ if $C_{jt} > 0$.



Study 1: Geo-political forecasting tournament

Item/event

- Binary
- Ordered multinomial
- Unordered multinomial
- Conditional



#1417 Will Kim Jong Un meet a *head of state from one of the G7 countries, South Korea, China, or Russia **before 1 June 2015?

Opened on 08/27/14, Scheduled to close on 05/30/15 - 90 days

Your last forecast **None**

How likely is this event? 50 %

Probabilistic judgment

Experimental design

- Expertise (training & teaming)

Period1	No Training	Training
Individual	Ind-NT (157)	Ind-T (148)
Team	Team-NT (123)	Team-T (96)

- Facilitation (professional coaches)

Period 2	No Training	Training	Facilitation
Individual	Ind-NT (116)	Ind-T (105)	
Team		Team-NF (126)	Team-F (80)

Data collection

- Data from Jun'12-Jun'13 and from Jun'13-Jun'14
- Collect forecasts from voluntary judges.
- Items from international business, economy, military, policy, politics, etc.
- Judges answer items based on their interest (about 20% of items). We use those who answered ≥ 20 items
- Score (0-100), where 75 score = 0.5 probability

CWM compare to alternative models

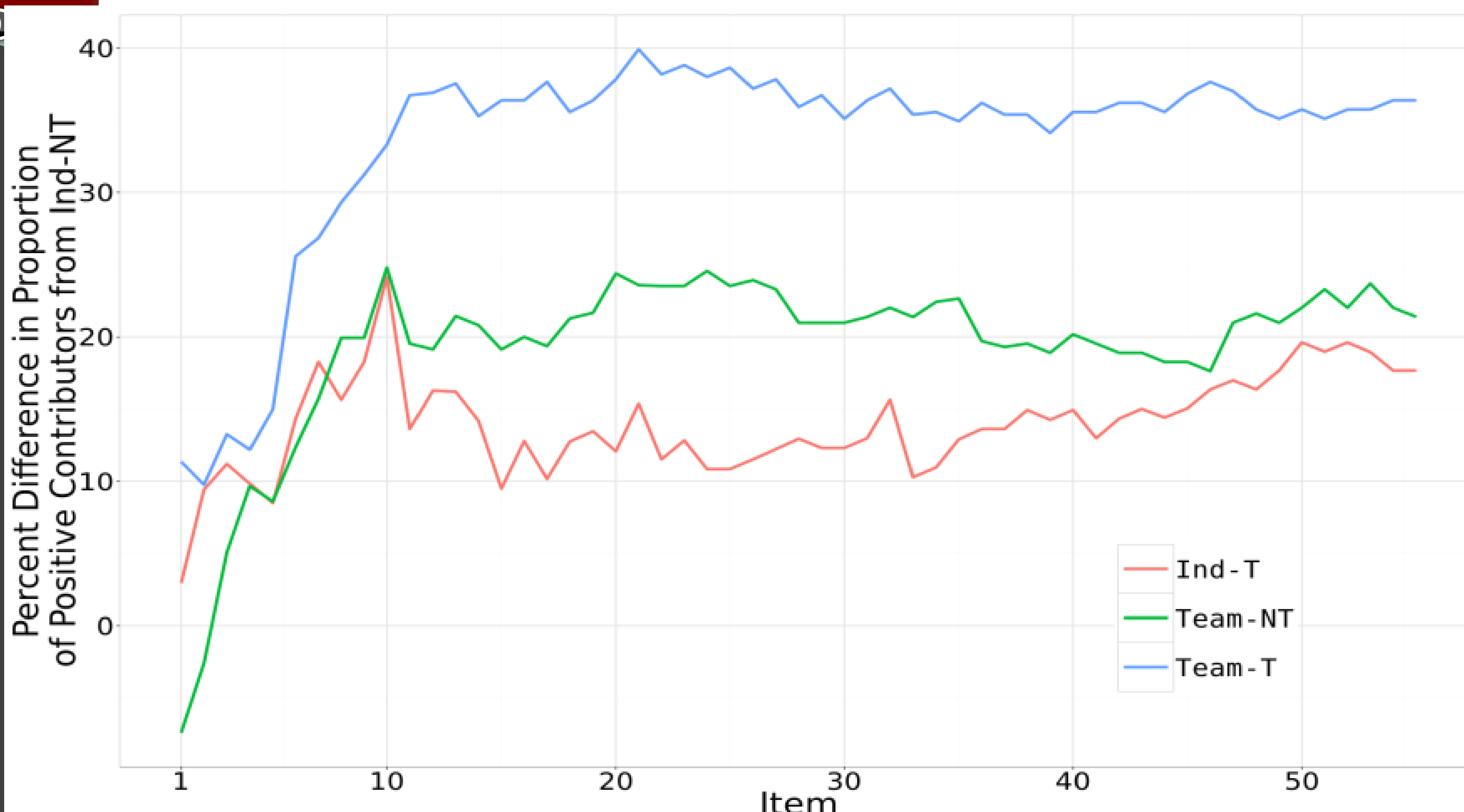
Models	Description
UWM	Unweighted mean of judges with 20 or more items
BWM	Weighted mean based on **past** Scores of judges who answered at least 20 items

- BWM was cross-validated.

CWM beats all models in Period 1

	Conditions			
	Independents		Teams	
	(Ind-NT)	(Ind-T)	(Team-NT)	(Team-T)
Mean Score of **CWM**	94.08	96.64	95.20	97.23
Mean Score of **UWM**	87.98	90.61	90.77	93.12
Mean Score of **BWM**	90.69	92.84	93.40	95.20
Proportion of relative improvement* (PRI) of CWM over UWM (in%)	**50.72**	**64.23**	**48.01**	**50.82`**
Proportion of items when CWM > UWM (in%)	96.43	98.21	91.07	96.42
PRI of CWM over BWM (in%)	**36.38**	**53.13**	**27.25**	**42.45**
Proportion of items when CWM > BWM (in%)	92.86	96.43	89.28	81.07

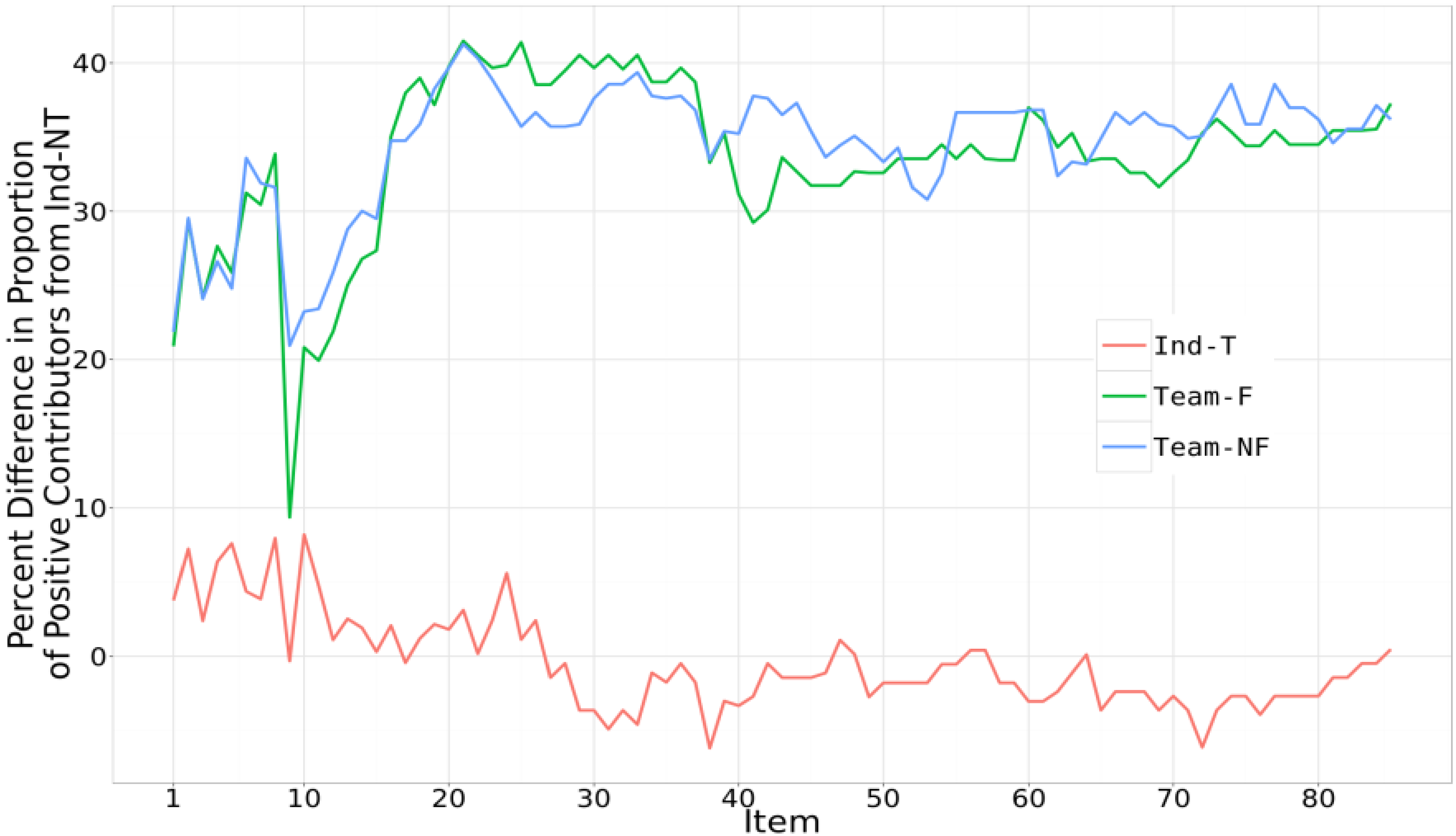
Effect of training and team



CWM beats all models in Period 2

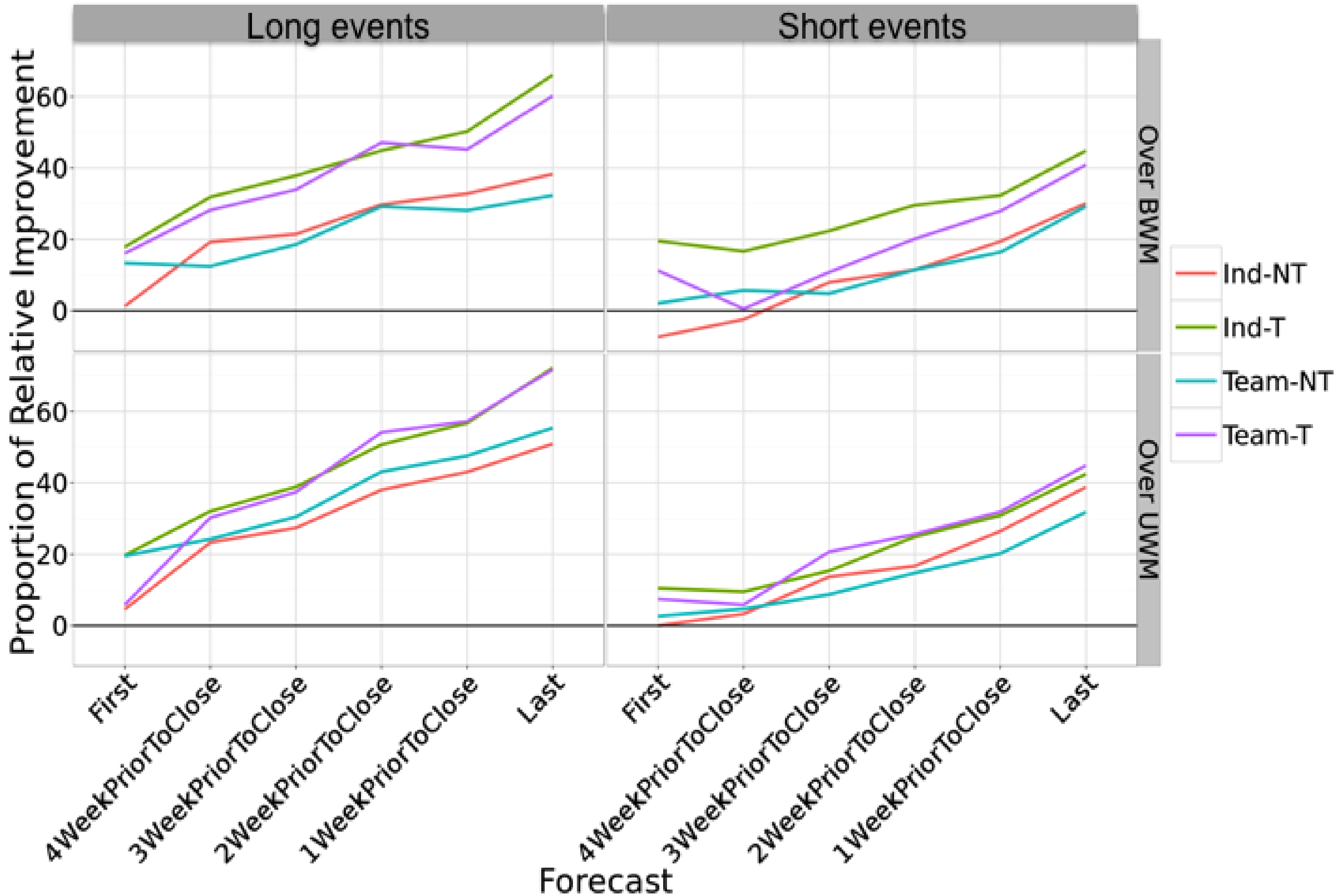
	Conditions			
	Independents		Teams	
	No training (Ind-NT)	Training (Ind-T)	No facilitation (Team-NF)	Facilitation (Team-F)
Mean Score of **CWM**	93.67	93.33	95.77	95.67
Mean Score of **UWM**	89.82	90.67	95.30	95.13
Mean Score of **BWM**	91.83	92.38	95.67	95.09
PRI of CWM over UWM (in%)	**37.84**	**28.51**	**10.00**	**11.02**
Proportion of events when CWM > UWM (in%)	90.70	84.88	75.58	87.21
PRI of CWM over BWM (in%)	**22.55**	**12.42**	**2.18**	**11.77**
Proportion of events when CWM > BWM (in%)	81.40	74.41	67.44	70.93

Effect of facilitation

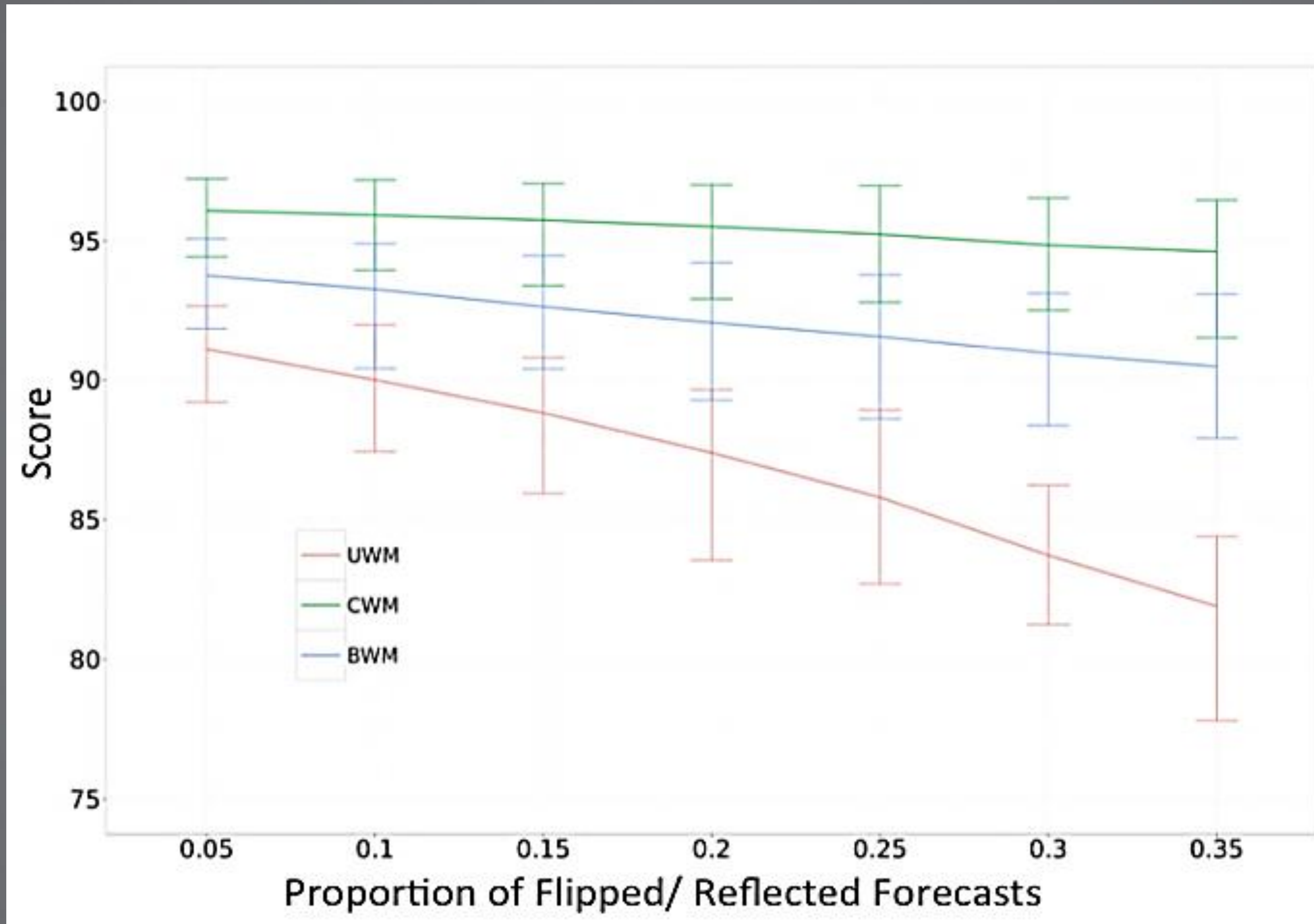


Discrimination

Effect of time



Robustness: Dishonest forecasters



* 50 run simulations using Teams form Period 1

Cost benefit analysis

Cost function= *Items (I)* * *Judges(J)* * *Cost (C)*

- Experts are costly (subset *J*, *w*, where $0 < w < 1$)
- Training questions require time (subset *I*, *p*, where $0 < p < 1$)

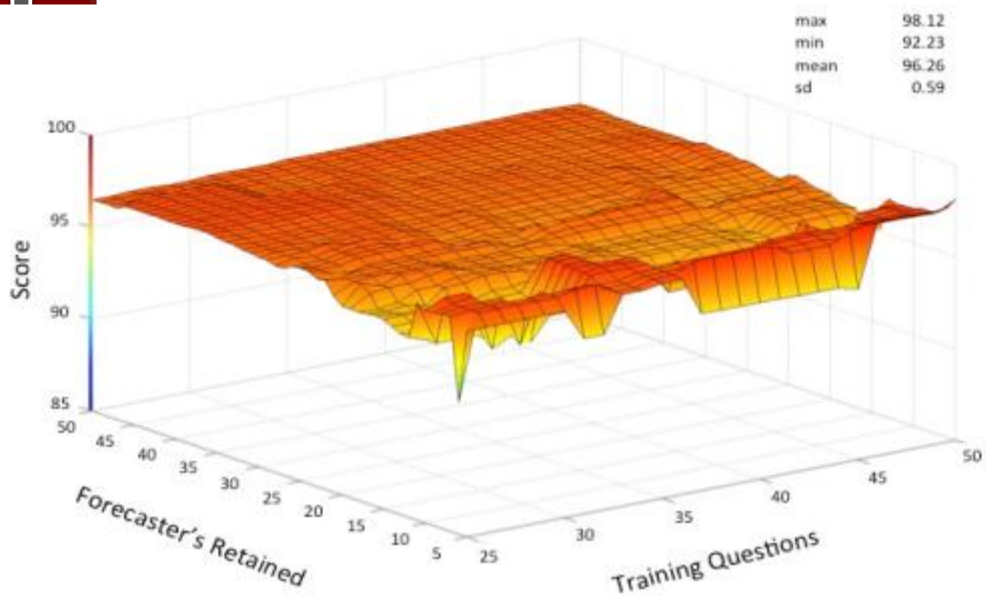
➔ **Maintain accuracy level**

Two scenarios (Ind-T from Period 2, to predict 36 items)**:**

1. Reduce cost by eliminating less contributing judges
2. Reduce cost by randomly eliminating judges

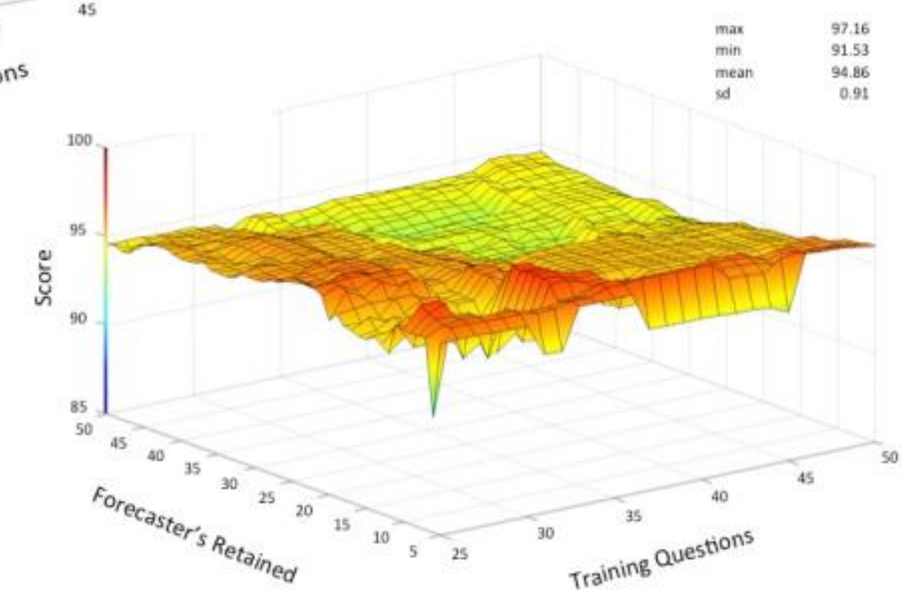
Reduce Cost function = $(p + (1-p)w)\, I\, J\, C$

Cost benefit analysis with top contributors

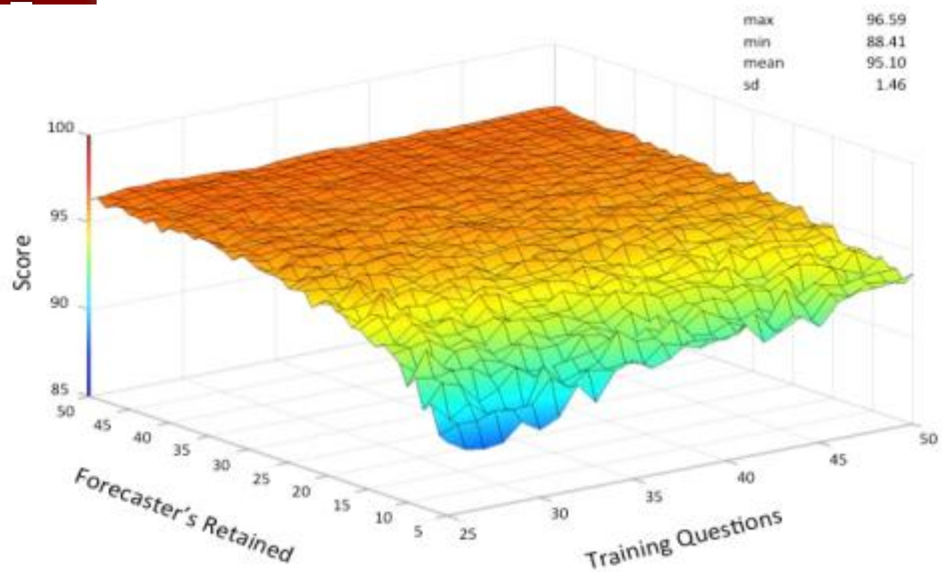


CWM:
Top 20 contributors
25 practice questions
57% saving => 95.29 Score

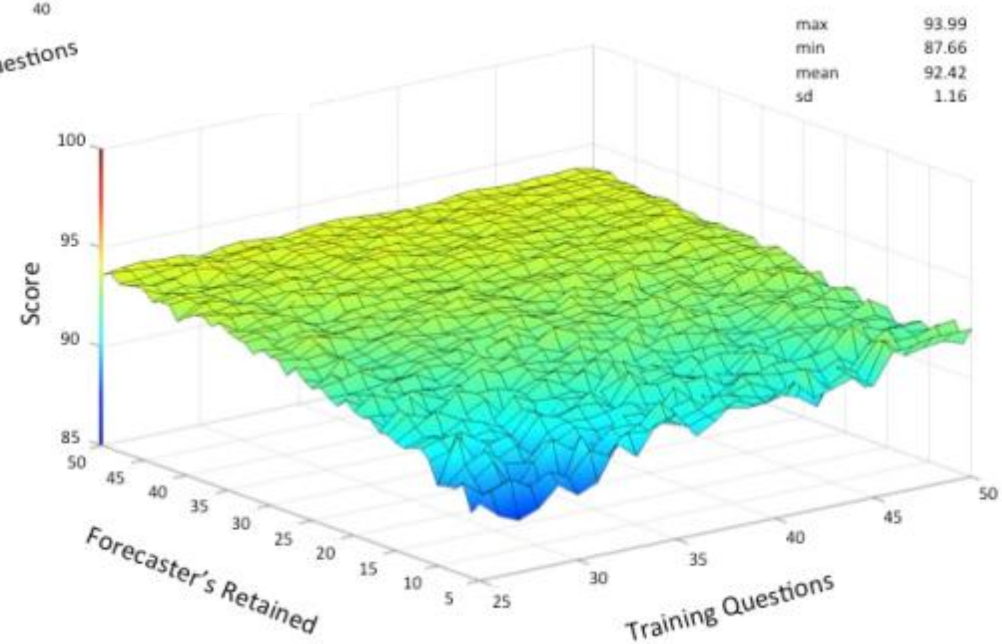
CWM vs. BWM:
PRI: 27.22% better than BWM
SD_{cwm}: 0.59
SD_{bwm}: 0.91



Cost benefit analysis with random forecasters



CWM:
15 contributors
40 practice questions
46% saving => 93.97 Score



* 50 run simulations

Summary of contribution

- Measure of contribution is simple, reliable and useful for assessing forecaster's performance.
- CWM is a better weighting tool in the aggregation process than those built solely on past, individual performance (BWM).

=> **weighting people who have knowledge against the crowd**

- CWM works best when there is expertise in the crowd: training or teaming
- CWM is robust (time, length of items and dishonest forecasters).
- CWM can reduce the cost of expert judgment.

GJ
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www.goodjudgmentproject.com

Budescu, D.V. & Chen, E. (2015). Identifying expertise to extract the Wisdom of Crowds. *Management Science*, 61(2), 267-280.

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