How does training reduce miscalibration? nsights from the Good Judgment Project

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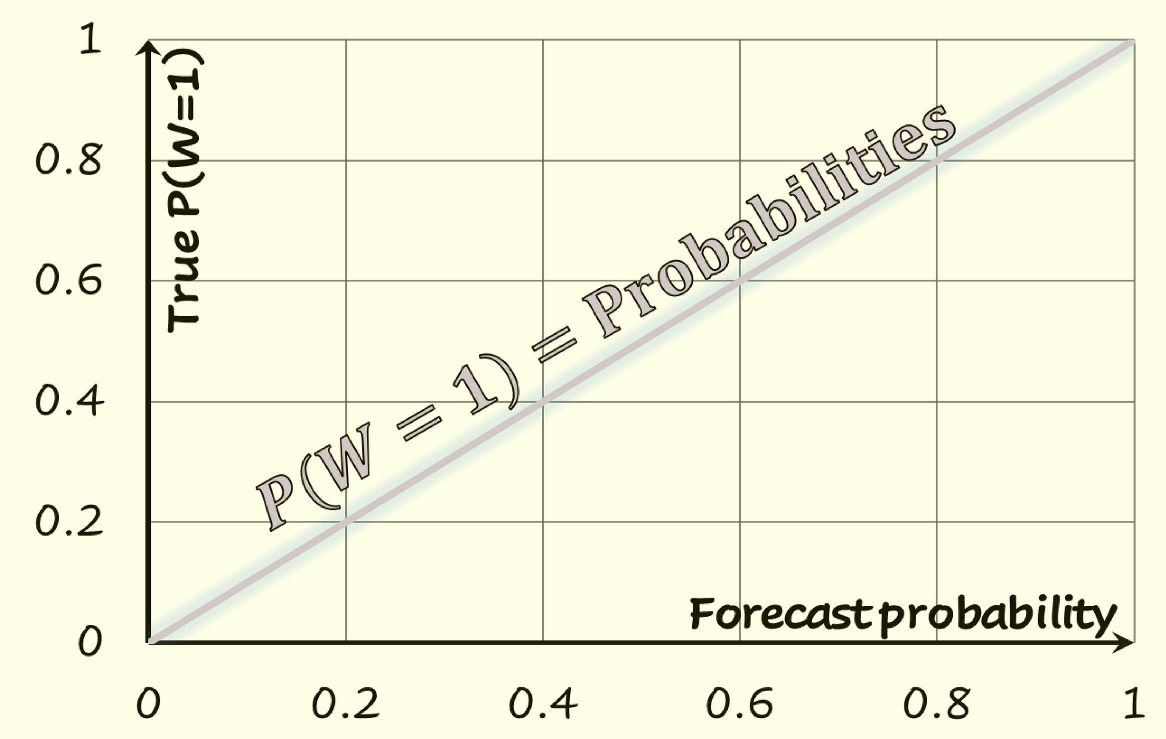
Introduction

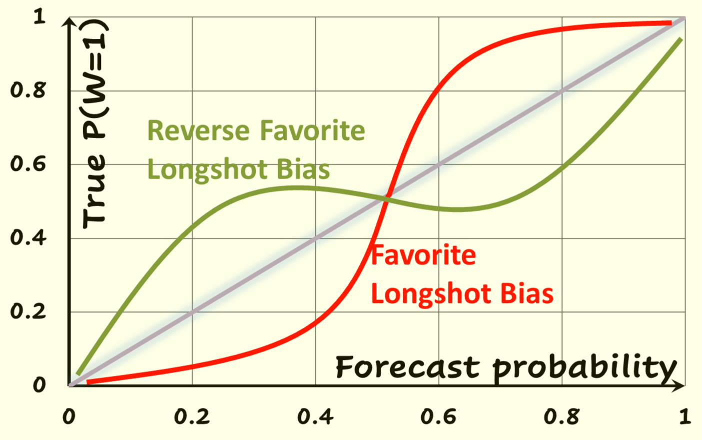
Zoom Meeting: https://uiowa.zoom.us/j/98646196961

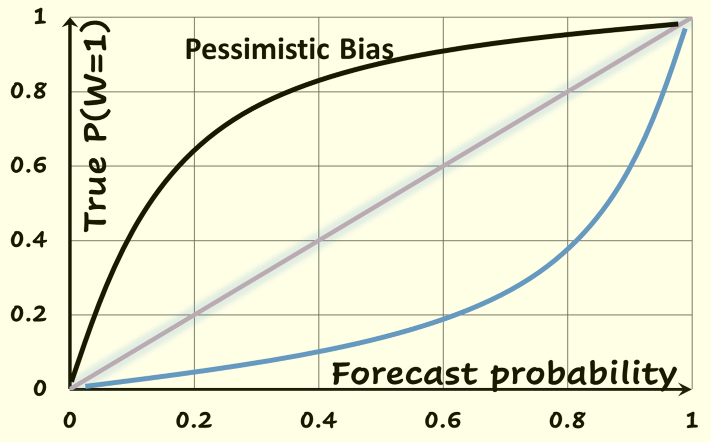
- ***Probability estimation training*** **has been shown to help individuals to produce better forecasts:**
  - **It reduces forecast error, i.e., the Brier Score** (Mellers etl al. 2014, Moore et al. 2017).
  - **It reduces the miscalibration component of the Brier Score = forecaster's average absolute divergence from the "well-calibrated" 45-degree line** (Chang et al. 2016).

- **Set of well-calibrated forecasts:**



- **Research Question: Consider these two types of miscalibration biases (Left: Compensatory, Right: Non-compensatory). How impactful is training in reducing either of these biases?**





Overview of Data and Methods

- **Publicly available data set called the "Good Judgment Project", winner of a multi-year geopolitical forecasting tournament.**
- **An example of forecasted question:**
  - **Will Greece remain a member of the EU through 1 June 2012?**
- **We explore biases among 307 individual forecasters (with at least 22 forecasts) who randomly were assigned to either go through a probability training (n=137) or not (n=170).**
- **Initial forecasts in the first year of the tournament are studied.**
- **Logit model** (Berg and Rietz 2019)
  - **Dependent Variable = Actual outcome (0 or 1),**
  - **Independent Variables: Log ratio transformation of the forecast, training (1: gone through training or 0:otherwise)**

Logit Method: $\frac{P(W=1)}{1-P(W=1)} = \exp\left(b_0 + b_1 * \log\frac{F}{1-F} + b_2 * training + b_3 * training * \log\frac{F}{1-F}\right)$

Notes:
- Log ratio of forecasts as an IV
- Dummy training IV
- Individual differences are controlled

$$\frac{P(W=1)}{1-P(W=1)} = \exp\left((b_0 + b_2 * training) + (b_1 + (b_3 * training))\log\frac{F}{1-F}\right)$$

Case of No Bias: $True\ P(W=1) = F\ (Forecast)$

Estimation greater than 0: Pessimistic Bias
Estimation less than 0: Optimistic Bias

Estimation greater than 1: Favorite Longshot Bias
Estimation less than 1: Reverse Favorite Longshot Bias

Results

Parameter	**Coefficient (Std. Error)**	**Bias Detection**
Intercept (Null: b_0=0)	**-1.18 (0.27) *****	*Non-compensatory type*: Optimistic bias
Training (versus non-trained)	0.55 (0.43)	
Forecasts' Log ratio (Null: $b_1 = 1$)	**0.54 (0.22) ****	*Compensatory type*: Reverse Favorite-Longshot bias (marginally helped by probability training)
Forecasts' Log ratio * training	**0.65 (0.39) ***	
McFadden pseudo-r2	0.166	

Conclusions

- **We use a novel model to detect both *non-compensatory* and *compensatory* biases in a set of repeated probabilistic forecasts.**
- **Probability estimation training helps by (marginally) reducing the extent of the reverse favorite longshot bias.**

Important References

- Berg, J. E., & Rietz, T. A. (2019). Longshots, overconfidence and efficiency on the Iowa Electronic Market. *International Journal of Forecasting*, *35*(1), 271-287.
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- Moore, D. A., Swift, S. A., Minster, A., Mellers, B., Ungar, L., Tetlock, P., ... & Tenney, E. R. (2017). Confidence calibration in a multiyear geopolitical forecasting competition. *Management Science*, *63*(11), 3552-3565.