Ensemble size: How suboptimal is less than infinity?

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Ensemble size at ECMWF





ECMWF 25 YEARS OF ENSEMBLE PREDICTION



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50 Ensemble Members

Ensemble size at ECMWF





Ensemble size at ECMWF

50 member since Dec 1996

Why 50?





Ensemble size at ECMWF

50 member since Dec 1996

Why 50?

Are the benefits of more than 50 members marginal?



Talagrand, Vautard and Strauss (1997)



⁽adapted from their Fig. 4.5)

4.2.3 Dependence on the size of forecast ensembles

One particularly interesting question is whether one should continue increasing the size of the ensembles or rather concentrate efforts on other points. Figure 4.5 attempts to address this issue. We display the global BSS values as a function of the number of members N, for the median threshold ($\tau = 0$ K) and the extreme threshold ($\tau = 8$ K). One argument for the extension of the ensemble size is the better estimation of probabilities of extreme events. We should therefore see in Figure 4.5 a larger sensitivity to N for the threshold $\tau = 8$ K than for the threshold $\tau = 0$ K. Such is not the case. It is to be noticed that convergence is actually reached quite quickly at all lead times, for, say, N = 20-30.



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According to Talagrand et al (1997) not more than 30 members are needed.



Buizza and Palmer (1998)

Comparison of 2, 4, 8, 16, 32 members



(adapted from their Fig. 11) Z500 in NH; T63L19 model, initial uncertainty represented with singular vectors, no representation of model uncertainty Careful conclusions that do not rule out increases in skill beyond 32 members.



Buizza et al. (1998)

Impact of resolution and ensemble size

TABLE 2. Characteristics of the Ensemble Prediction System (EPS) configurations tested

TABLE 9. Brier skill score for probability prediction of precipitation amounts of 1 and 10 mm day $^{-1},$ over the northern hemisphere, at forecast-days 5 and 7

Member size	Forecast resolution	Singular vectors' resolution		Forecast-day 5		Forecast-day 7	
			Configuration	1 mm day ⁻¹	10 mm day ⁻¹	1 mm day ⁻¹	10 mm day ⁻¹
32	T63L19	T42L19			· · · · · · · · · · · · · · · · · · ·		
128	T63L19	T42L19	32*T63	0.286	0.066	0.201	0.009
32	T106L31	T42L19	32*T106	0.286	0.095	0.219	0.078
32	T106L31	T42L19	32*T106SV31	0.285	0.097	0.219	0.078
50*T106SV31 50 T106L31	T42L31	50*T106SV31 128*T63	0.298 0.299	0.104 0.087	0.230 0.238	0.091 0.049	
	Member size 32 128 32 32 50	Member size Forecast resolution 32 T63L19 128 T63L19 32 T106L31 30 T106L31	Member size Forecast resolution Singular vectors' resolution 32 T63L19 T42L19 128 T63L19 T42L19 32 T106L31 T42L19 32 T106L31 T42L31 50 T106L31 T42L31	Member size Forecast resolution Singular vectors' resolution Configuration 32 T63L19 T42L19 32*T63 32 T63L19 T42L19 32*T63 32 T106L31 T42L19 32*T106 32 T106L31 T42L31 32*T106SV31 50 T106L31 T42L31 50*T106SV31 128*T63 128*T63 128*T63	Member size Forecast resolution Singular vectors' resolution Foreca 32 T63L19 T42L19 1mm day ⁻¹ 32 T63L19 T42L19 32*T63 0.286 32 T106L31 T42L19 32*T106 0.286 32 T106L31 T42L31 32*T106SV31 0.286 32 T106L31 T42L31 50*T106SV31 0.298 50 T106L31 T42L31 50*T106SV31 0.298 128*T63 0.299 128*T63 0.299	Member size Forecast resolution Singular vectors' resolution Forecast-day 5 32 T63L19 T42L19 1 mm day ⁻¹ 10 mm day ⁻¹ 32 T63L19 T42L19 32*T63 0.286 0.066 32 T106L31 T42L19 32*T106 0.286 0.095 32 T106L31 T42L31 32*T106SV31 0.285 0.097 50 T106L31 T42L31 50*T106SV31 0.298 0.104 128*T63 0.299 0.087 128*T63 0.299 0.087	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $

For each precipitation amount, bold figures identify the most skilful results.

In December 1996, resolution was increased from T63 (quadratic grid) to TL159 (linear grid) and ensemble size was increased from 32 to 50 members.



Miyoshi et al (2014)

identical twin EnKF using SPEEDY model





Machete and Smith (2016)



Guess the ensemble size

i.i.d. members; pdfs for 20 realisations; ensemble size fixed in each panel



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Ensemble size at ECMWF





Experiments with IFS ensembles

- IFS cycle 41r2
- as operational ensemble but lower resolution: TCo399
- 200 members
- June-July-August 2016 (92 cases)
- probabilistic skill evaluated with continuous ranked probability score (CRPS): mean squared error of cumulative distribution



Impact of ensemble size on CRPS



Impact of ensemble size on CRPS

Predictions of CRPS for infinite ensemble size $\cdots \diamond \cdots \diamond \cdots \diamond \cdots$



Where does increased skill come from?

Sampling uncertainty of Z500 ensemble mean at D7



CRPS and ensemble size: What to expect? Kernel representation of CRPS

• kernel representation of CRPS

$$CRPS(x_j, y) = \frac{1}{M} \sum_{j=1}^{M} |x_j - y| - \frac{1}{2M^2} \sum_{j=1}^{M} \sum_{k=1}^{M} |x_j - x_k|$$

• With exchangeability of members, the expected CRPS is

$$\mathbb{E}_{x} \mathsf{CRPS}(x_{j}, y) = \mathbb{E}_{x} |x - y| - \frac{M - 1}{2M} \mathbb{E}_{x, x'} |x - x'|$$

For an infinite size ensemble we get

$$\mathbb{E}_{x} \mathsf{CRPS}(x_{j}, y) = \mathbb{E}_{x} |x - y| - \frac{1}{2} \mathbb{E}_{x, x'} |x - x'|$$

How can CRPS for infinite ensemble size be predicted with a finite ensemble?

- The fair CRPS is a modified version of the CRPS that removes the bias in the score due to the finite ensemble size (see Chris Ferro's talk)
- From the kernel representation, one can see easily that the CRPS for infinite ensemble size is obtained by the estimator

$$CRPS^*(x_j, y) = CRPS(x_j, y) - \frac{1}{2M^2(M-1)} \sum_{j=1}^M \sum_{k=1}^M |x_j - x_k|$$

• The correction term is a measure of ensemble spread.

Analytic result for statistically consistent ensembles

 When members are statistically consistent (iid) draws from same distribution as observation (perfectly reliable ensemble), the CRPS for an m-member ensemble satisfies

$$CRPS_M = \left(1 - \frac{M-1}{2M}\right) \mathbb{E} \left|x - x'\right| = \left(1 + \frac{1}{M}\right) CRPS_{\infty}$$

• Eqns. (8) and (9) in Richardson (2001) show that the Brier score also satisfies $BS_M = (1 + M^{-1})BS_{\infty}$.

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- Eqns. (8) and (9) in Richardson (2001) show that the Brier score also satisfies $BS_M = (1 + M^{-1})BS_{\infty}$.
- Extreme events? Relationship for BS implies that for any weighting in the twCRPS (Gneiting and Ranjan, 2011) we also have

$$\mathsf{twCRPS}_{M} = \left(1 + \frac{1}{M}\right)\mathsf{twCRPS}_{\infty}$$

Actual convergence with ensemble size

- Data from 200 member TCo399 IFS experiment, JJA2016
- 120 data points for each ensemble size
- 15 lead times \times 4 variables (z500, T850, u850, u200) \times 2 regions (NH and SH extratropics)
- 50 and 200 members are 2% and 0.5% worse than ∞ , respectively

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Quantile score and CRPS

$$\mathsf{QS}_{\alpha}(q, y) = 2(\mathbb{I}\{y < q\} - \alpha)(q - y)$$

with indicator function $\mathbb{I}(\text{true}) = 1$ and $\mathbb{I}(\text{false}) = 0$, quantile qand observation y; $\alpha \in (0, 1)$ denotes the probability level

$$\mathsf{CRPS}(F, y) = \int_0^1 \mathsf{QS}_\alpha \left(F^{-1}(\alpha), y \right) \, \mathrm{d}\alpha$$

where the quantile q for cumulative distribution F is $F^{-1}(\alpha)$

Quantile score for a standard Gaussian

Simulations with M = 20 to 1000 members

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Ensemble size at ECMWF

Research and development

What is a good ensemble size?

- Large ensemble size can delay progress in R&D
- It would be most efficient to use the smallest ensemble size that is sufficient to estimate impact for operational ensemble size
- Using proper scores with small ensembles can mislead though

 $\Delta CRPS$ for 850 hPa temperature in northern extratropics

 $\Delta CRPS$ for 850 hPa temperature in northern extratropics

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 ΔCRPS for 850 hPa zonal wind in tropics

 ΔCRPS for 850 hPa zonal wind in tropics

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 ΔCRPS for 850 hPa zonal wind in tropics

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50 member 2 member (1,2) 0.13 0.1 0.07--0.1 $CRPS... - CRPS_N$ 0.04 R, M=50 R, M=2 0.01 O, M=50 O, M=2 -0.2--0.02-N. M=50 N. M=2 -0.05 ġ. 6 9 fc-step (d) 12 ż 6 9 fc-step (d) 12 0 15 15 6 0--0.1fair -0.1 R, M=50 R, M=2 CRPS O. M=50 O. M=2 -0.2--0.2-N. M=50 N. M=2 ò ġ. ġ 12 15 Ó ż 6 ġ 12 15 6 fc-step (d) fc-step (d)

Ensemble configurations R, O and N

 ΔCRPS for 850 hPa zonal wind in tropics

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Small ensemble sizes

- Can be used for R&D if evaluation uses fair scores
- Can be used in reforecasts for estimating skill
- Applicability of fair scores is linked to ensemble generation
- Current ensemble generation at ECMWF not fully consistent with exchangeability required for fair scores
- Benefits for R&D
 - faster turnaround time
 - more configurations can be explored
 - scope for increasing statistical significance by using less members but more start dates

How suboptimal is less than infinity?

Three possible answers:

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• A bit or maybe a lot, tell me the score and your ensemble size

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How suboptimal is less than infinity?

Three possible answers:

- A bit or maybe a lot, tell me the score and your ensemble size
- **Operational ensemble forecasts:** 50 members are too few let's increase the ensemble size to . . .
- **Research & Development:** Small ensembles are highly efficient. Two to four members may be enough for standard evaluations (provided exchangeability in the ensemble generation and use of fair scores)

Discussion

- How can we increase ensemble size when we need to increase resolution too?
- Different users will have different needs, how to obtain a good compromise for all of them?
- How to increase ensemble size in a computationally efficient way for all forecast ranges from medium-range to extended-range?
- What is an adequate ensemble size for the reforecasts?
- Which other proper scores permit the construction of an associated fair score?

