Ensemble forecasting at ECMWF

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Initial conditions

T850hPa
HRES Analysis 00 UTC

EDA-Pert 1

SV-Pert 1

Initial conditions for ENS member 1
Singular vectors and reliability

EDA and SPPT generate spread also in the directions of the leading SVs. Just not enough though.

When to stop using SVs?
Future directions for ICs

- Centre of ensemble at initial time
  - single deterministic AN
  - EDA (Lang, Bonavita and Leutbecher, 2015, QJ)
  - multiple deterministic analyses (Hólm et al. 2018, FUSION)

- Exchangeable initial conditions for atmosphere (Lang et al 2019, ECMWF Newsletter No. 158)
  - abandon ± symmetry
  - 50 EDA members
  - joint distribution of members does not depend on their order
  - efficient testing configuration with small ensemble size based on fair scores (Leutbecher, 2018)
Stochastically Perturbed Parametrization Tendencies

- More realistic diurnal cycle of tendency perturbations in SPPT by not perturbing the clear-sky radiative tendency;
- Perturbations in stratosphere and weaker tapering of perturbations in boundary layer;
- Same SPPT in ENS and EDA, and cycling of random fields in EDA;
- 20% reduced SPPT amplitude;
- SKEB deactivation (2.5% saving)

Temperature tendency perturbations due to SPPT only (K/3h, shading) precipitation (ens. mean, .5/1/2/4/8/... mm, black contours) 2015011000, t=+21–24 h
Future directions for representation of MU

- represent uncertainty close to the assumed sources of the errors
- physical consistency of perturbation
- e.g. preserve local energy or moisture budget through flux perturbations at surface and at the top-of-the-atmosphere consistent with the tendency perturbation
- beyond an amplitude error, e.g. uncertainty in shape of heating profile
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Ongoing research on model uncertainties

- Stochastically Perturbed Parametrization Tendencies (SPP)
- Quantitative comparison of the tendency perturbations from SPP and SPPT
- Dynamical Core uncertainties

see Ollinaho et al. (2017) and Leutbecher et al. (2017).
Predictive verification for design of multi-model ensembles

- Consider: $m_A$ members from model A, $m_B$ members from model B, \ldots
- How does the skill of the multi-model ensemble depend on $m_A, m_B, \ldots$? 
- If computational cost was constrained globally for all NWP centers, how many members would we like to have from model A, B, C, \ldots? 
- Can this be answered without having to run ensembles with largest $m_A, m_B, \ldots$ one would like to consider.
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• Answer for CRPS using kernel representation and assuming a kind of exchangeability

\[
\sum_{i=1}^{k} \frac{\lambda_i}{m_i} \sum_{g=1}^{m_i} \left| z_{ig} - y \right| - \frac{1}{2} \sum_{i,j} \frac{\lambda_i \lambda_j}{m_i m_j} \sum_{g=1}^{m_i} \sum_{h=1}^{m_j} \left| z_{ig} - z_{jh} \right|
\]

$\sum$ denote sums over different models $i,j$ with respective weights $\lambda_j$ and number of members $m_j$ and $\sum$ denote sums over members of a specific model.
Predictive verification for dual-resolution ensembles

- $p$ members with lower resolution (say TCo399) and $q$ members at higher resolution (say TCo639).
- Cost ratio for example is 4; $(p, q) = (200, 0), (160, 10), (120, 20), (40, 40), (0, 50)$ have same computational cost.
- Compute 5 terms that enter in kernel representation of CRPS for two distinct models from small ensembles $(p_E, q_E) = (8, 8)$.
- Derive formula that gives expected CRPS for any $(p, q)$.
- Expression for optimum weights as function of stats.

Ben Bouallègue et al. (2019)
Tellus in review
• Flow-dependent initial perturbations from EDA and SVs: Both components essential to achieve reasonable reliability

• Revision of SPPT brings different flow-dependent representation of model uncertainties through removing spurious diurnal cycle in perturbations

• The desire for physical consistency of perturbations motivates development of alternative schemes that represent uncertainty close to its sources

• Work on CRPS score adjustments permits to study large range of multi-model combinations without having to run/verify each configuration separately; optimum weights can be determined directly (without need for numerical optimisation).