Exploring uncertainty in model representation of atmospheric convection through

**Universal Structural Parameterisation**

**Hugo Lambert**, with thanks to
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Hannah Christensen and Nathan Mayne

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What I want

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   - do the same with process-based models.
   - create new, plausible parameterisations that don't exist yet.
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4. *Run* the representations in **FORTRAN 90**.
Some statistical / machine learning frameworks

- Linear regression
- Genetic algorithm
- Gaussian Process
- Neural network
Some previous work with ML frameworks

**Krasnopolsky (2010):** Neural network for radiation trained on parameterisation. (Work goes back 25 years...)

**O’Gorman and Dwyer (2018):** Random forest for convection trained on parameterisation.

**Rasp et al. (2018):** Neural network of radiation and convection trained on cloud resolving simulation.
Statistical method (1)

- Write data inputted into and outputted by a convection scheme in terms of one enthalpy vector per model column.

- Express data in terms of its eigenvectors to aid parsimony and orthogonality.

- Build a regression model that links outputs to inputs.
  - Class-based logistic regression for convective trigger. (Does it convect or not?)
  - Ordinary linear regression model of convecting cases.

- Discard eigenvectors that don’t account for much variance and obtain a human-readable description of one or more convection schemes.
Trigger?

\[
\hat{\text{class}} = \frac{\exp(\sum_i \gamma_i (u_i . \text{input}))}{1 + \exp(\sum_i \gamma_i (u_i . \text{input}))}
\]

IF \(\hat{\text{class}} > 0.5\), THEN convect.

Convection cases:

\[
\hat{\text{output}}_j = \sum_i \beta_{ij} (u_i . \text{input}) v_j,
\]
\[
\hat{\text{output}} = \sum_j \hat{\text{output}}_j.
\]
Experimental set-up

- Met Office UM vn11.1. (Close to HadGEM3-A.)

- Aquaplanet with slab ocean.

- No cloud interaction with radiation. No convective cloud.

- Emulators fitted to 60 days of 30° N–S data from January and July. Somewhat suboptimal.

- Two convection schemes. Met Office simplified Lambert-Lewis scheme (LLCS) and Gregory-Rowntree mass-flux scheme.
What do first modes of response look like?

![Graphs showing LLCS and GR with Q1 and Q2](image-url)
What causes them?

Convection is rare, so investigate $\sum_i \beta_{ij} u_i$. 
<table>
<thead>
<tr>
<th></th>
<th>LLCS</th>
<th>GR</th>
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</thead>
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<tr>
<td><strong>Convecting</strong></td>
<td>84 %</td>
<td>90 %</td>
</tr>
<tr>
<td><strong>Non-convecting</strong></td>
<td>82 %</td>
<td>93 %</td>
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</table>
LLCS mid-upper tropospheric warming

![Graph showing LLCS mid-upper tropospheric warming](image)
GR mid-upper tropospheric warming

![Graph showing the relationship between emulator warming and actual warming in Kelvin. The graph contains a scatter plot with a diagonal line indicating the perfect match. The x-axis represents emulator warming in Kelvin, ranging from -0.1 to 0.7, and the y-axis represents actual warming in Kelvin, ranging from 0 to 0.6. The color bar on the right side indicates the temperature range from -6 to 6 Kelvin.](image-url)
Combined $v_1$ and $u_{1,2,3}$ for LLCS and GR

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**First joint output**

**Pressure [hPa]**

- Q1
- Q2

**Second joint input**

**Pressure [hPa]**

**First joint input**

- dry
- moist

**Third joint input**

**Pressure [hPa]**
Sensitivity of $v_1$ to $u_{1,2,3}$
Emulating convection in the GCM...
First CASCADE data prepared by Hannah Christensen

CASCADE mid-upper tropospheric warming

Emulator warming [K]

Actual warming [K]

Convecting: 84%
Non-convecting: 89%
for 9434 cases.
Conclusion

- **Universal structural parameterisation** is a way of writing down model parameterisations using variables on the model grid that are observable in principle.

- **USP** was successful in expressing two convection schemes simply and highlighting differences between them.

- Some **success** in trying to run USP examples within a GCM.

- **Future work:** Analyse high resolution data. Evaluate the extent to which schemes represent our knowledge of convection.
