*Paper*: **Beyond temperature scaling: Obtaining well-calibrated multiclass probabilities with Dirichlet calibration**  
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*Label:* Calibration (WP2)

## **Theory** (type of innovation, improving X, task(s) description, uniqueness)

Native (not pairwise / one-vs-rest) general-purpose (non-NN and NN) multi-class *post-hoc* calibration with Dirichlet calibration maps as an extension of Beta calibration (binary); focus on class-wise calibration, not only confidence calibration (argmax).

Propose new metric for class-wise calibration evaluation and visualization.   
Introduce Dirichlet calibration maps for increased interpretability of calibration effect.   
Secret sauce might be ODIR regularization (enables calibration for larger K classes output space).

Task: multiclass (image) classification; similar approaches: temperature, vector, matrix scaling.

Uniqueness: extension on beta calibration, results improve slightly improve temperature scaling, mainly impact on class-wise calibration, less so for confidence-calibration.

## Methodology (support for claims, dataset, evaluation metrics):

*UCI benchmark dataset and CIFAR-10/100.*

Extensive experimentation which is overall extremely well-documented with a large appendix section.   
Large comparison to a range of calibration, loss metrics.  
Very nice statistical rank comparisons with Friedman tests and post-hoc Bonferonni-Dunn test to explain effect size in terms of “Critical (rank) Difference” over repeated measurements.   
Additional perfect calibration statistical test.

## **Open-source** material (code, dataset, tutorial, references):

<https://github.com/dirichletcal/experiments_neurips>  
https://github.com/dirichletcal/experiments\_dnn

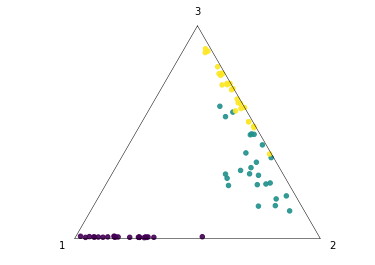
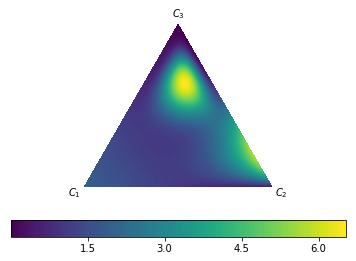
## Usefulness (task [classification, extraction, …], part-of-pipeline, extension / improvement on, domain/use-case):

*My two cents:* Better global thresholding with class-wise calibration; perception: K=2 ranking score: making an error where the second-best answer is almost equally probable is less a false positive than when being less confident.

General-purpose:

* General: fit small NN model taking in pickled val/test logits.
* NNs: replaces the softmax/tempscale layer with [logistic regression + feedforward + softmax].

Lovely visualization and interpretability:



## **Feasability** (short-term/long-term | nice-to-have, complexity / far-from-practice?)

Code is available, general-purpose method, easy comparison to temperature scaling.  
Warrants a run on our datasets and models.   
Code is a bit all over the place, yet attached notebooks are very insightful for ablation and design choices.

## Questions/Ideas

* How does it perform with fine-grained (>100) classification?
* Does it work well under class imbalance?
* Is there a combination possible with Bayesian model (deep ensemble / MC dropout) and calibration layer?

**BIBtex:**

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