

CALIBRATED CLASSIFIER

A binary classifier is calibrated, if:

- **it outputs a probability** of the instance to be positive instead of outputting a class label;
- **and that probability is calibrated**, i.e. it is equal to the proportion of positives among all instances with the same predicted probability;

WORKS IN ANY COST CONTEXT

The same calibrated classifier works for any false positive and false negative cost context without retraining:

1. Learn a calibrated classifier;
2. Apply the classifier on the given test instance to obtain an estimate \hat{p} of its probability to be positive;
3. Determine the costs c_{FP} and c_{FN} per false positive and false negative;
4. Predict positive if $\hat{p} > c_{FP}/(c_{FP}+c_{FN})$, otherwise predict negative.

Prediction and cost-sensitive decision making have been separated. This is required when the misclassification costs are not known during model training.

CLASSIFIER CALIBRATION

If the classifier outputs non-calibrated probabilities or any real-valued scores, then it can still be calibrated:

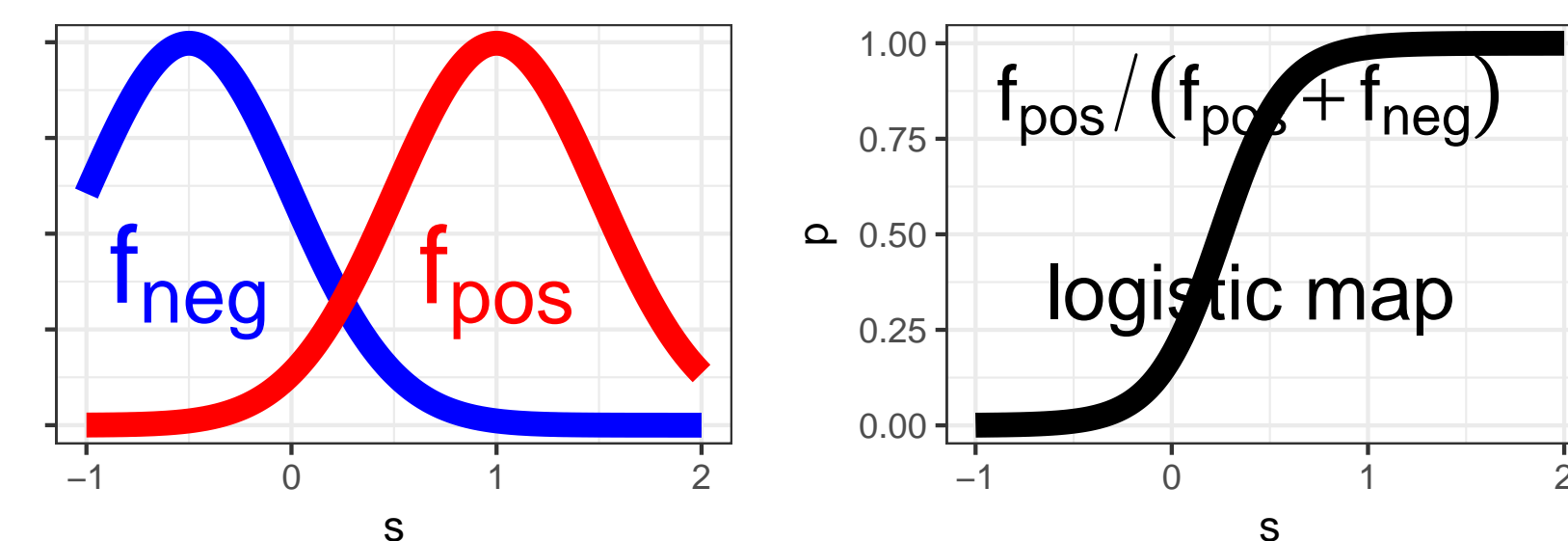
1. Learn a calibration map μ from classifier outputs to calibrated probabilities;
2. Apply the classifier on the given test instance to obtain the non-calibrated score s ;
3. Remap the score into a calibrated probability $\hat{p} = \mu(s)$.

LOGISTIC CALIBRATION

- Also known as Platt scaling [Platt 2000]
- Fits a parametric family with 2 parameters:

$$\mu_{\text{logistic}}(s; \gamma, \delta) = \frac{1}{1 + 1/(e^{\gamma \cdot s + \delta})}$$

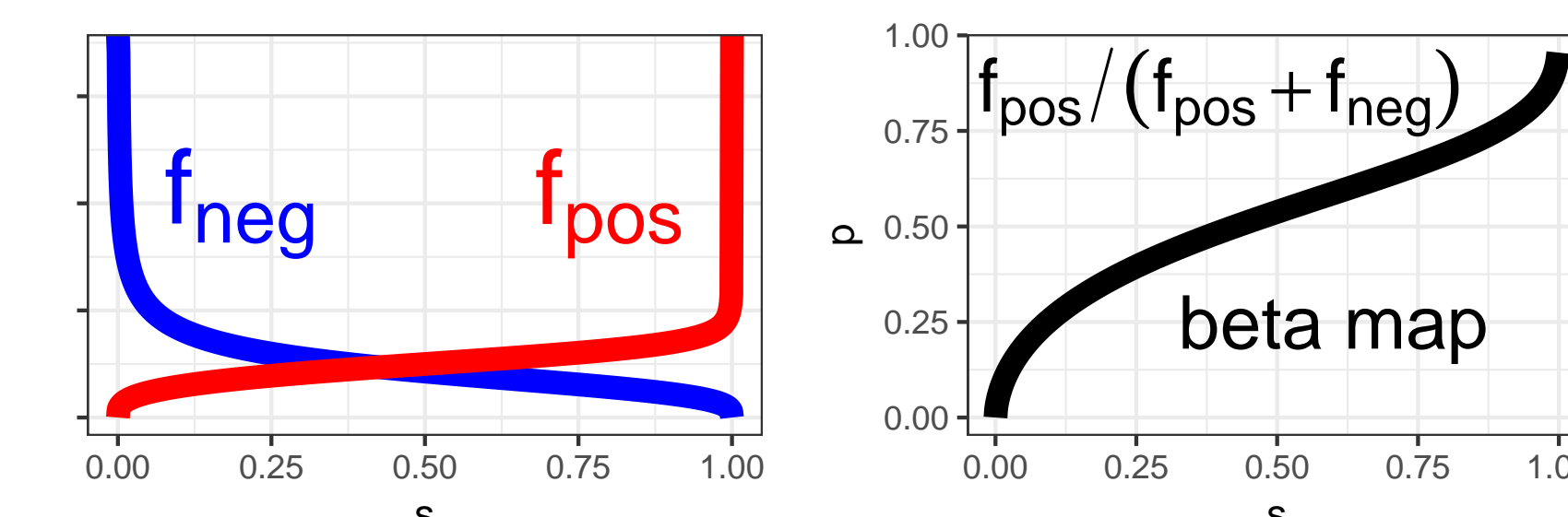
- Family contains only sigmoids.
- Logistic calibration is perfect if the class-conditional score densities f_{neg} and f_{pos} are Gaussian with equal variance.



- Easily implemented by fitting logistic regression on the single feature s .

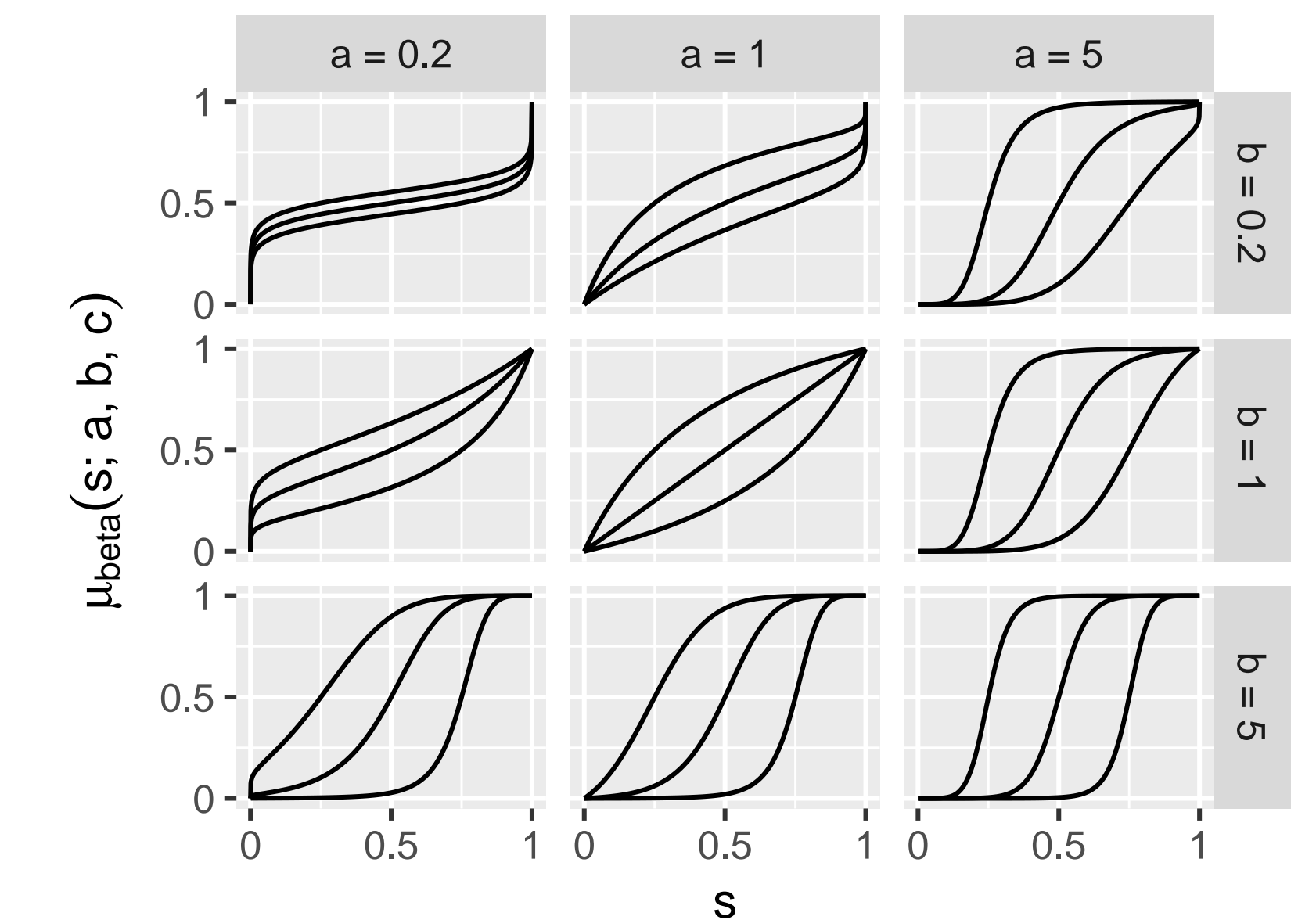
BETA CALIBRATION

- Our novel contribution.
 - Fits a parametric family with 3 parameters:
- $$\mu_{\text{beta}}(s; a, b, c) = \frac{1}{1 + 1/\left(e^c \frac{s^a}{(1-s)^b}\right)}$$
- Sigmoids, inverse sigmoids, identity and more.
 - Beta calibration is perfect if the class-conditional score densities f_{neg} and f_{pos} are beta distributions.



- Easily implemented by fitting logistic regression on two features $\ln(s)$ and $-\ln(1-s)$.

BETA CALIBRATION FAMILY



TAKE HOME MESSAGES

Beta calibration:

- **Well-founded:** derived from beta distribution;
- **Easily-implemented:** logistic regression after log-transform;
- **Better calibrated probabilities than from logistic** in our experiments on 3 model classes.

CODE AND PACKAGES

The source code for experiments, beta calibration packages for Python and R and tutorials for both languages:



<https://betacal.github.io>

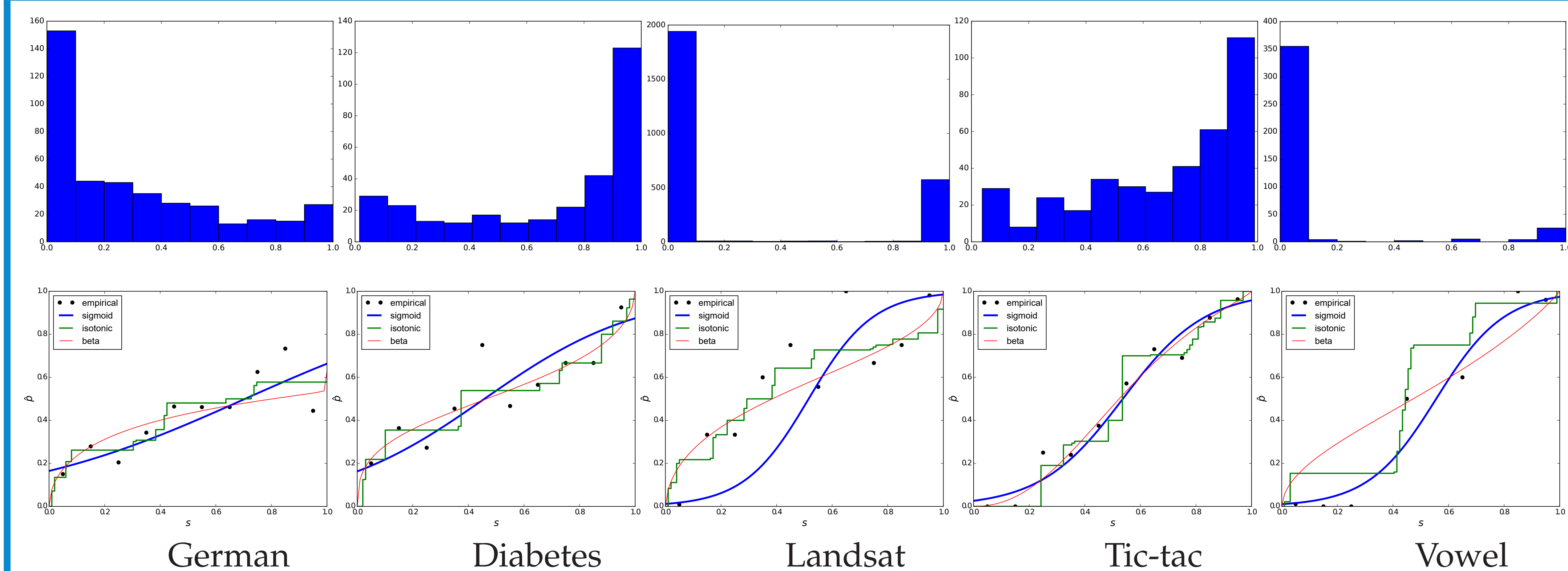
ACKNOWLEDGEMENTS

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MULTICLASS?

Dirichlet calibration is the upcoming generalisation to multi-class classifier calibration available at <https://dircal.github.io>

SCORE HISTOGRAMS, CALIBRATION MAPS (ADABOOST-ORIGINAL)



EXPERIMENTS ON 41 DATASETS (LOG-LOSS)

