

# Calzone: A Python package for measuring calibration of probabilistic models for classification

Kwok Lung Fan<sup>1</sup>, Gene Pennello<sup>1</sup>, Qi Liu<sup>1</sup>, Nicholas Petrick<sup>1</sup>, Ravi K. Samala<sup>1</sup>, Frank W. Samuelson<sup>1</sup>, Yee Lam Elim Thompson<sup>1</sup>, and Qian Cao<sup>1</sup>

<sup>1</sup> U.S. Food and Drug Administration ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

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Submitted: 01 January 1970

Published: unpublished

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## Summary

Calzone is a Python package for evaluating the calibration of probabilistic outputs of classifier models. It provides a set of functions for visualizing calibration and computing of calibration metrics given a representative dataset with the model's predictions and the true class labels. The metrics provided in Calzone include: expected calibration error (ECE), maximum calibration error (MCE), Hosmer-Lemeshow (HL) statistic, integrated calibration index (ICI), Spiegelhalter's Z-statistics and Cox's calibration slope/intercept. The package is designed with versatility in mind. For many of the metrics, users can adjust the binning scheme and toggle between top-class or class-wise calculations.

## Statement of need

Classification is one of the most common applications in machine learning. Metrics associated with discrimination performance (resolution), such as area under the curve (AUC), sensitivity (Se, true positive rate), and specificity (Sp, 1 - false positive rate) are typically used to characterize classification performance Hastie et al. (2001). These metrics may be sufficient if the outputs of the model are not meant to be interpreted as a probability.

However, Diamond (1992) showed that the resolution (i.e., high performance) of a model does not indicate the reliability/calibration of the model. Calibration is the agreement between predicted and true probabilities,  $P(D = 1 | \hat{p} = p) = p$ , defined as moderate calibration by Van Calster & Steyerberg (2018), also known as model reliability. Bröcker (2009) later showed that any proper scoring rule can be decomposed into the resolution and reliability. Thus, a model with high resolution may still lack reliability. In high-risk medical applications such as computer-aided diagnosis, reliability enables the correct interpretation of model output, and for making downstream treatment decisions.

While existing libraries such as scikit-learn include basic tools like reliability diagrams and expected calibration error, they lack support for more comprehensive and flexible evaluation metrics—such as reliability diagrams with error bars, class-conditional calibration error, different binning schemes, or statistical significance testing for miscalibration. This is also the case with other calibration-focused libraries, such as ml-calibration, uncertainty-toolbox, and pycalleva. For example, ml-calibration provides advanced controls for plotting reliability diagrams and computing smooth expected calibration error but does not include statistical tests for miscalibration (Blasiok & Nakkiran, 2024). The uncertainty-toolbox focuses on calibration methods rather than assessment (Chung et al., 2021). The pycalleva package overlaps with many functionalities in calzone, but it does not support Cox's calibration analysis, Wald intervals for reliability, or custom curve fitting methods for expected calibration error (Martin Weigl, 2022). In contrast, Calzone emphasizes the evaluation of calibration. It

42 features a comprehensive set of calibration metrics, statistical tests (e.g., hypothesis testing  
43 for miscalibration), and visualization tools tailored for many types of classification tasks (e.g.,  
44 multi-class metrics). The package is designed to help users not only visualize miscalibration  
45 but also quantify and statistically validate it in a consistent and interpretable way.

## 46 Software description

### 47 Input data

48 To evaluate the calibration of a model, users need a representative dataset from the intended  
49 population. The dataset should contain the true class labels and the model's predicted  
50 probabilities. In Calzone, the dataset can be a CSV file or two NumPy arrays containing true  
51 labels and predicted probabilities.

### 52 Reliability Diagram

53 The reliability diagram is a graphical representation of the calibration (Bröcker & Smith, 2007;  
54 Murphy & Winkler, 1977). It groups the predicted probabilities into bins and plots the mean  
55 predicted probability against the empirical frequency in each bin. The reliability diagram can  
56 be used to qualitatively assess the calibration of the model. The confidence intervals of the  
57 empirical frequency are calculated using the Wilson's score interval (Wilson, 1927).

```
from calzone.utils import reliability_diagram
from calzone.vis import plot_reliability_diagram
reliability, confidence, bin_edges, bin_counts = reliability_diagram(
    labels,
    probs,
    num_bins=15,
    class_to_plot=1
)

plot_reliability_diagram(
    reliability,
    confidence,
    bin_counts,
    error_bar=True,
    title='Reliability diagram'
)
```

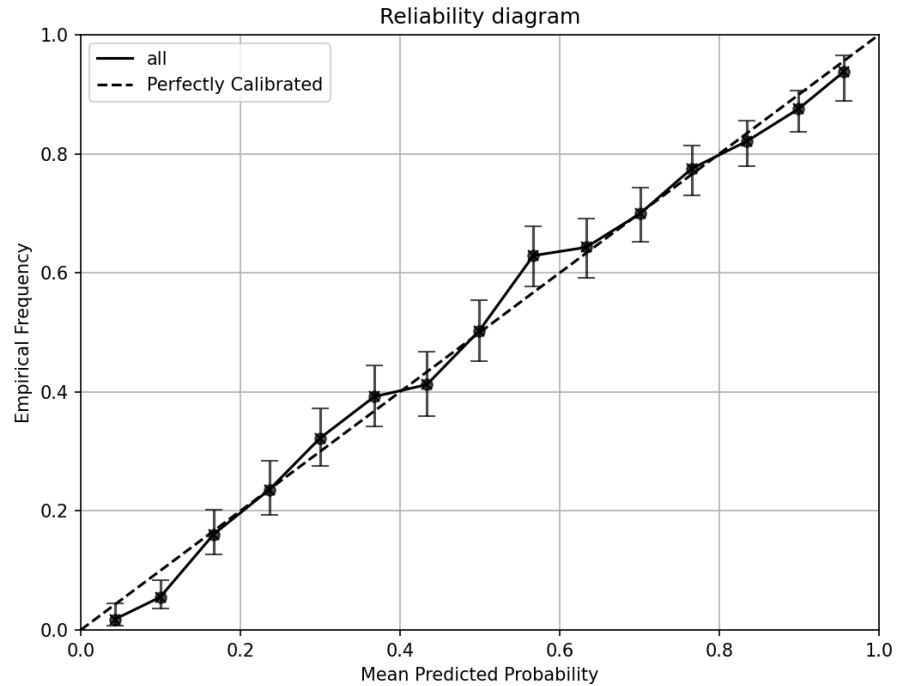


Figure 1: Reliability Diagram for class 1 with simulated data.

## Calibration metrics

Calzone provides functions to compute various calibration metrics, including methods to compute expected calibration error and statistical tests to assess calibration. These functions provide quantitative metrics for users to evaluate the calibration performance of the model. The `CalibrationMetrics()` class allows the user to compute the calibration metrics in a more convenient way. The following are metrics that are currently supported in Calzone:

### Expected Calibration Error (ECE) and Maximum Calibration Error (MCE)

Expected calibration error (ECE) and maximum calibration error (MCE) (Guo et al., 2017; Pakdaman Naeini et al., 2015) measure the average and maximum deviation between predicted and true probabilities. Calzone supports equal-width (ECE-H) and equal-count (ECE-C) binning. Users can compute these metrics for the top-class (highest probability) or class-of-interest (one-vs-rest classification).

### Hosmer-Lemeshow statistic (HL)

The Hosmer-Lemeshow (HL) test (Hosmer & Lemeshow, 1980) evaluates model calibration using a chi-square test comparing observed and expected events in bins. The null hypothesis is that the model is well calibrated. Calzone supports equal-width (ECE-H) and equal-count (ECE-C) binning. The test statistic is:

$$HL = \sum_{m=1}^M \frac{(O_{1,m} - E_{1,m})^2}{E_{1,m} \left(1 - \frac{E_{1,m}}{N_m}\right)} \sim \chi_{M-2}^2$$

where  $E_{1,m}$  and  $O_{1,m}$  are the expected and observed events in the  $m^{th}$  bin,  $N_m$  is the total observations in the bin, and  $M$  is the number of bins. For validation sets, the degrees of

freedom change from  $M - 2$  to  $M$  (Hosmer Jr et al., 2013). The increase in degree of freedom for validation samples has often been overlooked but it is crucial for the test to maintain the correct type 1 error rate. In Calzone, the default is  $M - 2$ , adjustable via the `df` parameter.

#### Cox's calibration slope/intercept

Cox's calibration slope/intercept assesses model calibration without binning (Cox, 1958). A logistic regression is fit with predicted odds ( $\frac{p}{1-p}$ ) as the independent variable and the outcome as the dependent variable. Perfect calibration is indicated by a slope of 1 and intercept of 0. To test calibration, fit the intercept with slope fixed at 1; if the intercept differs from 0, the model is not calibrated. Similarly, fit the slope with intercept fixed at 0; if the slope differs from 1, the model is not calibrated. Alternatively, fit both simultaneously using a bivariate distribution (McCullagh & Nelder, 1989). This feature is not in Calzone, but users can manually test using the covariance matrix.

A slope  $>1$  indicates overconfidence at high probabilities and underconfidence at low probabilities, while a slope  $<1$  indicates the opposite. A positive intercept indicates general overconfidence. Even with ideal slope and intercept, non-linear miscalibration may still exist.

#### Integrated calibration index (ICI)

The integrated calibration index (ICI) measures the average deviation between predicted and true probabilities using curve smoothing techniques (Austin & Steyerberg, 2019). It is calculated as:

$$ICI = \frac{1}{n} \sum_{i=1}^n |f(p_i) - p_i|$$

where  $f$  is the fitting function and  $p$  is the predicted probability. Typically, Locally Weighted Scatterplot Smoothing (LOWESS) is used, but any curve fitting method can be applied. Calzone supports both Cox ICI and LOWESS ICI, allowing users to choose their preferred method. Users should visualize the fitting results to avoid overfitting or underfitting, as flexible methods like LOWESS are sensitive to span and delta parameters.

#### Spiegelhalter's Z-test

Spiegelhalter's Z-test is a test of calibration proposed by Spiegelhalter in 1986 (Spiegelhalter, 1986). It uses the fact that the Brier score can be decomposed into:

$$B = \frac{1}{N} \sum_{i=1}^N (x_i - p_i)^2 = \frac{1}{N} \sum_{i=1}^N (x_i - p_i)(1 - 2p_i) + \frac{1}{N} \sum_{i=1}^N p_i(1 - p_i)$$

And the test statistic (TS) of Z test is defined as:

$$Z = \frac{B - E(B)}{\sqrt{\text{Var}(B)}} = \frac{\sum_{i=1}^N (x_i - p_i)(1 - 2p_i)}{\sum_{i=1}^N (1 - 2p_i)^2 p_i(1 - p_i)}$$

and it is asymptotically distributed as a standard normal distribution.

#### Metrics class

Calzone also provides a class called `CalibrationMetrics()` to calculate all the metrics mentioned above. The function will return a dictionary containing the metrics name and their values. The metrics can be specified as a list of strings. The string 'all' can be used to calculate all the metrics.

```
from calzone.metrics import CalibrationMetrics
```

```
metrics = CalibrationMetrics(class_to_calculate=1)

metrics.calculate_metrics(
    labels,
    probs,
    metrics='all'
)
```

## Other features

### Confidence intervals

Calzone also provides functionality to compute confidence intervals for all metrics using bootstrapping. The user can specify the number of bootstrap samples and the confidence level.

```
from calzone.metrics import CalibrationMetrics

metrics = CalibrationMetrics(class_to_calculate=1)

CalibrationMetrics.bootstrap(
    labels,
    probs,
    metrics='all',
    n_samples=1000
)
```

and a structured NumPy array will be returned.

### Subgroup analysis

Calzone will perform subgroup analysis by default in the command line user interface. If the user input CSV file contains a subgroup column, the program will compute metrics for the entire dataset and for each subgroup. A detailed description of the input format can be found in the documentation.

### Prevalence adjustment

Calzone offers prevalence adjustment to correct for differences in disease prevalence between training and testing data. Calibration is based on posterior probability, so a shift in prevalence can cause miscalibration. The adjusted probability is calculated as:

$$P'(D = 1|\hat{p} = p) = \frac{\eta'/(1 - \eta')}{(1/p - 1)(\eta/(1 - \eta))} = p'$$

where  $\eta$  is the testing data prevalence,  $\eta'$  is the training data prevalence, and  $p$  is the predicted probability. The optimal  $\eta'$  is found by minimizing cross-entropy loss, or users can specify  $\eta'$  directly if known (Chen et al., 2018; Gu & Pepe, 2010; Horsch et al., 2008; Tian et al., 2020).

### Multiclass extension

Calzone supports multiclass classification using a 1-vs-rest approach or top-class calibration. In top-class calibration, class 1 probability is the highest predicted probability, and class 0 is 1 minus this probability. Metrics interpretation may change in this transformation.

## 133 Verification of methods

134 To ensure the accuracy and reliability of the metrics implemented in calzone, we performed  
135 comprehensive validation against established external packages. Reliability diagrams were  
136 compared with `sklearn.calibration.calibration_curve()` (Pedregosa et al., 2011), top-  
137 class ECE and Spiegelhalter's Z scores were validated against MAPIE (Taquet et al., 2022), and  
138 the Hosmer-Lemeshow statistic was checked against ResourceSelection (Lele et al., 2024) in  
139 R. Additional tests were conducted using the `relplot` and `pycalleva` Python packages to further  
140 confirm metric consistency. All differences were within 0.1%, demonstrating strong agreement.  
141 These validation tests are documented in `test_results.py`. Furthermore, synthetic data tests  
142 (see `test_metrics.py`) were used to confirm the expected behavior of the calibration metrics  
143 under controlled conditions.

## 144 Command line interface

145 Calzone offers a command line interface for visualizing calibration curves, calculating metrics,  
146 and confidence intervals. Run `python cal_metrics.py -h` for help.

## 147 Acknowledgements

148 The mention of commercial products, their sources, or their use in connection with material  
149 reported herein is not to be construed as either an actual or implied endorsement of such  
150 products by the Department of Health and Human Services. This is a contribution of the U.S.  
151 Food and Drug Administration and is not subject to copyright.

152 The authors acknowledge the Research Participation Program at the Center for Devices and  
153 Radiological Health administered by the Oak Ridge Institute for Science and Education through  
154 an interagency agreement between the U.S. Department of Energy and the U.S. Food and  
155 Drug Administration.

## 156 Conflicts of interest

157 The authors declare no conflicts of interest.

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