




calzone: A Python package for measuring calibration of probabilistic models for classification

Kwok Lung Fan¹, Gene Pennello¹, Qi Liu¹, Nicholas Petrick¹, Ravi K. Samala¹, Frank W. Samuelson¹, Yee Lam Elim Thompson¹, and Qian Cao^{1¶}

¹ U.S. Food and Drug Administration ¶ Corresponding author

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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 computation of calibration metrics given a representative dataset with the model's predictions and 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. Classification models are often evaluated by a proper scoring rule - a scoring function that assigns the best score when predicted probabilities match the true probabilities - such as cross-entropy or mean square error ([Gneiting & Raftery, 2007](#)). Examination of the discrimination performance (resolution), such as AUC or Se/Sp are also used to evaluate the model performance. However, the reliability or calibration performance of the model is often overlooked.

Diamond ([1992](#)) had shown that the resolution performance of a model does not indicate the reliability of the model. Bröcker ([2009](#)) later has shown that any proper scoring rule can be decomposed into the resolution and reliability. Thus even if the model has high resolution (high AUC), it may not be a reliable or calibrated model. In many high-risk machine learning applications, such as medical diagnosis, the reliability of the model is of paramount importance.

We define calibration as the agreement between the predicted probability and the true posterior probability of a class-of-interest, $P(D = 1|\hat{p} = p) = p$. This has been defined as moderate calibration by Van Calster & Steyerberg ([2018](#)) .

In the calzone package, we provide a set of functions and classes for visualizing calibration and evaluating calibration metrics. Existing libraries such as scikit-learn are often not dedicated to calibration metrics computation or lacks calibration metrics that are widely used in the statistical literature. Other libraries such as uncertainty-toolbox are focused on implementing calibration methods instead of calibration assessment. ([Chung et al., 2021](#)).

36 Functionality

37 Reliability Diagram

38 The reliability diagram (also referred to as the calibration plot) is a graphical representation of
39 the calibration of a classification model (Bröcker & Smith, 2007; Murphy & Winkler, 1977). It
40 groups the predicted probabilities into bins and plots the mean predicted probability against the
41 empirical frequency in each bin. The reliability diagram can be used to assess the calibration
42 of the model and to identify any systematic errors in the predictions. In addition, calzone
43 gives the option to also plot the confidence interval of the empirical frequency in each bin.
44 The confidence intervals are calculated using Wilson's score interval (Wilson, 1927). We
45 provide example data in the example_data folder which are simulated using a beta-binomial
46 distribution (Griffiths, 1973). The predicted probabilities are sampled from a beta distribution
47 and the true labels are assigned by performing Bernoulli trials with the sampled probabilities.
48 Users can generate simulated data using the fake_binary_data_generator class in the utils
49 module.

```
from calzone.utils import reliability_diagram
from calzone.vis import plot_reliability_diagram

wellcal_dataloader = data_loader(
    data_path="example_data/simulated_welldata.csv"
)

reliability, confidence, bin_edges, bin_counts = reliability_diagram(
    wellcal_dataloader.labels,
    wellcal_dataloader.probs,
    num_bins=15,
    class_to_plot=1
)

plot_reliability_diagram(
    reliability,
    confidence,
    bin_counts,
    error_bar=True,
    title='Class 1 reliability diagram for well calibrated data'
)
```

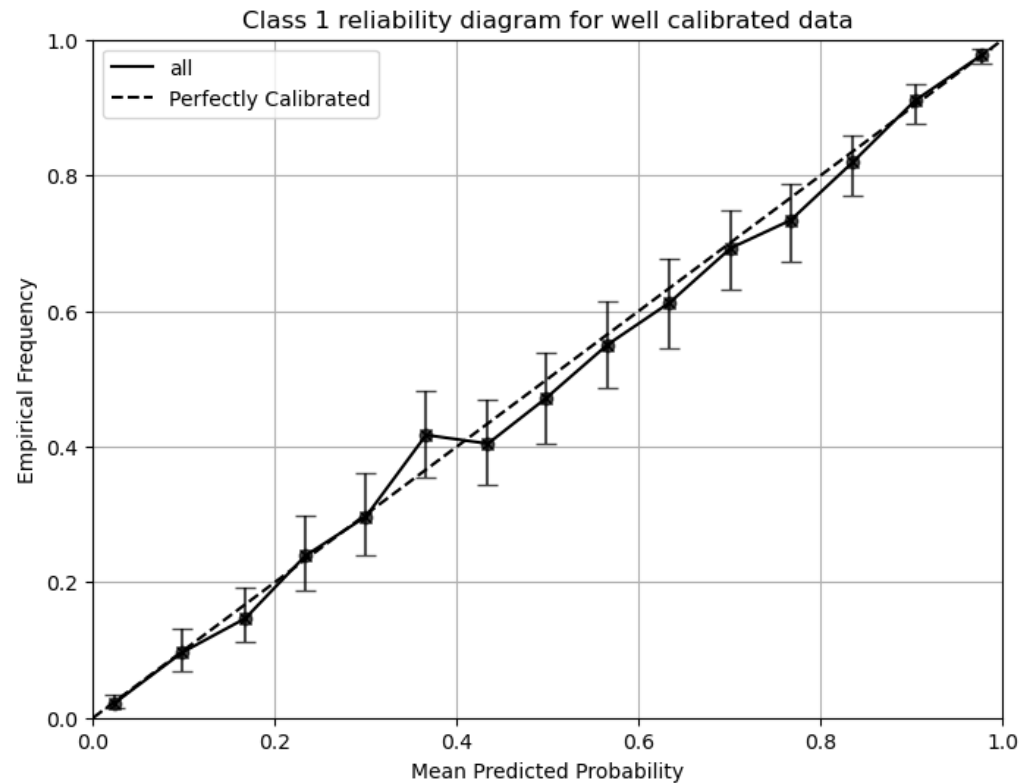


Figure 1: Reliability Diagram for well calibrated data

Calibration metrics

calzone provides functions to compute various calibration metrics. 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), Maximum Calibration Error (MCE) and other binning-based methods (Guo et al., 2017; Pakdaman Naeini et al., 2015) aim to measure the average absolute deviation between predicted probability and true probability. We provide the option to use equal-width binning or equal-count binning, labeled as ECE-H and ECE-C respectively. Users can also choose to compute the metrics for the class-of-interest or the top-class. In the case of class-of-interest, calzone will evaluate the calibration of a one-vs-rest classification problem. The following snippet demonstrates how these metrics are calculated in our package:

```
from calzone.metrics import calculate_ece_mce

reliability, confidence, bin_edges, bin_counts = reliability_diagram(
    wellcal_dataloader.labels,
    wellcal_dataloader.probs,
    num_bins=10,
    class_to_plot=1,
    is_equal_freq=False
)

ece_h_classone, mce_h_classone = calculate_ece_mce(
```

```

reliability,
confidence,
bin_counts=bin_counts
)

```

62 Hosmer-Lemeshow statistic (HL)

63 The Hosmer-Lemeshow (HL) statistical test is for evaluating the calibration of a probabilistic
64 model. It is a chi-square-based test that compares the observed and expected number of
65 events in each bin. The null hypothesis is that the model is well calibrated. HL-test first bins
66 data into predicted probability bins (equal-width H or equal-count C) and the test statistic is
67 calculated as:

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

68 where $E_{1,m}$ is the expected number of class-of-interest events in the m^{th} bin, $O_{1,m}$ is the
69 observed number of class-of-interest events in the m^{th} bin, N_m is the total number of
70 observations in the m^{th} bin, and M is the number of bins. In calzone, the HL-test can be
71 computed as follows:

```

from calzone.metrics import hosmer_lemeshow_test

HL_H_ts, HL_H_p, df = hosmer_lemeshow_test(
    reliability,
    confidence,
    bin_count=bin_counts
)

```

72 When performing the HL test on validation sets that are not used in training, the degree
73 of freedom of the HL test changes from $M - 2$ to M (Hosmer Jr et al., 2013). Intuitively,
74 $\frac{(O_{1,m} - E_{1,m})^2}{E_{1,m}(1 - \frac{E_{1,m}}{N_m})}$ is the difference squared divided by the variance of a binomial distribution and
75 follows a chi-square distribution with 1 degree of freedom. Hence, the sum of M chi-square
76 distributions with 1 degree of freedom is a chi-square distribution with M degrees of freedom if
77 the data has no effect on the model. The increase in degree of freedom for validation samples
78 has often been overlooked but it is crucial for the test to maintain the correct type 1 error
79 rate. In calzone, users can specify the degree of freedom of the HL test by setting the df
80 parameter.

81 Cox's calibration slope/intercept

82 Cox's calibration slope/intercept is a regression analysis method for assessing the calibration of
83 a probabilistic model (COX, 1958), which doesn't require binning. A new logistic regression
84 model is fitted to the data, with the predicted odds ($\frac{p}{1-p}$) as the independent variable and the
85 outcome as the dependent variable. The slope and intercept of the regression line are then
86 used to assess the calibration of the model. A slope of 1 and intercept of 0 indicates perfect
87 calibration. To test whether the model is calibrated, fix the slope to 1 and fit the intercept.
88 If the intercept is significantly different from 0, the model is not calibrated. Then, fix the
89 intercept to 0 and fit the slope. If the slope is significantly different from 1, the model is not
90 calibrated. Alternatively, the slope and intercept can be fitted and tested simultaneously using
91 bivariate distribution (McCullagh & Nelder, 1989). This feature is not provided in calzone but
92 user can extract the covariance matrix by printing the result and perform the test manually. In
93 calzone, Cox's calibration slope/intercept can be computed as follows:

```

from calzone.metrics import cox_regression_analysis

cox_slope, cox_intercept, cox_slope_ci, cox_intercept_ci = cox_regression_analysis(

```

```

wellcal_dataloader.labels,
wellcal_dataloader.probs,
class_to_calculate=1,
print_results=True,
fix_slope=True
)

```

94 The slope and intercept values indicate the type of miscalibration. A slope >1 shows overcon-
95 fidence at high probabilities and underconfidence at low probabilities (and vice versa). In other
96 word, a slope < 1 (> 1) indicates that the spread of the predicted risks is too large (small)
97 relative to the true risks. A positive intercept indicates general overconfidence (and vice versa).
98 However, even with ideal slope and intercept values, the model may still be miscalibrated due
99 to non-linear effects that Cox's analysis cannot detect.

100 Integrated calibration index (ICI)

101 The integrated calibration index (ICI) is very similar to Expected calibration error (ECE). It
102 also tries to measure the average deviation between predicted probability and true probability.
103 However, ICI does not use binning to estimate the true probability of a group of samples with
104 similar predicted probability. Instead, ICI uses curve smoothing techniques to fit the regression
105 curve and uses the regression result as the true probability (Austin & Steyerberg, 2019). The
106 ICI is then calculated using the following formula:

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

107 where f is the fitting function and p is the predicted probability. The curve fitting is usually
108 done with loess regression. However, it is possible to use any curve fitting method to calculate
109 the ICI. In calzone, we provide Cox's ICI and loess ICI support while the user can also use any
110 curve fitting method to calculate the ICI using functions in calzone.

```

from calzone.metrics import (
    cox_regression_analysis,
    lowess_regression_analysis,
    cal_ICI_cox
)

### calculating cox ICI
cox_ici = cal_ICI_cox(
    cox_slope,
    cox_intercept,
    wellcal_dataloader.probs,
    class_to_calculate=1
)

### calculating loess ICI
loess_ici, lowess_fit_p, lowess_fit_p_correct = lowess_regression_analysis(
    wellcal_dataloader.labels,
    wellcal_dataloader.probs,
    class_to_calculate=1,
    span=0.5,
    delta=0.001,
    it=0
)

```

111 Notice that flexible curve fitting methods such as Loess regression are very sensitive to the
112 choice of span and delta parameters. The user can visualize the fitting result to avoid overfitting
113 or underfitting.

114 Spiegelhalter's Z-test

115 Spiegelhalter's Z-test is a test of calibration proposed by Spiegelhalter in 1986 (Spiegelhalter,
116 1986). It uses the fact that the Brier score can be decomposed into:

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

117 And the TS of Z test is defined as:

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

118 and it is asymptotically distributed as a standard normal distribution. In calzone, it can be
119 calculated using:

```
from calzone.metrics import spiegelhalter_z_test
```

```
z, p_value = spiegelhalter_z_test(  
    wellcal_dataloader.labels,  
    wellcal_dataloader.probs,  
    class_to_calculate=1  
)
```

120 Metrics class

121 calzone also provides a class called CalibrationMetrics() to calculate all the metrics men-
122 tioned above. The user can also use this class to calculate the metrics.

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

```
metrics = CalibrationMetrics(class_to_calculate=1)
```

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

123 Other features

124 Confidence intervals

125 In addition to point estimates of calibration performance, calzone also provides functionality
126 to compute confidence intervals for all metrics. For most metrics, this is computed through
127 bootstrapping. The user can specify the number of bootstrap samples and the confidence
128 level.

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

```
metrics = CalibrationMetrics(class_to_calculate=1)
```

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

129 and a structured NumPy array will be returned.

130 Subgroup analysis

131 calzone will perform subgroup analysis by default in the command line user interface. If the
132 user input CSV file contains a subgroup column, the program will compute metrics for the
133 entire dataset and for each subgroup.

134 Prevalence adjustment

135 calzone also provides prevalence adjustment to account for prevalence changes between
136 training data and testing data. Since calibration is defined using posterior probability, a mere
137 shift in the disease prevalence of the testing data will result in miscalibration. It can be fixed
138 by searching for the optimal derived original prevalence such that the adjusted probability
139 minimizes a proper scoring rule such as cross-entropy loss. The formula of prevalence adjusted
140 probability is:

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

141 where η is the prevalence of the testing data, η' is the prevalence of the training data, and p
142 is the predicted probability (Chen et al., 2018; Gu & Pepe, 2010; Horsch et al., 2008; Tian et
143 al., 2020). We search for the optimal η' that minimizes the cross-entropy loss. The user can
144 specify also specify η' and adjust the probability output directly if that is available.

145 Multiclass extension

146 calzone also provides multiclass extension to calculate the metrics for multiclass classification.
147 The user can specify the class to calculate the metrics using a 1-vs-rest approach and test
148 the calibration of each class. Alternatively, the user can transform the data and make the
149 problem become a top-class calibration problem. The top-class calibration has a similar format
150 to binary classification, but the class 0 probability is defined as 1 minus the probability of the
151 class with the highest probability, and the class 1 probability is defined as the probability of
152 the class with the highest probability. The labels are transformed into whether the predicted
153 class equals the true class, 0 if not and 1 if yes. Notice that the interpretation of some metrics
154 may change in the top-class transformation.

155 Validation of methods

156 We compared the results calculated by calzone with external packages for some metrics to
157 ensure the correctness of the implementation. For reliability diagram, we compared the result
158 with the `sklearn.calibration.calibration_curve()` function in `scikit-learn` (Pedregosa
159 et al., 2011). For top-class ECE and Spiegelhalter's Z score, we compared the result with
160 the `MAPIE` package (Taquet et al., 2022). For Hosmer-Lemeshow statistic, we compared the
161 result with the `ResourceSelection` package in R language (Lele et al., 2024). Their results
162 are consistent with ours. For other metrics such as ICI, no external package is available, so we
163 compared the result with ECE as they are similar and we obtained reasonably similar results.
164 We include the validation codes in our documentation.

165 Command line interface

166 calzone also provides a command line interface. Users can visualize the calibration curve,
167 calculate calibration metrics and their confidence intervals using the command line interface.
168 To use the command line interface, the user can run `python cal_metrics.py -h` to see the
169 help message.

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Conflicts of interest

The authors declare no conflicts of interest.

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