Classification task: other models

There are several models that perform Classification, each with a different behavior.

We briefly explore some of the differences.

Decision boundaries

Just as we saw for the Regression task:

- there are multiple models for solving a Classification task

For Binary Classification

- the models create different decision boundaries

Output: probabilities or just classes ?

The ultimate output of a classifier

- is a single class label
- prediction of the class to which the example belongs

But many Classifiers output a *probability distribution* over all the classes

$$p(\mathbf{y} \mid \mathbf{x})$$

where $p(\mathbf{y} \mid \mathbf{x})$

- is a vector whose length is the number of classes

There are several possibilities for converting the probability vector to a single class

- choose the class with highest probability
    - e.g., in KNN
        - we chose the class for a test example
        - by comparing against k training examples
        - and choosing the class c that whose label was most frequent among the k examples
- for Binary Classification
    - compare probability of the Positive class to a threshold
    - choose class "Positive" only if the predicted probability of Positive exceeds the threshold

Some (but not all) classifiers in `sklearn`

- implement a method `predict_proba`
    - that returns the probability vector

For Classifiers that return probability vectors

- the ultimate class label predicted
- *can be adjusted by the user*

Here is some pseudo-code:

```
# Train a logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Get predicted probabilities for new data
probabilities = model.predict_proba(X_test)[:, 1]  # Probability of positive cl
ass

# Set a custom threshold (e.g., 0.7)
custom_threshold = 0.7

# Make predictions based on the custom threshold
predictions = (probabilities >= custom_threshold).astype(int)
```

In the [Precision/Recall tradeoff (Error_Analysis.ipynb#Precison/Recall-Tradeoff)](Error_Analysis.ipynb#Precison/Recall-Tradeoff) module

- we will examine the effect of changing the threshold
- on conditional Performance Metrics
    - recall, precision
- this is a kind of Fine Tuning of a hyper-parameter

There is a [good discussion (https://scikit-learn.org/stable/modules/classification_threshold.html)](https://scikit-learn.org/stable/modules/classification_threshold.html) on adjusting the probability threshold in the `sklearn` documentation.

Confidence

We can also compare Classifiers

- by comparing the predictions
- across a wide range of examples

For Classifiers that produce probability distributions

- how confident is the Classifier in its prediction ?
    - examine the distribution of probability mass across many examples

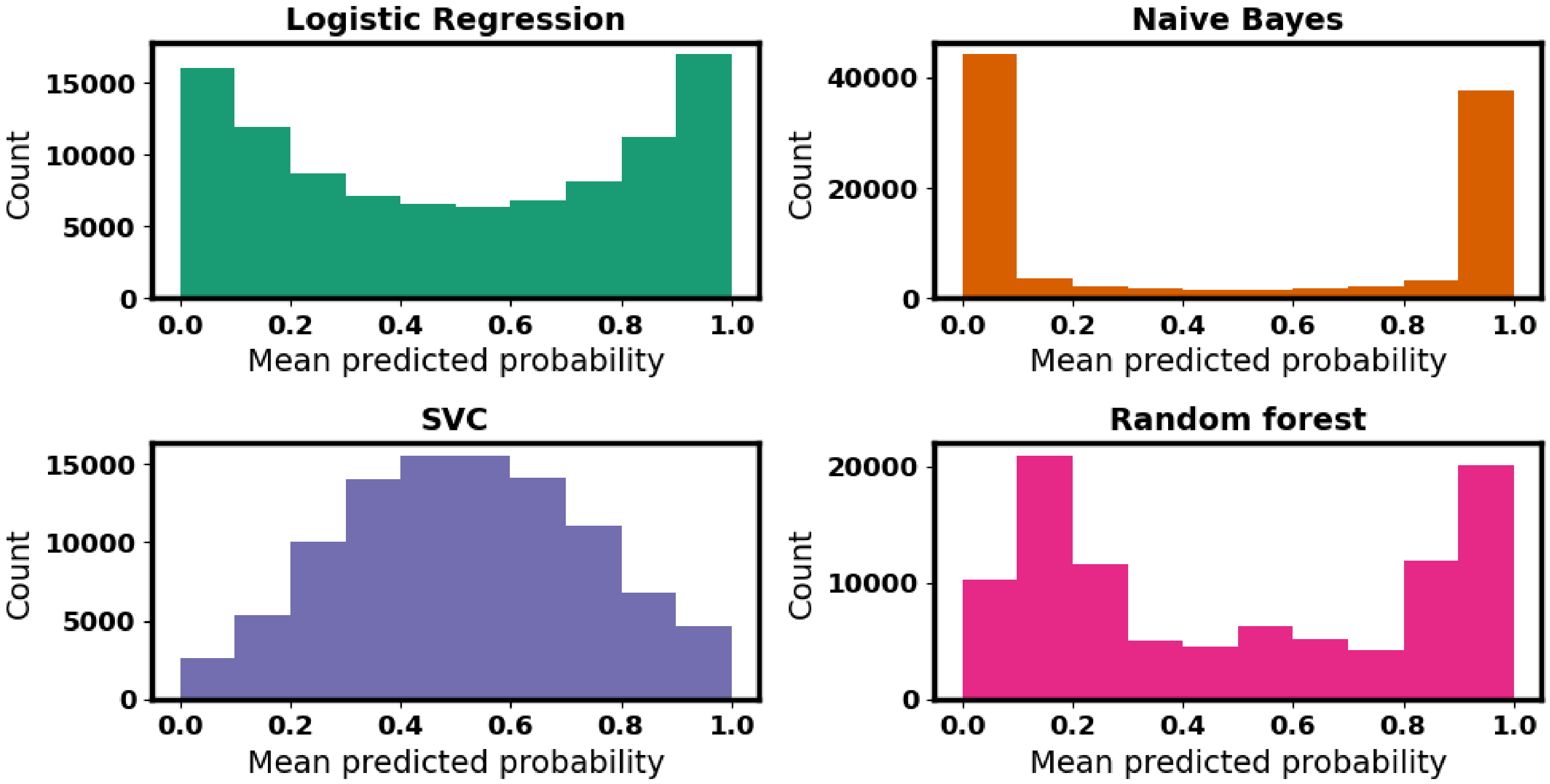
A confident Classifier's distribution is bimodal

- most of the probability mass near 0 or 1

In [10]:

```
prediction_hist_fig
```

Out[10]:



Reliability diagrams

Another property:

How reliable is the prediction ?

- for Binary Classification
- examine all the examples assigned predicted probability $\hat{p} = P$ of being Positive
- the fraction p of these examples whose true labels are Positive
- should be close to $\hat{p}$

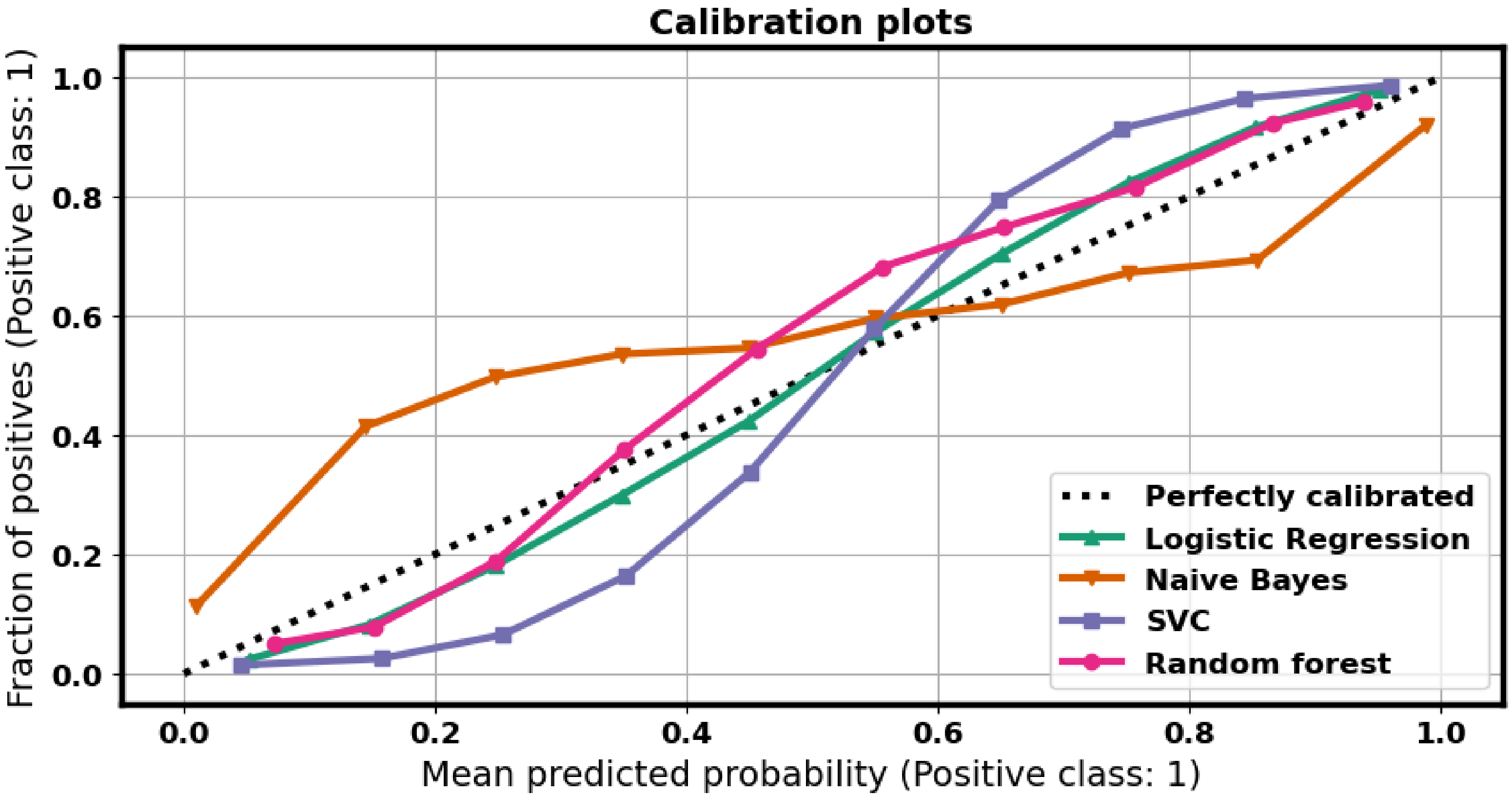
A plot of p versus $\hat{p}$ is called a *Reliability diagram*

See [here (https://scikit-learn.org/stable/modules/calibration.html)](https://scikit-learn.org/stable/modules/calibration.html) for explanation and [here (https://scikit-learn.org/stable/auto_examples/calibration/plot_compare_calibration.html)](https://scikit-learn.org/stable/auto_examples/calibration/plot_compare_calibration.html) for code.

In [11]:

```
calibration_fig
```

Out[11]:



In [12]:

```
print("Done")
```

```
Done
```