SMOTE for Imbalanced Classification with Python

by **Jason Brownlee** on January 17, 2020 in **Imbalanced Classification**

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Imbalanced classification involves developing predictive models on classification datasets that have a severe class imbalance.

The challenge of working with imbalanced datasets is that most machine learning techniques will ignore, and in turn have poor performance on, the minority class, although typically it is performance on the minority class that is most important.

One approach to addressing imbalanced datasets is to oversample the minority class. The simplest approach involves duplicating examples in the minority class, although these examples don't add any new information to the model. Instead, new examples can be synthesized from the existing examples. This is a type of data augmentation for the minority class and is referred to as the **Synthetic Minority Oversampling Technique**, or **SMOTE** for short.

In this tutorial, you will discover the SMOTE for oversampling imbalanced classification datasets.

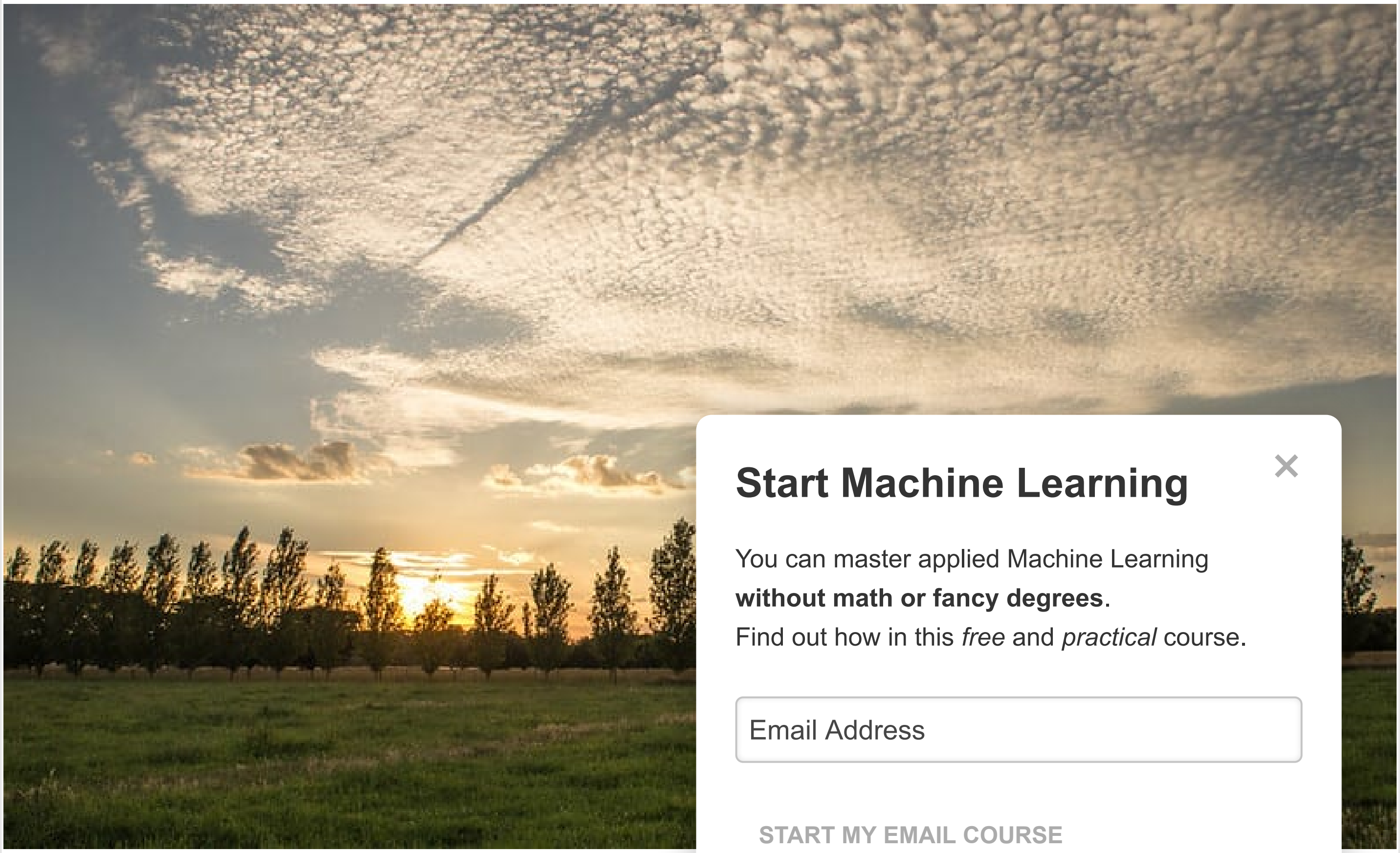
After completing this tutorial, you will know:

- How the SMOTE synthesizes new examples for the minority class.
- How to correctly fit and evaluate machine learning models on SMOTE-transformed training datasets.
- How to use extensions of the SMOTE that generate synthetic examples along the class decision boundary.

Kick-start your project with my new book Imbalanced Classification with Python, including *step-by-step tutorials* and the *Python source code* files for all examples.

Let's get started.

- **Updated Jan/2021**: Updated links for API documentation.



SMOTE Oversampling for Imbal
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Tutorial Overview

This tutorial is divided into five parts; they are:

1. Synthetic Minority Oversampling Technique
2. Imbalanced-Learn Library
3. SMOTE for Balancing Data
4. SMOTE for Classification
5. SMOTE With Selective Synthetic Sample Generation
    1. Borderline-SMOTE
    2. Borderline-SMOTE SVM
    3. Adaptive Synthetic Sampling (ADASYN)

Synthetic Minority Oversampling Technique

A problem with imbalanced classification is that there are too few examples of the minority class for a model to effectively learn the decision boundary.

One way to solve this problem is to oversample the examples in the minority class. This can be achieved by simply duplicating examples from the minority clas s can balance the class distribution but does not provide any additional information to the model.

An improvement on duplicating examples from the minority class is to synthesize new examples from the minority class. This is a type of data augmentation for tabular data and can be very effective.

Perhaps the most widely used approach to synthesizing new examples is called the **Synthetic Minority Oversampling TEchnique**, or SMOTE for short. This technique was described by Nitesh Chawla, et al. in their 2002 paper named for the technique titled "SMOTE: Synthetic Minority Over-sampling Technique."

SMOTE works by selecting examples that are close in the feature space, drawing a line between the examples in the feature space and drawing a new sample at a point along that line.

Specifically, a random example from the minority class … or that example are found (typically *k=5*). A randomly sel… e is created at a randomly selected point between the two…

> *… SMOTE first selects a minority class instan… class neighbors. The synthetic instance is then… neighbors b at random and connecting a and b… synthetic instances are generated as a convex…*

— Page 47, Imbalanced Learning: Foundations, Algor…

This procedure can be used to create as many synthetic examples for the minority class as are required. As described in the paper, it suggests first using random undersampling to trim the number of examples in the majority class, then use SMOTE to oversample the minority class to balance the class distribution.

> *The combination of SMOTE and under-sampling performs better than plain under-sampling.*

— SMOTE: Synthetic Minority Over-sampling Technique, 2011.

The approach is effective because new synthetic examples from the minority class are created that are plausible, that is, are relatively close in feature space to existing examples from the minority class.

> *Our method of synthetic over-sampling works to cause the classifier to build larger decision regions that contain nearby minority class points.*

— SMOTE: Synthetic Minority Over-sampling Technique, 2011.

A general downside of the approach is that synthetic examples are created without considering the majority class, possibly resulting in ambiguous examples if there is a strong overlap for the classes.

Now that we are familiar with the technique, let's look at a worked example for an imbalanced classification problem.

Imbalanced-Learn Library

In these examples, we will use the implementations provided by the imbalanced-learn Python library, which can be installed via pip as follows:

```
sudo pip install imbalanced-learn
```

You can confirm that the installation was successful by printing the version of the installed library:

```
# check version number
import imblearn
print(imblearn.__version__)
```

Running the example will print the version number of the installed library; for example:

```
0.5.0
```


SMOTE for Balancing Data

In this section, we will develop an intuition for the SMOTE by applying it to an imbalanced binary classification problem.

First, we can use the make_classification() scikit-learn function to create a synthetic binary classification dataset with 10,000 examples and a 1:100 class distribution.

```
...
# define dataset
X, y = make_classification(n_samples=10000, n_features=2, n_redundant=0,
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
```

We can use the Counter object to summarize the number of examples in each class to confirm the dataset was created correctly.

```
...
# summarize class distribution
counter = Counter(y)
print(counter)
```

Finally, we can create a scatter plot of the dataset and color the examples for each class a different color to clearly see the spatial nature of the class imbalance.

```
...
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1], label=str(label))
pyplot.legend()
pyplot.show()
```

Tying this all together, the complete example of generating and plotting a synthetic binary classification problem is listed below.

```
# Generate and plot a synthetic imbalanced classification dataset
from collections import Counter
from sklearn.datasets import make_classificat
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], f
# summarize class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1]
pyplot.legend()
pyplot.show()
```


Running the example first summarizes the class distribution, confirms the 1:100 ratio, in this case with about 9,900 examples in the majority class and 100 in the minority class.

```
Counter({0: 9900, 1: 100})
```

A scatter plot of the dataset is created showing the large mass of points that belong to the majority class (blue) and a small number of points spread out for the minority class (orange). We can see some measure of overlap between the two classes.

Scatter Plot of Imbalanced Binary Classification Problem

Next, we can oversample the minority class using SMOTE and plot the transformed dataset.

We can use the SMOTE implementation provided by the imbalanced-learn Python library in the SMOTE class.

The SMOTE class acts like a data transform object from scikit-learn in that it must be defined and configured, fit on a dataset, then applied to create a new transformed version of the dataset.

For example, we can define a SMOTE instance with default parameters that will balance the minority class and then fit and apply it in one step to create a transformed version of our dataset.

```
...
# transform the dataset
oversample = SMOTE()
X, y = oversample.fit_resample(X, y)
```

Once transformed, we can summarize the class distribution of the new transformed dataset, which would expect to now be balanced through the creation of many new synthetic examples in the minority class.

```
...
# summarize the new class distribution
```

```
counter = Counter(y)
print(counter)
```

A scatter plot of the transformed dataset can also be created and we would expect to see many more examples for the minority class on lines between the original examples in the minority class.

Tying this together, the complete examples of applying SMOTE to the synthetic dataset and then summarizing and plotting the transformed result is listed below.

```
# Oversample and plot imbalanced dataset with SMOTE
from collections import Counter
from sklearn.datasets import make_classification
from imblearn.over_sampling import SMOTE
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], f
# summarize class distribution
counter = Counter(y)
print(counter)
# transform the dataset
oversample = SMOTE()
X, y = oversample.fit_resample(X, y)
# summarize the new class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1]
pyplot.legend()
pyplot.show()
```


Running the example first creates the dataset and summarizes the class distribution, showing the 1:100 ratio.

Then the dataset is transformed using the SMOTE and the new class distribution is summarized, showing a balanced distribution now with 9,900 examples in the minority class.

```
Counter({0: 9900, 1: 100})
Counter({0: 9900, 1: 9900})
```

Finally, a scatter plot of the transformed dataset is created.

It shows many more examples in the minority class created along the lines between the original examples in the minority class.

Scatter Plot of Imbalanced Binary Classification Problem Transformed by SMOTE

The original paper on SMOTE suggested combining SMOTE with random undersampling of the majority class.

The imbalanced-learn library supports random undersampling via the RandomUnderSampler class.

We can update the example to first oversample the minority class to have 10 percent the number of examples of the majority class (e.g. about 1,000), then use random undersampling to reduce the number of examples in the majority class to have 50 percent more than the minority class (e.g. about 2,000).

To implement this, we can specify the desired ratios as arguments to the SMOTE and *RandomUnderSampler* classes; for example:

```
...
over = SMOTE(sampling_strategy=0.1)
under = RandomUnderSampler(sampling_strategy=0.5)
```

We can then chain these two transforms together into a Pipeline.

The Pipeline can then be applied to a dataset, performing each transformation in turn and returning a final dataset with the accumulation of the transform applied undersampling.

```
...
steps = [('o', over), ('u', under)]
pipeline = Pipeline(steps=steps)
```

The pipeline can then be fit and applied to our dataset just like a single transform:

```
...
# transform the dataset
X, y = pipeline.fit_resample(X, y)
```

We can then summarize and plot the resulting dataset.

We would expect some SMOTE oversampling of the minority class, although not as much as before where the dataset was balanced. We also expect fewer exan ing.

Tying this all together, the complete example is listed l

```
# Oversample with SMOTE and random undersampl
from collections import Counter
from sklearn.datasets import make_classificat
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnd
from imblearn.pipeline import Pipeline
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
# summarize class distribution
counter = Counter(y)
print(counter)
# define pipeline
over = SMOTE(sampling_strategy=0.1)
under = RandomUnderSampler(sampling_strategy=0.5)
steps = [('o', over), ('u', under)]
pipeline = Pipeline(steps=steps)
# transform the dataset
X, y = pipeline.fit_resample(X, y)
# summarize the new class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1], label=str(label))
pyplot.legend()
pyplot.show()
```


Running the example first creates the dataset and summarizes the class distribution.

Next, the dataset is transformed, first by oversampling the minority class, then undersampling the majority class. The final class distribution after this sequence of transforms matches our expectations with a 1:2 ratio or about 2,000 examples in the majority class and about 1,000 examples in the minority class.

```
Counter({0: 9900, 1: 100})
Counter({0: 1980, 1: 990})
```

Finally, a scatter plot of the transformed dataset is created, showing the oversampled minority class and the undersampled majority class.

Scatter Plot of Imbalanced Dataset Transformed by SMOTE and Random Undersampling

Now that we are familiar with transforming imbalanced datasets, let's look at using SMOTE when fitting and evaluating classification models.

SMOTE for Classification

In this section, we will look at how we can use SMOTE as a data preparation method when fitting and evaluating machine learning algorithms in scikit-learn.

First, we use our binary classification dataset from the previous section then fit and evaluate a decision tree algorithm.

The algorithm is defined with any required hyperparameters (we will use the defaults), then we will use repeated stratified k-fold cross-validation to evaluate the model. We will use three repeats of 10-fold cross-validation, meaning that 10-fold cross-validation is applied three times fitting and evaluating 30 models on the dataset.

The dataset is stratified, meaning that each fold of the cross-validation split will have the same class distribution as the original dataset, in this case, a 1:100 ratio. We will evaluate the model using the ROC area under curve (AUC) metric. This can be optimistic for severely imbalanced datasets but will still show a relative change with better performing models.

```
...
# define model
model = DecisionTreeClassifier()
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)
```

Once fit, we can calculate and report the mean of the scores across the folds and repeats.

```
...
print('Mean ROC AUC: %.3f' % mean(scores))
```

We would not expect a decision tree fit on the raw imb

Tying this together, the complete example is listed bel

```
# decision tree evaluated on imbalanced datas
from numpy import mean
from sklearn.datasets import make_classificat
from sklearn.model_selection import cross_val
from sklearn.model_selection import RepeatedS
from sklearn.tree import DecisionTreeClassifi
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
# define model
model = DecisionTreeClassifier()
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)
print('Mean ROC AUC: %.3f' % mean(scores))
```


Running the example evaluates the model and reports the mean ROC AUC.

Note: Your results may vary given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, we can see that a ROC AUC of about 0.76 is reported.

```
Mean ROC AUC: 0.761
```

Now, we can try the same model and the same evaluation method, although use a SMOTE transformed version of the dataset.

The correct application of oversampling during k-fold cross-validation is to apply the method to the training dataset only, then evaluate the model on the stratified but non-transformed test set.

This can be achieved by defining a Pipeline that first tr... its the model.

```
...
# define pipeline
steps = [('over', SMOTE()), ('model', DecisionTreeClassifier())]
pipeline = Pipeline(steps=steps)
```

This pipeline can then be evaluated using repeated k-fold cross-validation.

Tying this together, the complete example of evaluating a decision tree with SMOTE oversampling on the training dataset is listed below.

```
# decision tree evaluated on imbalanced dataset with SMOTE oversampling
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifi
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], f
# define pipeline
steps = [('over', SMOTE()), ('model', Decisio
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_r
scores = cross_val_score(pipeline, X, y, scor
print('Mean ROC AUC: %.3f' % mean(scores))
```


Running the example evaluates the model and reports ... lds and repeats.

Note: Your results may vary given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, we can see a modest improvement in performance from a ROC AUC of about 0.76 to about 0.80.

```
Mean ROC AUC: 0.809
```

As mentioned in the paper, it is believed that SMOTE performs better when combined with undersampling of the majority class, such as random undersampling.

We can achieve this by simply adding a *RandomUnderSampler* step to the Pipeline.

As in the previous section, we will first oversample the minority class with SMOTE to about a 1:10 ratio, then undersample the majority class to achieve about a 1:2 ratio.

```
...
# define pipeline
model = DecisionTreeClassifier()
over = SMOTE(sampling_strategy=0.1)
under = RandomUnderSampler(sampling_strategy=0.5)
steps = [('over', over), ('under', under), ('m
pipeline = Pipeline(steps=steps)
```

Tying this together, the complete example is listed below.

```
# decision tree  on imbalanced dataset with SMOTE oversampling and random undersampling
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
# define dataset
X, y = make_classification(n_samples=10000, n_features=2, n_redundant=0,
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
# define pipeline
model = DecisionTreeClassifier()
over = SMOTE(sampling_strategy=0.1)
under = RandomUnderSampler(sampling_strategy=
steps = [('over', over), ('under', under), ('
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_r
scores = cross_val_score(pipeline, X, y, scor
print('Mean ROC AUC: %.3f' % mean(scores))
```


Running the example evaluates the model with the pip
undersampling on the training dataset.

Note: Your results may vary given the stochastic natu
differences in numerical precision. Consider running th
outcome.

In this case, we can see that the reported ROC AUC shows an additional lift to about 0.83.

```
Mean ROC AUC: 0.834
```

You could explore testing different ratios of the minority class and majority class (e.g. changing the *sampling_strategy* argument) to see if a further lift in performance is possible.

Another area to explore would be to test different values of the k-nearest neighbors selected in the SMOTE procedure when each new synthetic example is created. The default is *k=5*, although larger or smaller values will influence the types of examples created, and in turn, may impact the performance of the model.

For example, we could grid search a range of values of *k*, such as values from 1 to 7, and evaluate the pipeline for each value.

```
...
# values to evaluate
k_values = [1, 2, 3, 4, 5, 6, 7]
for k in k_values:
    # define pipeline
    ...
```

The complete example is listed below.

```
# grid search k value for SMOTE oversampling
```

```
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
# define dataset
X, y = make_classification(n_samples=10000, n_features=2, n_redundant=0,
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
# values to evaluate
k_values = [1, 2, 3, 4, 5, 6, 7]
for k in k_values:
    # define pipeline
    model = DecisionTreeClassifier()
    over = SMOTE(sampling_strategy=0.1, k_neighbors=k)
    under = RandomUnderSampler(sampling_strat
    steps = [('over', over), ('under', under)
    pipeline = Pipeline(steps=steps)
    # evaluate pipeline
    cv = RepeatedStratifiedKFold(n_splits=10,
    scores = cross_val_score(pipeline, X, y,
    score = mean(scores)
    print('> k=%d, Mean ROC AUC: %.3f' % (k,
```


Running the example will perform SMOTE oversampli procedure, followed by random undersampling and fitt t.

The mean ROC AUC is reported for each configuratio

Note: Your results may vary given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, the results suggest that a *k=3* might be good with a ROC AUC of about 0.84, and *k=7* might also be good with a ROC AUC of about 0.85.

This highlights that both the amount of oversampling and undersampling performed (sampling_strategy argument) and the number of examples selected from which a partner is chosen to create a synthetic example (*k_neighbors*) may be important parameters to select and tune for your dataset.

```
> k=1, Mean ROC AUC: 0.827
> k=2, Mean ROC AUC: 0.823
> k=3, Mean ROC AUC: 0.834
> k=4, Mean ROC AUC: 0.840
> k=5, Mean ROC AUC: 0.839
> k=6, Mean ROC AUC: 0.839
> k=7, Mean ROC AUC: 0.853
```

Now that we are familiar with how to use SMOTE when fitting and evaluating classification models, let's look at some extensions of the SMOTE procedure.

SMOTE With Selective Synthetic Sample Generation

We can be selective about the examples in the minori

In this section, we will review some extensions to SMOTE that are more selective regarding the examples from the minority class that provide the basis for generating new synthetic examples.

Borderline-SMOTE

A popular extension to SMOTE involves selecting those instances of the minority class that are misclassified, such as with a k-nearest neighbor classification model.

We can then oversample just those difficult instances, providing more resolution only where it may be required.

> *The examples on the borderline and the ones nearby […] are more apt to be misclassified than the ones far from the borderline, and thus mor*

— Borderline-SMOTE: A New Over-Sampling Method

These examples that are misclassified are likely ambi
decision boundary where class membership may over
Borderline-SMOTE and was proposed by Hui Han, et … A
New Over-Sampling Method in Imbalanced Data Sets

The authors also describe a version of the method tha
examples that cause a misclassification of borderline i … as
Borderline-SMOTE1, whereas the oversampling of just the borderline cases in minority class is referred to as Borderline-SMOTE2.

> *Borderline-SMOTE2 not only generates synthetic examples from each example in DANGER and its positive nearest neighbors in P, but also does that from its nearest negative neighbor in N.*

— Borderline-SMOTE: A New Over-Sampling Method in Imbalanced Data Sets Learning, 2005.

We can implement Borderline-SMOTE1 using the BorderlineSMOTE class from imbalanced-learn.

We can demonstrate the technique on the synthetic binary classification problem used in the previous sections.

Instead of generating new synthetic examples for the minority class blindly, we would expect the Borderline-SMOTE method to only create synthetic examples along the decision boundary between the two classes.

The complete example of using Borderline-SMOTE to oversample binary classification datasets is listed below.

```
# borderline-SMOTE for imbalanced dataset
from collections import Counter
from sklearn.datasets import make_classificat
```

```
from imblearn.over_sampling import BorderlineSMOTE
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n_features=2, n_redundant=0,
    n_clusters_per_class=1, weights=[0.99], flip_y=0, random_state=1)
# summarize class distribution
counter = Counter(y)
print(counter)
# transform the dataset
oversample = BorderlineSMOTE()
X, y = oversample.fit_resample(X, y)
# summarize the new class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1]
pyplot.legend()
pyplot.show()
```

Running the example first creates the dataset and sur
1:100 relationship.

The Borderline-SMOTE is applied to balance the class
class summary.

```
Counter({0: 9900, 1: 100})
Counter({0: 9900, 1: 9900})
```


Finally, a scatter plot of the transformed dataset is created. The plot clearly shows the effect of the selective approach to oversampling. Examples along the decision boundary of the minority class are oversampled intently (orange).

The plot shows that those examples far from the decision boundary are not oversampled. This includes both examples that are easier to classify (those orange points toward the top left of the plot) and those that are overwhelmingly difficult to classify given the strong class overlap (those orange points toward the bottom right of the plot).

Scatter Plot of Imbalanced Dataset With Borderline-SMOTE Oversampling

Borderline-SMOTE SVM

Hien Nguyen, et al. suggest using an alternative of Borderline-SMOTE where an SVM algorithm is used instead of a KNN to identify misclassified examples on the decision boundary.

Their approach is summarized in the 2009 paper titled "Borderline Over-sampling For Imbalanced Data Classification." An SVM is used to locate the decision boundary defined by the support vectors and examples in the minority class that close to the support vectors become the focus for generating synthetic examples.

> *… the borderline area is approximated by the support vectors obtained after training a standard SVMs classifier on the original training set. New instances will be randomly created along the lines joining each minority class support vector with a number of its nearest neighbors using the interpolation*

— Borderline Over-sampling For Imbalanced Data Classification, 2009.

In addition to using an SVM, the technique attempts to select regions where there are fewer examples of the minority class and tries to extrapolate towards the class boundary.

> *If majority class instances count for less than a half of its nearest neighbors, new instances will be created with extrapolation to expand minority class area toward the majority class.*

— Borderline Over-sampling For Imbalanced Data Classification, 2009.

This variation can be implemented via the SVMSMOTE class from the imbalanced-learn library.

The example below demonstrates this alternative approach to Borderline SMOTE on the same imbalanced dataset.

```
# borderline-SMOTE with SVM for imbalanced da
from collections import Counter
from sklearn.datasets import make_classificat
from imblearn.over_sampling import SVMSMOTE
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], f
# summarize class distribution
counter = Counter(y)
print(counter)
# transform the dataset
oversample = SVMSMOTE()
X, y = oversample.fit_resample(X, y)
# summarize the new class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1], label=str(label))
pyplot.legend()
pyplot.show()
```


Running the example first summarizes the raw class distribution, then the balanced class distribution after applying Borderline-SMOTE with an SVM model.

```
Counter({0: 9900, 1: 100})
Counter({0: 9900, 1: 9900})
```

A scatter plot of the dataset is created showing the directed oversampling along the decision boundary with the majority class.

We can also see that unlike Borderline-SMOTE, more examples are synthesized away from the region of class overlap, such as toward the top left of the plot.

Scatter Plot of Imbalanced Dataset With Borderline-SMOTE Oversampling With SVM

Adaptive Synthetic Sampling (ADASYN)

Another approach involves generating synthetic samples inversely proportional to the density of the examples in the minority class.

That is, generate more synthetic examples in regions of the feature space where the density of minority examples is low, and fewer or none where the density is high.

This modification to SMOTE is referred to as the Adaptive Synthetic Sampling Method, or ADASYN, and was proposed to Haibo He, et al. in their 2008 paper named for the method titled "ADASYN: Adaptive Synthetic Sampling Approach For Imbalanced Learning."

> *ADASYN is based on the idea of adaptively generating minority data samples according to their distributions: more synthetic data is generated for minority class samples that are harder to learn compared to those minority samples that are easier to learn.*

— ADASYN: Adaptive synthetic sampling approach fc

With online Borderline-SMOTE, a discriminative model is not created. Instead, examples in the minority class are weighted according to their density, then those examples with the lowest density are the focus for the SMOTE synthetic example generation process.

> *The key idea of ADASYN algorithm is to use a density distribution as a criterion to automatically decide the number of synthetic samples that need to be generated for each minority data example.*

— ADASYN: Adaptive synthetic sampling approach for imbalanced learning, 2008.

We can implement this procedure using the ADASYN class in the imbalanced-learn library.

The example below demonstrates this alternative app

classification dataset.


```
# Oversample and plot imbalanced dataset with
from collections import Counter
from sklearn.datasets import make_classificat
from imblearn.over_sampling import ADASYN
from matplotlib import pyplot
from numpy import where
# define dataset
X, y = make_classification(n_samples=10000, n
    n_clusters_per_class=1, weights=[0.99], f
# summarize class distribution
counter = Counter(y)
print(counter)
# transform the dataset
oversample = ADASYN()
X, y = oversample.fit_resample(X, y)
# summarize the new class distribution
counter = Counter(y)
print(counter)
# scatter plot of examples by class label
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1], label=str(label))
pyplot.legend()
pyplot.show()
```

Running the example first creates the dataset and summarizes the initial class distribution, then the updated class distribution after oversampling was performed.

```
Counter({0: 9900, 1: 100})
Counter({0: 9900, 1: 9899})
```

A scatter plot of the transformed dataset is created. Like Borderline-SMOTE, we can see that synthetic sample generation is focused around the decision boundary as this region has the lowest density.

Unlike Borderline-SMOTE, we can see that the examples that have the most class overlap have the most focus. On problems where these low density examples might be outliers, the ADASYN approach may put too much attention on these areas of the feature space, which may result in worse model performance.

It may help to remove outliers prior to applying the oversampling procedure, and this might be a helpful heuristic to use more generally.

Scatter Plot of Imbalanced Dataset With Adaptive Synthetic Sampling (ADASYN)

Further Reading

This section provides more resources on the topic if you are looking to go deeper.

Books

- Learning from Imbalanced Data Sets, 2018.
- Imbalanced Learning: Foundations, Algorithms, and Applications, 2013.

Papers

- SMOTE: Synthetic Minority Over-sampling Technique, 2002.
- Borderline-SMOTE: A New Over-Sampling Method in Imbalanced Data Sets Learning, 2005.
- Borderline Over-sampling For Imbalanced Data Classification, 2009.
- ADASYN: Adaptive Synthetic Sampling Approach

API

- imblearn.over_sampling.SMOTE API.
- imblearn.over_sampling.SMOTENC API.
- imblearn.over_sampling.BorderlineSMOTE API.
- imblearn.over_sampling.SVMSMOTE API.
- imblearn.over_sampling.ADASYN API.

Articles

- Oversampling and undersampling in data analysis, Wikipedia.

Summary

In this tutorial, you discovered the SMOTE for oversar

Specifically, you learned:

- How the SMOTE synthesizes new examples for t
- How to correctly fit and evaluate machine learning s.
- How to use extensions of the SMOTE that genera boundary.

Do you have any questions?
Ask your questions in the comments below and I will do my best to answer.

About Jason Brownlee

Jason Brownlee, PhD is a machine learning specialist who teaches developers how to get results with modern machine learning methods via hands-on tutorials.

View all posts by Jason Brownlee →

< Imbalanced Classification With Python (7-Day Mini-Course) Undersampling Algorithms for Imbalanced Classification >

264 Responses to *SMOTE for Imbalanc*

Markus January 17, 2020 at 10:52 pm #

Hi

print('Mean ROC AUC: %.3f' % mean(scores))

For calculatng ROC AUC, the examples make use of t

Thanks

Jason Brownlee January 18, 2020 at 8:48 am # REPLY

The ROC AUC scores are calculated automatically via the cross-validation process in scikit-learn.

Ram pratapa April 1, 2020 at 6:13 pm # REPLY

Hi Jason,
Is there any way to use smote for multilabel problem.

Jason Brownlee April 2, 2020 at 5:44 am # REPLY

Yes, you must specify to the smote config which are the positive/negative clasess and how much to oversample them.

Camara Mamadou January 21, 2020 at 12:52 am # REPLY

Hi Jason,

thanks for sharing machine learning knowledge.

How to get predictions on a holdout data test after getting best results of a classifier by SMOTE oversampling?

Best regards!

Mamadou.

Jason Brownlee January 21, 2020 at 7:15 am

Call model.predict() as per normal.

Recall SMOTE is only applied to the training set w

Akil February 20, 2020 at 11:47 pm #

Hi Jason,

As you said, SMOTE is applied to training only, won't that affect the accuracy of the test set?

Jason Brownlee February 21, 2020 at 8:23 am # REPLY

Yes, the model will have a better idea of the boundary and perform better on the test set – at least on some datasets.

Akshay October 16, 2020 at 5:17 am #

Just a clarifying question: As per what Akil mentioned above, and the code below, i am trying to understand if the SMOTE is NOT being applied to validation data (during CV) if the model is defined within a pipeline and it is being applied even on the validation data if I use oversampke.fit_resample(X, y). I want to make sure if it's working as expected.

I saw a drastic difference in say, accuracy when I ran SMOTE with and without pipeline.

# define pipeline
steps = [('over', SMOTE()), ('model', DecisionTreeClassifier())]
pipeline = Pipeline(steps=steps)
# evaluate pipeline

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(pipeline, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)
print('Mean ROC AUC: %.3f' % mean(scores))

Jason Brownlee October 16, 2020 at 5:58 am #

SMOTE is only applied on the training set, even when used in a pipeline, even when evaluated via cross-validation.

Akshay October 17, 2020 at 12:2

Makes sense! Like our fellow
validation have close accuracy metric
improve the performance of the test se

P.S:
Just to be clear again, in my case – 3-
What I define as X_train is used to fit a
under the hood is a 5-fold CV meaning
20% of the data set is where SMOTE i

Jason Brownlee October 17, 2020 at 6:07 am #

Try the list of techniques here to improve model performance:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

And here:
http://machinelearningmastery.com/machine-learning-performance-improvement-cheat-sheet/

Rafael Eder January 21, 2020 at 3:17 pm # REPLY

Hi !
SMOTE works for imbalanced image datasets too ?

Best Regards;

Jason Brownlee January 22, 2020 at 6:17 am # REPLY

No, it is designed for tabular data.

You might be able to use image augmentation in the same manner.

Rafael Eder January 22, 2020 at 10:07 am #

REPLY

Yours books and blog help me a lot ! Thank you very much !

Jason Brownlee January 22, 2020 at 1:55 pm #

REPLY

Thanks, I'm happy to hear that!

zaidi July 8, 2021 at 4:23 pm #

Hello, I used image augmentation for
results for some classes so that influences the
that I used it for all my data, I mean that I didn'
all my data. Can you help me with this? Thank

Jason Brownlee July 9, 2021 at 5:05 am #

REPLY

Perhaps the model requires tuning, some of these suggestions will help:
https://machinelearningmastery.com/start-here/#better

brian January 31, 2020 at 12:28 am #

REPLY

Hi Jason, thanks for another series of excellent tutorials. I have encountered an error when running

X, y = pipeline.fit_resample(X, y)

on my own X & y imbalanced data. The error is :

"ValueError: The specified ratio required to remove samples from the minority class while trying to generate new samples. Please increase the ratio."

from _validation.py", line 362, in _sampling_strategy_float in imblearn/utils in the library.

Could you or anyone else shed some light on this error?

Thanks.

brian January 31, 2020 at 1:50 am # REPLY

as a followup it seems I've not understood how SMOTE and undersampling function.

My input data size is:

{0: 23558, 1: 8466}

so a little under 1:3 for minority:majority examples of the classes

Now I understand I had the ratios for SMOTE() and RandomUnderSampler() "sampling_strategy" incorrect.

Onwards and upwards!

Jason Brownlee January 31, 2020 at 7:5

Happy to hear that, nice work!

Volkan Yurtseven July 22, 2020 at 7:32

Hi
When used with a gridsearchcv, does Smote apply the oversampling to whole train set or does it disregard the validation set?

Jason Brownlee July 22, 2020 at 7:38 am # REPLY

You can use it as part of a Pipeline to ensure that SMOTE is only applied to the training dataset, not val or test.

Kevin November 28, 2020 at 6:17 pm #

Hi Jason,

Nice blog! And nice depth on variations on SMOTE. I was wondering:

Why do you first oversample with SMOTE and then undersample the majority class afterwards in your pipelines? Wouldn't it be more effective the other way around?

Jason Brownlee November 2

Thanks!

It is an approach that has worked well for me. Perhaps try the reverse on your dataset and compare the results.

April January 26, 2021 at 3:59 pm #

Hi Jason,

I've been perusing through your extremely helpful articles on imbalanced classification for days now. Thank you for providing such valuable knowledge to the machine learning community!

I had a question regarding the conseq
apply SMOTE only to the train set but
be stratified. For example, if the train s
class 2, validation and test sets still ma
not a concern at all since we just care
will be based only on the train set? If w
model also assume that the real-world
1 and class 2?

Thanks for your help in advance!

Jason Brownlee January 27, 2021 at 6:03 am #

Thank you for your support!

No, you would stratify the split of the data before resampling. Then use a metric (not accuracy) that effectively evaluates the capability of natural looking data (val and test sets).

This is critical. Changing the nature of test and val sets would make the test harness invalid.

Jason Brownlee January 31, 2020 at 7:55 am #

REPLY

Confirm you have examples of both classes in the y.

Jeong miae March 21, 2020 at 10:56 am #

REPLY

Thank you for your tutorial.
I'd like to ask several things.

1. Could I apply this sampling techniques to image

2. After making balanced data with these thechniques, Could I use not machine learning algorithms but deep learning algorithms such as CNN?

Jason Brownlee March 22, 2020 at 6:47 am #

REPLY

Yes, but it is called data augmentation and works a little differently:
https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/

Yes, this tutorial will show you how:
https://machinelearningmastery.com/cost-sensitive-neural-network-for-imbalanced-classification/

Jeong miae March 22, 2020 at 5:32 p

Thank you for your answer.

I've used data augmentation technique on
data augmentation and oversampling like

In fact, I'd like to find other method except
So, I wanted to try oversampling.

But, as follow as I understand as your answer, I can't use oversampling such as SMOTE at image data . Am I right to understand?
Thank you again for your kind answer.

Jason Brownlee March 23, 2020 at 6:12 am #

Correct, SMOTE does not make sense for image data, at least off the cuff.

Here are ideas for improving model performance:
https://machinelearningmastery.com/start-here/#better

Valdemar February 11, 2020 at 2:06 am #

REPLY

Hello Jason,

In your ML cheat sheet you have advice to invent more data if you have not enough. Can you suggest methods or libraries which are good fit to do that?

Imblearn seams to be a good way to balance data. What about if you wish to increase the entire dataset size as to have more samples and potentially improve model?

Jason Brownlee February 11, 2020 at 5:15 am # REPLY

SMOTE can be used.

Feature engineering is the more general approach:
https://machinelearningmastery.com/discover-feature-engineering-how-to-engineer-features-and-how-to-get-good-at-it/

Frank February 28, 2020 at 11:41 pm # REPLY

Thank you for the great tutorial, as always sup

I'm working throught the wine quality dataset(white) an
are below.

{6: 2198, 5: 1457, 7: 880, 8: 175, 4: 163, 3: 20, 9: 5}

In your opinion would it be possible to apply SMOTE ir

I've managed to use a Regression model (KNN) that I
take how to deal with similar class imbalance on multil

Jason Brownlee February 29, 2020 at 7:13 am # REPLY

Yes, SMOTE can be used for multi-class, but you must specify the positive and negative classes.

Akshay October 15, 2020 at 1:53 am # REPLY

What does positive and negative means for multi-class? Based on the problem/domain, it can vary but let's say if I identify which classes are positive and which are negative, what next?

Jason Brownlee October 15, 2020 at 6:15 am # REPLY

You can apply SMOTE directly fir multi-class, or you can specify the preferred balance of the classes to SMOTE.

Also see an example here:
https://machinelearningmastery.com/multi-class-imbalanced-classification/

Thomas March 1, 2020 at 6:33 am # REPLY

Thanks for sharing Jason.
In imblearn.pipeline the predict method says tahar it applies transforms AND sampling and then the final predict of the estimator.

Therefore isnt that a problem in crossvalscore the sampling will be applied on each validation sets ?

Thanks

Jason Brownlee March 2, 2020 at 6:07 am # REPLY

Sorry, I don't follow your question. Can yo

Yong March 1, 2020 at 6:19 pm #

you mentioned that : " As in the previous secti
SMOTE to about a 1:10 ratio, then undersample the m
why? what is the idea behind this operation and why d

Jason Brownlee March 2, 2020 at 6:16 am # REPLY

This approach can be effective. It is important to try a range of approaches on your dataset to see what works best.

Vijay M March 2, 2020 at 8:37 pm # REPLY

Sir Jason,
Can we use the above code for images

Jason Brownlee March 3, 2020 at 5:58 am # REPLY

No, you would use data augmentation:
https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/

Ernest Montañà March 18, 2020 at 3:40 am # REPLY

Hello Jason, thanks for the tutorial.

When using the lines:

# define pipeline
steps = [('over', SMOTE()), ('model', RandomForestClassifier(n_estimators=100, criterion='gini', max_depth=None, random_state=1))]
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=2, random_state=1)
acc = cross_val_score(pipeline, X_new, Y, scoring='ac

I assume the SMOTE is performed for each cross vali
correct? Thank you

Jason Brownlee March 18, 2020 at 6:13 am

Correct. That is why we use pipelines.

AP February 19, 2021 at 1:59 am # REPLY

Hello Jason,
Thank you for the post. I have some questions. My dataset consists NaN values and I am not allowed to drop them due to less no. of records. If I impute values with mean or median before splitting data or cross validation, there will be information leakage. To solve that problem, I need to use pipeline including SMOT and a model, and need to apply cross validation. Now, my question is, what if I have huge data set and I want to apply feature engineering (PCA or RFE) and want to explore all the steps step by step? If I define every steps in pipeline, how can I explore, where is the real problem in which method? Also I need more computation power to do trial and error methods on huge dataset. What is your suggestion for that?

My second question is, that I do not understand SMOT that you defined initially.
" SMOTE first selects a minority class instance a at random and finds its k nearest minority class neighbors. The synthetic instance is then created by choosing one of the k nearest neighbors b at random and connecting a and b to form a line segment in the feature space. The synthetic instances are generated as a convex combination of the two chosen instances a and b. "
I couldn't imagine what you want to say. Because of that I did not understand borderline SMOT as well. Could you please rephrase it and if possible could you please explain it with a small example?

Thank you in advance.

Jason Brownlee February 19, 2021 at 6:04 am #

REPLY

You must fit the imputer on the train set and apply to train and test within cv, a pipeline will help.

You can also step the k-fold cv manually and implement the pipeline manually – this might be preferred to you can keep track of what changes are made and any issues that might occur.

SMOTE works by drawing lines between close examples in feature space and picking a random point on the line as the new instance.

I hope that helps.

David March 29, 2020 at 1:35 am #

Hi! A quick question, SMOTE should be appli Standardization for example) ? Or it's irrelevant?

Thank you!

Jason Brownlee March 29, 2020 at 6:01 am

Probably after.

It is doing a knn, so data should be scaled first.

San April 2, 2020 at 6:13 am #

REPLY

How to use SMOTE or any other technique related with SMOTE such as ADASYN, Borderline SMOTE, when a dataset has classes with only a few instances?

Some of the classes in my dataset has only 1 instance & some have 2 instances. When using these SMOTE techniques I get the error 'Expected n_neighbors <= n_samples, but n_samples = 2, n_neighbors = 6'.

Is there any way to overcome this error? With RandomOversampling the code works fine..but it doesn't seem to give a good performance. And I'm unable to all the SMOTE based oversampling techniques due to this error.

Jason Brownlee April 2, 2020 at 6:41 am #

REPLY

I don't think modeling a problem with one instance or a few instances of a class is appropriate.

Perhaps collect more data?
Perhaps delete the underrepresented classes?
Perhaps reframe the problem?

Garv April 8, 2020 at 9:59 pm #

REPLY

Hello I did tuning of smote parameters(k,sampling strategy) and took roc_auc as scoring on training data but how along with cross val score my model is evaluated on testing data (that ideally should not be the one on which smote should apply)
can you help me with how to apply best model on testing data(code required)

```
#Using Decsion Tree
Xtrain1=Xtrain.copy()
ytrain1=ytrain.copy()
k_val=[i for i in range(2,9)]
p_proportion=[i for i in np.arange(0.2,0.5,0.1)]
k_n=[]
proportion=[]
score_m=[]
score_var=[]
modell=[]
for k in k_val:
for p in p_proportion:
oversample=SMOTE(sampling_strategy=p,k_neighbors=k,random_state=1)
Xtrain1,ytrain1=oversample.fit_resample(Xtrain,ytrain)
model=DecisionTreeClassifier()
cv=RepeatedStratifiedKFold(n_splits=10,n_repeats=3,random_state=1)
scores=cross_val_score(model,X1,y1,scoring='roc_auc',cv=cv,n_jobs=-1)
k_n.append(k)
proportion.append(p)
score_m.append(np.mean(scores))
score_var.append(np.var(scores))
modell.append('DecisionTreeClassifier')
scorer=pd.DataFrame({'model':modell,'k':k_n,'proportion':proportion,'scores':score_m,'score_var':score_var}
)
print(scorer)
models.append(model)
models_score.append(scorer[scorer['scores']==max(scorer['scores'])].values[0])
models_var.append(scorer[scorer['score_var']==min(scorer['score_var'])].values[0])
```


Jason Brownlee April 9, 2020 at 8:02 am #

REPLY

This is a common question that I answer h
https://machinelearningmastery.com/faq/single-faq

Kabilan April 10, 2020 at 7:02 am # REPLY

Hey Jason,
What kind of an approach can we use to over-sample time series data?

Jason Brownlee April 10, 2020 at 8:38 am # REPLY

Good question, I hope I can cover that topic in the future.

John White April 10, 2020 at 7:11 pm #

Hello Jason,

Do you currently have any ideas on how to ove
like to do some research/experiment on it in th

Jason Brownlee April 11, 2020 at 6:14 am #

No, in general I rather make recommendations after doing my homework.

Kabilan April 10, 2020 at 11:40 pm # REPLY

Thank you very much!

Jason Brownlee April 11, 2020 at 6:21 am # REPLY

You're welcome.

Vamshi April 11, 2020 at 7:56 am # REPLY

Hi Jason Brownie,

Thank you for the great description over handling imbalanced datasets using SMOTE and its alternative methods. I know that SMOTE is only for multi Class Da of using SMOTE for multi label Datasets?? or Do you have any other method or ideas apart from SMOTE in order to handle imbalanced multi label datasets.

Jason Brownlee April 11, 2020 at 7:58 am # REPLY

Great question!

I'm not aware of an approach off hand for multi-label, perhaps check the literature?

Vamshi April 11, 2020 at 8:10 am #

I was working on a dataset as a part c
tried experimenting directly using OnevsRestC
classsifer gave worst results(the target value w
I tried testing with Random forest classifier tak
oversampled with a randomsampler class whic
not sure if I can do it in this way.

Jason Brownlee April 11, 2020 at 1

Perhaps the suggestions here will help:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

Vamshi April 11, 2020 at 8:21 am # REPLY

I also found this solution.
https://github.com/scikit-learn-contrib/imbalanced-learn/issues/340

Jason Brownlee April 11, 2020 at 11:53 am # REPLY

Nice.

Jooje April 16, 2020 at 4:23 am # REPLY

Hi! Thanks for the great tutorial. Can SMOTE be used with 1. high dimensional embeddings for text representation? if so, what is any preprocessing/dimer

Jason Brownlee April 16, 2020 at 6:06 am # REPLY

Not sure off the cuff, perhaps experiment to see if this makes sense.

rahul malik April 23, 2020 at 8:49 am # REPLY

hi Jason , I am having 3 input Text columns out of 2 are categorical and 1 is unstructured text. Can you please help me how to do sampling. Output column is categorical and is imbalanced.

Jason Brownlee April 23, 2020 at 1:34 pm #

Perhaps use a label or one hot encoding text data.

You can see many examples on the blog, try searc

rahul malik April 23, 2020 at 10:53 pm #

I have used Pipeline and columntransformer to pass multiplecolumns as X but for sampling I ma not to find any example.For single column I ma able to use SMOTE but how to pass more than in X?

Jason Brownlee April 24, 2020 at 5:43 am # REPLY

You may have to experiment, perhaps different smote instances, perhaps run the pipeline manually, etc.

Iraj April 30, 2020 at 8:28 am # REPLY

Hi,
SMOTE requires 6 examples of each class.
I have a dataset if 30 class 0, and 1 class 1 .
Please advise if any solution.
Thank you

Jason Brownlee April 30, 2020 at 11:36 am # REPLY

Perhaps try and get more examples from the minority class?

Perhaps try alternate techniques listed here:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

John Sammut May 2, 2020 at 9:25 am # REPLY

Hello Jason,

Many thanks for this article. I found it very interesting.

How can one apply the same ratio of oversampling (1:
when there are 3 classes?

The sampling strategy cannot be set to float for multi-c

Thank you.
John

Jason Brownlee May 3, 2020 at 6:05 am #

Thanks.

First step is to group classes into positive and negative, then apply the sampling.

Srisha May 4, 2020 at 12:35 pm # REPLY

Could you shed some light on how one could leverage the parameter sampling_strategy in SMOTE?

Jason Brownlee May 4, 2020 at 1:28 pm # REPLY

Yes, what would you like to know exactly?

Mohamad May 7, 2020 at 11:04 pm # REPLY

Hi Jason,
Thank you very much for this article, it's so helpful (as always)

I have an inquiry:
Now my data are highly imbalanced (99.5%:0.05%). I am having over than 40,000 samples with multiple features (36) for my classification problem. I oversampled with SMOTE to have balanced data, but the classifier is getting highly biased toward the oversampled data. I assumed that its because of the "sampling_strategy". So I tried {0.25, 0.5, 0.75,1} for the "sampling_strategy". Its either getting highly biased towards the abundant or the rare class.

What do you think could be the problem?

Jason Brownlee May 8, 2020 at 6:36 am # REPLY

SMOTE is not the best solution for all imb

Perhaps try and compare alternative solutions:
https://machinelearningmastery.com/framework-fo

john sen May 11, 2020 at 3:45 am #

please tell me how i can apply two balancing
algorithm on same dataset for better result

Jason Brownlee May 11, 2020 at 6:08 am # REPLY

You can apply smote to the training set, then apply the one class classifier directly.

I don't expect it would be beneficial to combine these two methods.

john sen May 12, 2020 at 3:54 am # REPLY

sir then what should i try for the best result by using smote and one more algo which makes an hybrid approch to handle imbalanced data.

Jason Brownlee May 12, 2020 at 6:50 am # REPLY

Use trial and error to discover what works well/best for your dataset.

Arnaud May 11, 2020 at 3:47 am #

Hi Jason,
First, thanks for your material, it's of great value!

I have a supervised classification problem with unbalanced class to predict (Event = 1/100 Non Event).

I have the intuition that using resampling methods such as SMOTE (or down/up/ROSE) with Naive Bayes models affect prior probabilities and such lead to lower performance when applied on test set.

Is that correct?
Thanks.

Jason Brownlee May 11, 2020 at 6:09 am # REPLY

You're welcome!

Yes.

Teixeira May 12, 2020 at 1:31 am #

Hi Dr.

Could SMOTE be applied to data that will be used for f
interfere with the data right?)

Thanks in advance!

Jason Brownlee May 12, 2020 at 6:46 am # REPLY

No, it is for tabular data only.

Teixeira May 13, 2020 at 2:04 am # REPLY

First of all, thanks for the response. Sorry, i think i don't understand. Maybe I am wrong, but SMOTE could be applied to tabular data, before the transformation into sliding windows. Even in this case is not recommend to apply SMOTE ?

Thanks!

Jason Brownlee May 13, 2020 at 6:39 am # REPLY

Perhaps, but I suspect data generation methods that are time-series-aware would perform much better.

Zina September 24, 2020 at 12:51 am #

Thanks you, Jason. Would you be able to point out an example of those time-series aware data generation methods?

Jason Brownlee September 2

Not off hand sorry. Perhaps tr

John D May 14, 2020 at 10:04 am #

Jason,

I have a highly imbalanced binary (yes/no) classificatio
'yes'.

I need to balance the dataset using SMOTE.

I came across 2 method to deal with the imbalance. The following steps after I have run MinMaxScaler on the variables

from imblearn.pipeline import Pipeline
oversample = SMOTE(sampling_strategy = 0.1, random_state=42)
undersample = RandomUnderSampler(sampling_strategy=0.5, random_state=42)
steps = [('o', oversample), ('u', undersample)]
pipeline = Pipeline(steps=steps)
x_scaled_s, y_s = pipeline.fit_resample(X_scaled, y)
This results in a reduction in the size of the dataset from 2.4million rows to 732000 rows And the imbalance improves from 0.008% to 33.33%

While this approach

sm = SMOTE(random_state=42)
X_sm , y_sm = sm.fit_sample(X_scaled, y)
This increases the number of rows from 2.4million rows to 4.8 million rows and the imbalance is now 50%.

After these steps I need to split data into Train Test datasets….

What is the right approach here?

What factors do I need to consider before I choose any of these methods?

Should I run the X_test, y_test on unsampled data. This would mean, I split the data and do upsampling/undersampling only on the train data.

Thanks again.

Jason Brownlee May 14, 2020 at 1:27 pm #

REPLY

No, the sampling is applied on the training dataset only, not the test set. E.g. split first then sample.

Shivam May 16, 2020 at 4:50 pm #

Hello Jason, Great article. One Issue i am fac
have only feature for categorization.

from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import SMOTENC

sm = SMOTENC(random_state=27,categorical_feature

X_new = np.array(X_train.values.tolist())
Y_new = np.array(y_train.values.tolist())

print(X_new.shape) # (10500,)
print(Y_new.shape) # (10500,)

X_new = np.reshape(X_new, (-1, 1)) # SMOTE require 2-D Array, Hence changing the shape of X_mew

print(X_new.shape) # (10500, 1)

sm.fit_sample(X_new, Y_new)

But i am getting Error:

ValueError: Found array with 0 feature(s) (shape=(10500, 0)) while a minimum of 1 is required.

Can you please suggest how to deal with SMOTE if there is only one feature ?

Jason Brownlee May 17, 2020 at 6:31 am #

REPLY

Interesting, I wonder if it is a bug in smote-nc?

Perhaps try duplicating the column and whether it makes a difference?

sukhpal May 26, 2020 at 7:23 pm #

sir how SMOTE can be applied on CSV file data

Jason Brownlee May 27, 2020 at 7:45 am # REPLY

Load the data as per normal:
http://machinelearningmastery.com/load-machine-learning-data-python/

Then apply smote.

John D May 27, 2020 at 8:19 am #

What is the criteria to UnderSample the major
OR
What is the criteria to Upsample the minority class only

Jason Brownlee May 27, 2020 at 1:25 pm #

I don't approach it that way. I think it's mis

Instead, I recommend do the experiment and use i

SUKHPAL May 28, 2020 at 3:51 pm # REPLY

SIR PLEASE PROVIDE TUTORIAL ON TEST TIME AUGMENTATION FOR NUMERICAL DATA

Jason Brownlee May 29, 2020 at 6:20 am # REPLY

No problem, I have one written and scheduled to appear next week.

sukhpal May 30, 2020 at 7:01 pm # REPLY

Sir is we apply feature selection technique first or data augmentation first.

Jason Brownlee May 31, 2020 at 6:20 am # REPLY

Feature selection first would be my first thought.

Suyash June 25, 2020 at 10:32 pm #

REPLY

Why are we implementing SMOTE on whole dataset "X, y = oversample.fit_resample(X, y)"? We should apply oversampling only on the training set. Am i right? What should be done to implement oversampling only on the training set and we also want to use stratified approach?

Jason Brownlee June 26, 2020 at 5:35 am #

REPLY

Correct, and we do that later in the tutoria

In the first example I am getting you used to the AP

suyash June 27, 2020 at 11:38 pm #

Can you please refer that tutorial to m data only and evaluating the model? I also wa the training dataset only.

Jason Brownlee June 28, 2020 at 5:51 am #

REPLY

Yes the section "SMOTE for Classification" in the above tutorial uses a pipeline to ensure SMOTE is only applied on training data.

If you are new to using pipelines, see this:
https://machinelearningmastery.com/data-preparation-without-data-leakage/

suyash June 28, 2020 at 12:10 am #

REPLY

cross_val_score oversample the data of training set only and do not oversample the training data. am i right?

Jason Brownlee June 28, 2020 at 5:52 am #

REPLY

When using a pipeline the transform is only applied to the training dataset, which is correct.

suyash June 29, 2020 at 3:44 pm #

Thank You very much.

Jason Brownlee June 30, 2020 at 6:11 am #

You're welcome.

Jose Q June 28, 2020 at 7:29 am #

Hi Jason!
Thank you for such a great post!

I am working with an imbalanced data set (500:1). I wa
with several classification algorithms, hyper parameter
SMOTE now !!!
From the last question, I understand that using CV and

I have another question. My imbalanced data set is ab
series. I used data from the first ten months for training, and data from the eleventh month for testing in order to explain it easier to my users, but I feel that it is not correct, and I guess I should use a random test split from the entire data set. Is this correct?

Jason Brownlee June 29, 2020 at 6:22 am #

REPLY

You're welcome.

Correct. Use a pipeline to only oversample the training set.

My best advice is to evaluate candidate models under the same conditions you expect to use them. If there is a temporal element to your data and how you expect to use the model in the future, try and capture that in your test harness.

I hope that helps.

Here are more ideas:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

Jose Q June 30, 2020 at 4:15 am #

REPLY

Thank you

Jose Q July 1, 2020 at 3:09 am # REPLY

Hi Jason,
I followed your ideas at:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

I tried oversampling with SMOTE, but my computer just can't handle it.
Then I tried using Decision Trees and XGB for imbalanced data sets after reading your posts:
https://machinelearningmastery.com/cost-sensitive-decision-trees-for-imbalanced-classification/
https://machinelearningmastery.com/xgboost-for-imbal
but I still get low values for recall.

I am doing random undersample so I have 1:1 class re
doing XGB/Decision trees varying max_depth and vary
class. My assumption is that I won't overfit the model a
Is that right?
Thanks

Jason Brownlee July 1, 2020 at 5:55 am #

Well don on your progress!

Perhaps. Assumptions can lead to poor results, test everything you can think of.

Jose Q July 1, 2020 at 3:33 pm # REPLY

Thank you

Jason Brownlee July 2, 2020 at 6:14 am # REPLY

You're welcome.

xplorer4us July 8, 2020 at 5:32 pm # REPLY

Hi Jason, excellent explanations on SMOTE, very easy to understand and with tons of examples!

I tried to download the free mini-course on Imbalance C

May I please ask for your help with this? Thanks in advance!

Jason Brownlee July 9, 2020 at 6:38 am # REPLY

Thanks.

Sorry to hear that, contact me directly and I will email it to you:
https://machinelearningmastery.com/contact/

xplorer4us July 9, 2020 at 4:42 pm #

Thank you, will do that!

Jason Brownlee July 10, 2020 at 5

You're welcome.

Landry July 13, 2020 at 8:01 pm # REPLY

Hi Jason, thanks for this tutorial it's so useful as usual,

I have one inquiry, I have intuition that SMOTE performs bad on dataset with high dimensionality i.e when we have many features in our dataset. Is it true ?

Jason Brownlee July 14, 2020 at 6:18 am # REPLY

Hmmm, that would be my intuition too, but always test. Intuitions breakdown in high dimensions, or with ml in general. Test everything.

Volkan Yurtseven July 22, 2020 at 7:34 am # REPLY

Hi
When used with a gridsearchcv, does Smote apply the oversampling to whole train set or does it disregard the validation set?

Jason Brownlee July 22, 2020 at 7:38 am # REPLY

You can use it as part of a Pipeline to ensure that SMOTE is only applied to the training dataset, not val or test.

Volkan Yurtseven July 23, 2020 at 6:52 am # REPLY

hi jason,
do you mean if i use it in a imblearn's own Pipeline class, it would be enough? no need for any parameter?

pipe = Pipeline(steps=[('coltrans', coltrans),
('scl',StandardScaler()),
('smote', SMOTE(random_state=42))
]
)

X_smote,y_smote=pipe.fit_resample(X_train,y

Jason Brownlee July 23, 2020 at 2

Yes.

Diego July 23, 2020 at 12:39 pm # REPLY

Hi Jason,

Thanks for sharing. It really helps in my work ☺

Let's say you train a pipeline using a train dataset and it has 3 steps: MinMaxScaler, SMOTE and LogisticRegression.

Can you use the same pipeline to preprocess test data ?
Or should you have a different pipleine without smote for test data ?

How does pipeline.predict(X_test) that it should not execute SMOTE ?

Thanks.

Jason Brownlee July 23, 2020 at 2:46 pm # REPLY

The pipeline is fit and then the pipeline ca

Yes, call pipeline.predict() to ensure the data is prepared correctly prior to being passed to the model.

More on this here:
https://machinelearningmastery.com/data-preparation-without-data-leakage/

SAM V July 29, 2020 at 3:52 pm #

REPLY

Hi Jason, SMOTE sampling is done before / after data cleaning or pre-processing or feature engineering??? I just want to know when we should do SMOTE sampling and why??

Jason Brownlee July 30, 2020 at 6:16 am #

It depends on what data prep you are doi

Probably after.

Gaël August 6, 2020 at 7:26 pm #

Hi, great article! I think there is a typo in sectio
points that belong to the minority class (blue)" –> shou

Jason Brownlee August 7, 2020 at 6:24 am #

REPLY

Thanks! Fixed.

Maria November 6, 2020 at 2:30 am #

REPLY

https://stackoverflow.com/questions/58825053/smote-function-not-working-in-make-pipeline

Jason Brownlee November 6, 2020 at 6:02 am #

REPLY

Sorry, I don't have the capacity to read off site stackoverflow questions:
https://machinelearningmastery.com/faq/single-faq/can-you-comment-on-my-stackoverflow-question

Luna August 6, 2020 at 7:30 pm # REPLY

Hi Jason,

TypeError: All intermediate steps should be transformers and implement fit and transform or be the string 'passthrough' 'SMOTE(k_neighbors=5, n_jobs=None, random_state=None, sampling_strategy='auto')' (type) doesn't

I get this error when running GridSearchCV. What is wrong?

Jason Brownlee August 7, 2020 at 6:24 am # REPLY

Perhaps confirm the content of your pipel

george August 12, 2020 at 1:30 pm #

Hi Jason,

if all my predictors are binary, can I still use SMOTE? s
Are there any methods other than random undersampl

Jason Brownlee August 12, 2020 at 1:37 pm # REPLY

Great question, I believe you can use an extension of SMOTE for categorical inputs called SMOTE-NC:
https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.SMOTENC.html

Franco August 19, 2020 at 7:18 am # REPLY

Brilliant post Jason!

I wonder if we upsampled the minority class from 100 to 9,900 with a bootstrap (with replacement of course), whether we would get similar results than SMOTE … I put on my to-do list.

Jason Brownlee August 19, 2020 at 1:34 pm # REPLY

Thanks!

Probably not, as we are generating entirely new sa
experiment and compare the results!

Franco August 19, 2020 at 3:52 pm # REPLY

Interesting …. I will. Thanks Jason!

Jason Brownlee August 20, 2020 at 6:35 am # REPLY

You're welcome.

SaHaR August 22, 2020 at 12:35 am #

Hi, Jason

Thank you for your great article. It is really informative
classification of a multiclass and imbalanced dataset. T
think it was not a correct methodology and the test dat
wrong and would you recommend a reference about th

Thank you

Jason Brownlee August 22, 2020 at 6:17 am # REPLY

Thanks!

Agreed, it is invalid to use SMOTE on the test set.

Vivek August 28, 2020 at 4:04 am # REPLY

Hi Jason

Q1. Do we apply SMOTE on the train set after doing train/ test split?

Guess, doing SMOTE first, then splitting, may result in data leak as same instances may be present in both test and test sets.

Q2. I understand why SMOTE is better instead of random oversampling minority class. But say for a class imbalance of 1:100, why not just random undersample majority class? Not sure how SMOTE helps here !

Thanks
Vivek

Jason Brownlee August 28, 2020 at 6:55 am #

REPLY

Yes. Training set only.

Try many methods and discover what works best for your dataset.

Shehab August 29, 2020 at 7:13 am #

REPLY

Hi Jason,

What if you have an unbalanced dataset that matches the realistic class distribution in production. Say Class A has 1000 rows, Class B 400 and Class C with 60. W dataset like this. Say I use a classifier like Naive Bayes oversampling Class C I mess up the prior probability a production. Should I try and get more data or augment unbalanced distribution or change the distribution by o

Thanks

Jason Brownlee August 29, 2020 at 8:10 am

The negative effects would be poor predictive performance.

I recommend testing a suite of techniques in order to discover what works best for your specific dataset.

This framework will help:
https://machinelearningmastery.com/framework-for-imbalanced-classification-projects/

Daniel September 10, 2020 at 7:34 pm #

REPLY

Hello,

Thanks for your work, it is really useful. I have a question about the combination of SMOTE and active learning.

I am trying to generate a dataset using active learning techniques. From a pool of unlabelled data I select the new points to label using the uncertainty in each iteration. My problem is that the classes repartition is imbalanced (1000:1), my current algorithm can't find enough points in Yes class. Do you think I could use SMOTE to generate new points of Yes class?
I am thinking about using borderline-SMOTE to generate new points and then label them. How can I be sure that the new points are not going to be concentrated in a small region?

I am not sure if I have explained the problem well. I need to find the feasible zone using the labeller in a smart way because labelling is expensive. Can you giv

Thanks.

Daniel

Jason Brownlee September 11, 2020 at 5:55 am # REPLY

Perhaps try it and see?

Bilal September 26, 2020 at 9:44 pm # REPLY

I do SMOTE on the whole dataset, then norm
Is it right that in cross_val_score, SMOTE will resampli

oversample = SMOTE()
X, Y = oversample.fit_resample(X, Y)

normalized = StandardScaler()
normalized_X = normalized.fit_transform(X)
clf_entropy = DecisionTreeClassifier(random_state = 4
y_pred = cross_val_predict(clf_entropy, normalized_X,

Jason Brownlee September 27, 2020 at 6:53 am # REPLY

No. If you use a pipeline it will work as you describe.

Vidya October 6, 2020 at 1:01 pm # REPLY

Hi Jason .

Thanks for your post. I have two Qs regards SMOTE + undersampling example above.
"under = RandomUnderSampler(sampling_strategy=0.5)" . Why would we undersample the majority class to have 1:2 ratio and not have an equal representation of both class?
2. If I were to have an imbalanced data such that minority class is 50% , wouldn't I need to use PR curve AUC as a metric or f1 , instead of ROC AUC ?
"scores = cross_val_score(pipeline, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)"

Thanks !!

Jason Brownlee October 6, 2020 at 1:59 pm # REPLY

It is a good idea to try a suite of different rebalancing ratios and see what works. I found this ratio on this dataset after some trial and error.

This will help you choose a metric:
https://machinelearningmastery.com/tour-of-evaluation-metrics-for-imbalanced-classification/

Vidya October 7, 2020 at 12:51 pm # REPLY

Thanks Jason. Applying the same now .

Jason Brownlee October 7, 2020 at 1:52 pm

Thanks!

Vidya October 7, 2020 at 1:34 pm #

Jason , I am trying out the various balancing r
convinced on how balancing the training data set will a
imbalanced test data ? Is this then dependent on how
various methods of balancing the train data set , the model does not generalise well on test data , I need to relook at the feature creation ??

Thanks!!

Jason Brownlee October 7, 2020 at 1:53 pm # REPLY

Hard to say, the best we can do is used controlled experiments to discover what works best for a given dataset.

Vidya October 8, 2020 at 3:16 pm # REPLY

Thanks !

Jason Brownlee October 9, 2020 at 6:39 am # REPLY

You're welcome.

Sophie October 7, 2020 at 2:09 pm # REPLY

Hi Jason,
Thank you so much for your explanation. I have a question when fitting the model with SMOTE:
Why you use .fit_resample instead of .fit_sample? What is the difference between the two functions?

Also, is there any way to know the index for original dataset after SMOTE oversampling? How can I know what data comes from the original dataset in the SMOTE upsampled dataset?

Thanks!

Jason Brownlee October 8, 2020 at 8:19 am

Sorry, the difference between he function
https://imbalanced-learn.readthedocs.io/en/stable/g

Perhaps experiment with both and compare the re

Fatima October 10, 2020 at 7:30 am #

Hi, I applied the SMOTE for Balancing Data C defined the dataset in make_classification, I wrote the n_features=27 instead of 2, Is It Correct? and Can I apply the SMOTE for Balancing Data when my goal from the model is Prediction?

Secondly, How can I save the new data set in a CSV?

Thanks!

Jason Brownlee October 10, 2020 at 8:15 am # REPLY

If you have your own data, you don't need to use make_classification as it is a function for creating a synthetic dataset.

Fatima October 10, 2020 at 11:07 pm # REPLY

Ok, I want to apply the SMOTE, my data contains 1,469 rows, the class label has Risk= 1219, NoRisk= 250, Imbalanced data, I want to apply the Oversampling (SMOTE) to let the data balanced.
firstly, I run this code that showed me diagram of the class label then I apllyied the SMOTE,

target_count = data['Having DRPs'].value_cou
print('Class 1:', target_count[1])

print('Class 0:', target_count[0])
print('Proportion:', round(target_count[1] / target_count[0], 2), ': 1')

target_count.plot(kind='bar', title='Count (Having DRPs)');
****
(Over-sampling: SMOTE):

from imblearn.over_sampling import SMOTE

smote = SMOTE(ratio='minority')
X_sm, y_sm = smote.fit_sample(X, y)

plot_2d_space(X_sm, y_sm, 'SMOTE over-sampling')

It gave me an error:
TypeError: __init__() got an unexpected keyw

How can I solve this issue!

Jason Brownlee October 11, 2020

Sorry to hear that, perhaps some
https://machinelearningmastery.com/faq/si

Fatima October 15, 2020 at 4:09 am # REPLY

Hi Jason, I applied the SMOTE on my data and I solved the imbalanced data, the next step I want to start Deep Learning(DL), in DL Do I have to save the new data (balanced) and then start DL algorithms on the new data ??

Thanks!

Jason Brownlee October 15, 2020 at 6:19 am # REPLY

Only the training set should be balanced, not the test set.

You can transform the data in memory before fitting your model. Or you can save it if that is easier for you.

Samuel Smets October 16, 2020 at 6:39 pm # REPLY

Dear Jason,

Thanks for the awesome article!

I tried to implement the SMOTE in my project, but the cross_val_score kept returning nan.

Then I tried your piece of code:

```
# decision tree evaluated on imbalanced dataset with SMOTE oversampling
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
# define dataset
X, y = make_classification(n_samples=10000, n_featu
n_clusters_per_class=1, weights=[0.99], flip_y=0, rand
# define pipeline
steps = [('over', SMOTE()), ('model', DecisionTreeClas
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=
scores = cross_val_score(pipeline, X, y, scoring='roc_a
print('Mean ROC AUC: %.3f' % mean(scores))
```

This also returned nan.

I can't figure out why it returns nan. In you article you c
snippet.

Thanks a lot!

Samuel

Jason Brownlee October 17, 2020 at 5:59 am # REPLY

That's surprising, perhaps change the cv to raise an error on nan and inspect the results.

Amit Pathak March 20, 2021 at 1:11 am # REPLY

Even I keep getting the same error

Jason Brownlee March 20, 2021 at 5:25 am # REPLY

Perhaps some of these tips will help:
https://machinelearningmastery.com/faq/si

Saranya July 2, 2021 at 12:20 pm # REPLY

Hi,

Even I keep getting nan values as scores. Were you guys able to resolve it? If so, can you please provide some tips?

deva October 17, 2020 at 10:33 pm # REPLY

```
from sklearn.model_selection import Stratifi
from sklearn import metrics
```

cv = StratifiedKFold(n_splits=10,shuffle=True)
classifier = AdaBoostClassifier(n_estimators=200)
y = df['label'].values
X = df
X = X.drop('label',axis=1)
X = X.values
X_train, X_test, y_train, y_test = train_test_split(X, y, te
oversampler= sv.CCR()
X_samp, y_samp= oversampler.sample(X_train, y_train)
X_train = X_samp
y_train = y_samp

tprs = []
aucs = []
mean_fpr = np.linspace(0, 1, 100)
plt.figure(figsize=(10,10))
i = 0
# cv.sh
for train, test in cv.split(X_train, y_train):
probas_ = classifier.fit(X_train[train], y_train[train]).predict_proba(X_train[test])
# Compute ROC curve and area the curve
fpr, tpr, thresholds = metrics.roc_curve(y_train[test], probas_[:, 1])
tprs.append(np.interp(mean_fpr, fpr, tpr))
tprs[-1][0] = 0.0
roc_auc = metrics.auc(fpr, tpr)
aucs.append(roc_auc)
plt.plot(fpr, tpr, lw=1, alpha=0.3,
label='ROC fold %d (AUC = %0.2f)' % (i, roc_auc))

i += 1
plt.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
label='Chance', alpha=.8)

mean_tpr = np.mean(tprs, axis=0)
mean_tpr[-1] = 1.0
mean_auc = metrics.auc(mean_fpr, mean_tpr)
std_auc = np.std(aucs)
plt.plot(mean_fpr, mean_tpr, color='b',
label=r'Mean ROC (AUC = %0.2f $\pm$ %0.2f)' % (mean_auc, std_auc),
lw=2, alpha=.8)

std_tpr = np.std(tprs, axis=0)
tprs_upper = np.minimum(mean_tpr + std_tpr, 1)
tprs_lower = np.maximum(mean_tpr - std_tpr, 0)
plt.fill_between(mean_fpr, tprs_lower, tprs_upper, color='grey', alpha=.2,
label=r'$\pm$ 1 std. dev.')

```
plt.xlim([-0.01, 1.01])
plt.ylim([-0.01, 1.01])
plt.xlabel('False Positive Rate',fontsize=18
plt.ylabel('True Positive Rate',fontsize=18)
plt.title('Cross-Validation ROC of ADABOOST'
plt.legend(loc="lower right", prop={'size':
plt.show()
```

check this output :
https://ibb.co/PYLs8qF

i am confused cause smote after adaboost for train works good but the test set is not good.
https://ibb.co/yPSrLx2

deva October 17, 2020 at 10:43 pm # REPLY

edit : I have used CCR which is a variant of smote. also It is CCR+Adaboost

Jason Brownlee October 18, 2020 at 6:09 am # REPLY

Well done!

nabila March 24, 2021 at 3:18 am # REPLY

hi jason, can i ask? i applied metode smote bagging svm and smote boosting svm but always eror, can u help me to found the coding in python?

Jason Brownlee March 24, 2021 at 5:53 am #

I don't have the capacity to debug your code sorry, perhaps these suggestions will help:
https://machinelearningmastery.com/faq/single-faq/can-you-read-review-or-debug-my-code

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Karrtik Iyer November 11, 2020 at 8:34 pm # REPLY

Hi @jasonBrowniee, Thanks for the above example. Quick Question, for SMOTE you have used over sampling followed by Random Under Sampling, wondering if we use ADASYN or SVMSMOTE do you suggest we use random under sampling as we do in ca

Jason Brownlee November 12, 2020 at 6:38

Perhaps try a few different combinations a dataset.

Marlon Lohrbach November 30, 2020 at 4:48 am #

Hi Jason,

I hope you are doing well! Is there a need to upsample with Smote() if I use Stratifiedkfold or RepeatedStratifiedkfold? I think that my stratified folding already takes care of class imbalance. So is there a situation where you would prefer Smote over Stratified folding?

Cheers

Jason Brownlee November 30, 2020 at 6:40 am # REPLY

SMOTE can be used with or without stratified CV, they address different problems – sampling the training dataset vs evaluating the model.

Michael Tamillow December 9, 2020 at 4:41 am # REPLY

I don't believe this technique "actually" works in many cases. You can read Jonas Peters' work to understand why. It is really an example of Machine Learning Hocus-Pocus, or the creative side of Data Science which defines "works" as "I tried it and saw an improvement" anecdotal evidence. It is bad overall to not rigorously evaluate such methods through analytica

Jason Brownlee December 9, 2020 at 6:32 am # REPLY

Thanks for sharing your thoughts Michael.

Mohammad January 2, 2021 at 8:00 pm # REPLY

Hi Jason,

Thanks for all of these heuristic alternatives you suggested for balancing datasets

Jason Brownlee January 3, 2021 at 5:55 am

You're welcome.

Ammar Sani January 3, 2021 at 2:50 am #

Hi Dr Jason. I saw at few articles, authors wer
Do you have an article for that?

Jason Brownlee January 3, 2021 at 5:58 am # REPLY

Almost all classes overlap – if not the problem would be trivial (e.g. linearly separable).

Not sure what you mean exactly?

Ammar Sani January 4, 2021 at 1:19 pm # REPLY

Thanks Dr.

I am actually new to ML and quite interested in imbalanced classification. While feeding my mind to understand the fundamentals of ML and imbalanced from here: https://machinelearningmastery.com/start-here/.

Then, I started read others just to strengthen and verify my understanding. I found this article: https://link.springer.com/chapter/10.1007/978-3-642-13059-5_22 telling the difference between imbalanced and overlap.

Maybe because of my fundamental is not really strong, I'm not really understand what they thought in this article. So, I came to your blog as usual (it really helps newbie like me), to find article that share about the different between overlap and imbalance. Unfortunately, I could not find any. 😅

Jason Brownlee January 4, 2021 at 1:42 pm #

REPLY ↩

Thanks for sharing, I'm not familiar with the article sorry.

Ammar Sani January 4, 2021 at

OK Dr. Jason

Btw, is it important for me to understar
maybe?

Thanks once again Dr

Jason Brownlee January 5, 2(

I don't think so, I've not heard

Ammar Sani January 5, 2021 at 2:01 pm #

REPLY ↩

OK Dr, Thank you so much

Keith January 26, 2021 at 5:32 pm #

REPLY ↩

Hi Jason thanks for this very informative post. But just wondering, does it make sense for me to tune the model hyperparameters on an over/undersampled data set, like this?

paramgrid_rf = {'n_estimators': [500],
'max_depth': [4],
'random_state': [0],
'max_features': ['sqrt'],
'criterion' :['mse']
}

rfc = GridSearchCV(RandomForestRegressor(), paramgrid, cv=5)

steps = [('over', SMOTE(sampling_strategy=0.2)), ('model', rfc)]
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(pipeline, x_train, y_train, scoring='f1′, cv=cv, n_jobs=-1)

Jason Brownlee January 27, 2021 at 6:03 am # REPLY

Perhaps.

Do anything you can to get better results on your test harness.

David February 2, 2021 at 2:13 pm #

Please specify which modules are needed. To
numpy

Jason Brownlee February 3, 2021 at 6:12 am

This tutorial will show you how to setup your development environment:
https://machinelearningmastery.com/setup-python-environment-machine-learning-deep-learning-anaconda/

David February 2, 2021 at 2:15 pm # REPLY

my above comment looks too negative. THIS IS AWESOME; just please specify which modules to import.

Thank you for your work

Jason Brownlee February 3, 2021 at 6:12 am # REPLY

The complete code example at the end of each sections has the import statements with the code.

This will help you copy the code from the tutorial:
https://machinelearningmastery.com/faq/single-faq/how-do-i-copy-code-from-a-tutorial

JAIKISHAN February 13, 2021 at 1:13 pm # REPLY

Hi Jason,
That was a very useful tutorial.
Thank u.

Jason Brownlee February 13, 2021 at 1:20 pm # REPLY

You're welcome!

Aya February 16, 2021 at 10:40 am #

thanks, but i confused with appling smote on t
the difference between them

Jason Brownlee February 16, 2021 at 1:38 p

This will explain X and y:
https://machinelearningmastery.com/faq/single-faq/what-are-x-and-y-in-machine-learning

Aya February 17, 2021 at 12:42 am # REPLY

ok, that are x and y (feature and target) but why you applying smote on it? is smote applying on the training data means x splits into train and test and y as it the applying smote on xtrain and ytrain

Jason Brownlee February 17, 2021 at 5:29 am # REPLY

Yes, SMOTE is applied to the training dataset only.

The above example shows you how to use the SMOTE class and the effect it has – so you feel comfortable with it and can start using it on your own project.

MS March 3, 2021 at 9:56 pm # REPLY

Hi,Jason
Can we implement SMOTENC with FAMD(prince) in a

some reference regarding the approach and code.

Jason Brownlee March 4, 2021 at 5:48 am # REPLY

I don't know off hand, sorry. Perhaps explore it with a prototype.

MS March 4, 2021 at 9:30 pm # REPLY

Thanks

Ethan March 16, 2021 at 1:14 pm #

Hi Jason, thanks for the great content of SMO
location. I can use that in resampling thanks to SMOTE
I can obtain homogeneity with respect to the minority c
data in locations that initially have low instances of the

Jason Brownlee March 17, 2021 at 5:58 am # REPLY

You might need to implement the algorithm yourself to have such fine grained control over where the algorithm chooses to resample.

Ethan March 17, 2021 at 7:19 am # REPLY

Thanks for your prompt reply, as always!

Jason Brownlee March 17, 2021 at 8:05 am # REPLY

You're welcome.

Anthony March 20, 2021 at 12:50 am # REPLY

Can we apply SMOTE for testing dataset also?

Jason Brownlee March 20, 2021 at 5:23 am # REPLY

No, SMOTe is only applied to the training dataset.

hou March 22, 2021 at 12:22 pm # REPLY

So how should I do if the testing data is imbalance? I split the date set into 70% training set and 30% testing set. After I use smote to balance training set and then I want to test the model on testing set,then AUC will very low due to the imbalance testing set ,how should I do?Thank you very much!

Jason Brownlee March 23, 2021 at 4:55 am

Perhaps AUC is not the best metric for yo
Perhaps you can use repeated k-fold cross-validat

sanket March 27, 2021 at 6:06 pm #

Hi Json,
This was very succinct article on imbalance class. Thanks a lot for the article and the links to original paper.

Jason Brownlee March 29, 2021 at 6:01 am # REPLY

Thanks!

Dorian March 31, 2021 at 2:07 am # REPLY

Hi, great article, but please do not recommend using sudo privileges when installing python packages from pip! You are basically giving admin privileges to some random script pulled from the internet which is really not good practice, and even dangerous. For more references, look here:
https://askubuntu.com/a/802594
Thanks a lot!

Jason Brownlee March 31, 2021 at 6:06 am # REPLY

Thanks for sharing.

Minh April 1, 2021 at 1:44 pm #

REPLY

Hello Jason
I'm newbie here. I'm dealing with time series forecasting regression problem. That's mean the prediction model is required to learn from the series of past observations to predict the next value in the sequence.
I'm using the dataset 1998 World Cup Web site (consists of all the requests made to the 1998 World Cup Web site between April 30, 1998 and July 26, 1998). Here the FTP link:
ftp://ita.ee.lbl.gov/html/contrib/WorldCup.html
I preprocess the dataset by aggregating all logs that occur within the same minute into one accumulative record.
I want to ask if my dataset imbalanced? and Why?
Thanks for your help.

Jason Brownlee April 2, 2021 at 5:35 am #

No. Typically imbalance is for classificatio
(predicting a numerical value).

m.cihat April 15, 2021 at 12:23 am #

REPLY

Hello Jason, thanks for article.
I saw an article about SMOTE and I am confused. Here is the code they used:

from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)

X_sm, y_sm = sm.fit_resample(X, y)

X_train, X_test, y_train, y_test = train_test_split(
X_sm, y_sm, test_size=0.25, random_state=42
)

model = RandomForestClassifier(random_state=42)

model.fit(X_train, y_train)

preds = model.predict(X_test)

You said SMOTE is applied only on training set. So the code above is wrong?

m.cihat April 15, 2021 at 12:23 am #

REPLY

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And here is article in case you want to take a look:
https://towardsdatascience.com/how-to-effortlessly-handle-class-imbalance-with-python-and-smote-9b715ca8e5a7

Jason Brownlee April 15, 2021 at 5:29 am #

REPLY

I try not to comment on other peoples code – they can do whatever they like.

Jason Brownlee April 15, 2021 at 5:27 am #

REPLY

Yes. Fatally.

Salah May 1, 2021 at 3:16 am #

Hi, i'd like to thank you for your blog. It's been
ask you a question please. Does applying SMOTE wit
when you set the pipeline to apply SMOTE then model
process on the original test set or the over sampled tes
use SMOTE it should be done only on the training set
data. Does cross validation meet this criteria too? Thanks.

Jason Brownlee May 1, 2021 at 6:10 am #

REPLY

When using SMOTE in a pipeline it is only applied to the training set, never the test set within a cross-validation evaluation/test harness.

Jainey May 7, 2021 at 1:14 pm #

REPLY

Hi, first of all, I just wanna say thanks for your contribution. And i have a question
scores = cross_val_score(pipeline, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)
score = mean(scores)
it's seen mean nothing when you caculate your cross_val_score on your training data, I mean AUC is matter when you caculate on your testing data. I have high auc cross-validation but 0.5 on testing data.

Jason Brownlee May 8, 2021 at 6:32 am #

REPLY

Sorry, I don't understand your question. Perhaps you could rephrase it?

emma May 17, 2021 at 10:59 pm # REPLY

Hello, thank you,

I would like toknow if smote method work for text data. I am dealing text classification with imbanlanced data.

Jason Brownlee May 18, 2021 at 6:15 am #

No, tabular data only.

Xu Zhang May 21, 2021 at 8:45 am #

Thank you for your great post. I think SMOTE
classification problem. Do you know any augmentation
dataset? Many thanks!

Jason Brownlee May 22, 2021 at 5:29 am # REPLY

You're welcome.

Correct.

No sorry. Most resampling methods are designed for imbalanced classification (not regression) as far as I have read.

ZJ June 1, 2021 at 8:20 pm # REPLY

Hope this makes sense, but I think the ROC scores in the CV as calculated is not right.

Here's the reason: in your pipeline code there is over sampling and undersampling done. But I want the scores to be computed on the original dataset, not on the sample. If you generate synthetic then of course you can make the ROC look better on the dataset with synthetic data, but I want to know how well the dataset perform on the original data.

Currenlty the scores are

score = ROC(sampled(X), sampled(y))

but I want

score = ROC(X, y)

actually, I have removed the part about k-fold, but you can what I mean. So i think the code is not doing things correctly

Jason Brownlee June 2, 2021 at 5:42 am #

REPLY

ROC scores are only calculated using original data, no synthetic data. E.g. SMOTE is only used on train, not test.

The pipeline ensures this to be the case.

Kingsley Udeh June 12, 2021 at 11:07 pm #

Hi Dr. Jason,

How do we apply SMOTE method to imbalanced class repeatedStratefied() applied to time series cv k-fold?

Thank you

Jason Brownlee June 13, 2021 at 5:49 am #

REPLY

SMOTE is not appropriate for time series.

Cross-validation is not appropriate for time series either, you must use methods like walk-forward validation:
https://machinelearningmastery.com/backtest-machine-learning-models-time-series-forecasting/

K.K.F. June 15, 2021 at 5:34 am #

REPLY

Hi Jason,

After balancing my severely imbalanced data (1:1000) using Smote, do I need to create an ensemble classifier in order to avoid overfitting with the minority class, due to oversampling of minority class and under sampling the majority class? Also if I used Random Forest which is an ensemble by itself, can I create an ensemble of random forests i.e. an ensemble of ensembles? Or would this lead to overfitting?

Thank you

Jason Brownlee June 15, 2021 at 6:10 am # REPLY

Try it and compare results.

Focus on the evaluation metric. Overfitting is one possible cause of poor results.

K.K.F. June 15, 2021 at 6:26 am # REPLY

Also, under-sampling and over-sampling may lead to loss of information from the dataset.

How do you compare this (Smote) to using weights for random forest instead?

Thank you.

Jason Brownlee June 16, 2021 at 6:15 am #

Perhaps compare a RF directly with a RF

Yasas Sandeepa June 17, 2021 at 6:46 pm #

Hello Jason,
Thank you for the great description over handling imbalanced datasets using SMOTE and its alternative methods.

I have a small doubt when applying SMOTE followed by PCA. What is the best approach to apply SMOTE? Is it PCA first and then SMOTE or vice versa? What is the rationale behind this?

Jason Brownlee June 18, 2021 at 5:38 am # REPLY

Perhaps try a few different approaches/orderings and discover what works best for your dataset and model.

Yasas Sandeepa June 18, 2021 at 12:12 pm # REPLY

Okay! Thanks Jason

Rajaram June 18, 2021 at 1:34 pm #

Hello Jason, As always, Thank you for the wonderful article. I am working on a disease progression prediction problem. Objective is to predict the disease state (one of the target classes) at a future point in time, given the progression of the disease condition over the time (temporal dependencies in the progression).

Majority of my dataset belongs to "Healthy" condition and I have only few samples representing various other disease conditions (other target classes). Can you pls advise on how to oversample the minority class samples in this particular scenario?, Thanks again.

Jason Brownlee June 19, 2021 at 5:45 am #

REPLY

Perhaps try SMOTE described above and

Rajaram July 4, 2021 at 1:52 pm #

Thank you Jason. Did you mean, com
using 'other' techniques? Can you pls elaborat

Jason Brownlee July 5, 2021 at 5:0

Yes, perhaps other oversampling methods or no oversampling methods.

tim June 20, 2021 at 9:38 pm #

REPLY

Hi Jason,

I have a question about the numbers on the axis of the scatterplot (-0,5 till 3 and -3 till 4) . What is de meaning of the axis values?

Jason Brownlee June 21, 2021 at 5:37 am #

REPLY

They are the values of the input variables, just a demonstration of what SMOTE does.

tim June 22, 2021 at 1:11 am #

REPLY

thnx, for your answer. I think I don't understand it completely yet:

I thought the values were the classlabels (input = classlabeld). But ho do I interpret then the x-axis and y-axis?

thanks a lot again?

Jason Brownlee June 22, 2021 at 6:33 am #

REPLY

X is variable 1, y is variable 2, color is class label.

L July 2, 2021 at 8:56 am #

Should developers always calibrate predicted
rebalancing techniques?

Jason Brownlee July 3, 2021 at 6:06 am #

Probably not – only when the model does

MUHAMAD FAUZI July 11, 2021 at 1:54 pm #

REPLY

Hi , Jason , it is great article and it is really helping me understanding SMOTE . I have more question about K mean SMOTE and CURE SMOTE , may you add that 2 with example into your paper ? because i thin it is difficult to implement since not many example out there. Thanks in advance

Jason Brownlee July 12, 2021 at 5:46 am #

REPLY

Thanks for the suggestion.

Eman July 13, 2021 at 8:16 am #

REPLY

How could I apply SMOTE to multivariate time series data like human activity dataset?

thanks

Jason Brownlee July 14, 2021 at 5:23 am #

SMOTE would not be appropriate for time series or sequence data.

Perhaps you can check the literature for an oversampling method that is appropriate for time series data.

THK July 22, 2021 at 10:39 am # REPLY

Thanks a lot!
Just one quick question.
In this sentence below
"This is referred to as Borderline-SMOTE1, whereas the oversampling of just the borderline cases in minority class is referred to as Borderline-SMOTE2."
I guess 1 and 2 should be switched if 1 affects only on
""'Borderline-SMOTE2 not only generates synthetic ex
positive nearest neighbors in P, but also does that from
Please let me know if I'm getting it wrong.
Thanks!

Jason Brownlee July 23, 2021 at 5:44 am #

Thanks.

Leave a Reply

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SUBMIT COMMENT

Welcome!
I'm *Jason Brownlee* PhD
and I **help developers** get results with **machine learning**.
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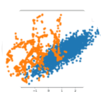

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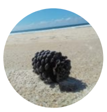

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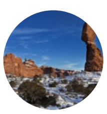

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