A Gentle Introduction to Cross-Entropy for Machine Learning

Brownlee on October 21, 2019 in **Probability**

Updated on December 22, 2020

Cross-entropy is commonly used in machine learning as a loss function.

Cross-entropy is a measure from the field of information theory, building upon entropy and generally calculating the difference between two probability distributions. It is closely related to but is different from KL divergence that calculates the relative entropy between two probability distributions, whereas cross-entropy can be thought to calculate the total entropy between the distributions.

Cross-entropy is also related to and often confused with logistic loss, called log loss. Although the two measures are derived from a different source, when used as loss functions for classification models, both measures calculate the same quantity and can be used interchangeably.

In this tutorial, you will discover cross-entropy for machine learning.

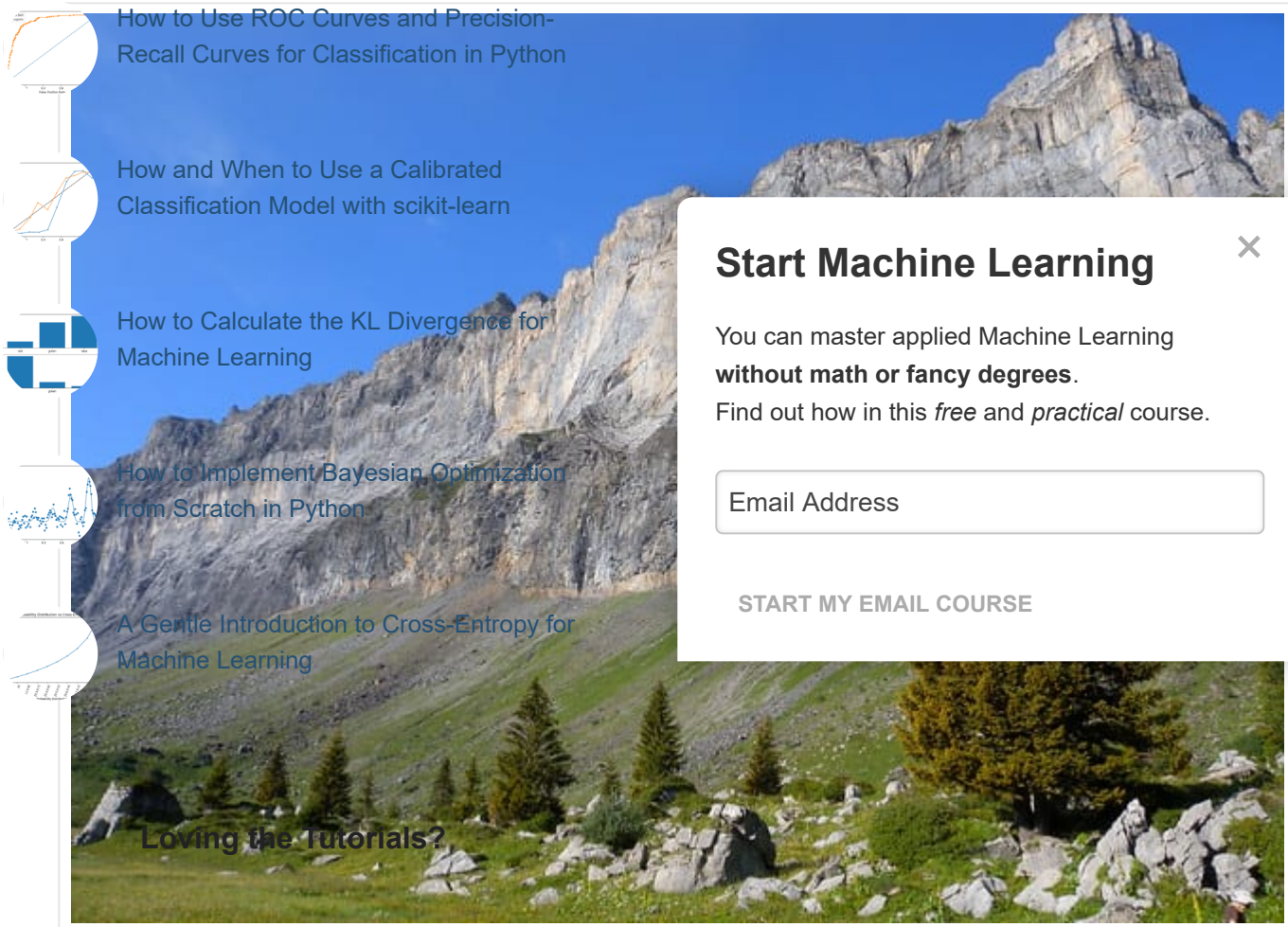
After completing this tutorial, you will know:

- How to calculate cross-entropy from scratch and using standard machine learning libraries.
- Cross-entropy can be used as a loss function when optimizing classification models like logistic regression and artificial neural networks.
- Cross-entropy is different from KL divergence but can be calculated using KL divergence, and is different from log loss but calculates the same quantity when used as a loss function.

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

Let's get started.

- **Update Oct/2019**: Gave an example of cross-entropy for identical distributions and updated description for this case (thanks Ron U). Added an example of calculating the entropy of the known class label.
- **Update Nov/2019**: Improved structure and added more explanation of entropy. Added intuition for predicted class probabilities.
- **Update Dec/2020**: Tweaked the introduction to information and entropy to be clearer.



A Gentle Introduction to Cross-Entropy for Machine Learning
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Tutorial Overview

This tutorial is divided into five parts; they are:

1. What Is Cross-Entropy?
2. Cross-Entropy Versus KL Divergence
3. How to Calculate Cross-Entropy
    1. Two Discrete Probability Distributions
    2. Calculate Cross-Entropy Between Distributions
    3. Calculate Cross-Entropy Between a Distribution and Itself
    4. Calculate Cross-Entropy Using KL Divergence
4. Cross-Entropy as a Loss Function
    1. Calculate Entropy for Class Labels

2. Calculate Cross-Entropy Between Class Labels and Probabilities
3. Calculate Cross-Entropy Using Keras
4. Intuition for Cross-Entropy on Predicted Probabilities
5. Cross-Entropy Versus Log Loss
   1. Log Loss is the Negative Log Likelihood
   2. Log Loss and Cross Entropy Calculate the Same Thing

What Is Cross-Entropy?

Cross-entropy is a measure of the difference between two probability distributions for a given random variable or set of events.

You might recall that **information** quantifies the number of bits required to encode and transmit an event. Lower probability events have more information, higher probability events have less information.

In information theory, we like to describe the "*surprise*" of an event. Low probability events are more surprising and therefore have more information than higher probability events. Entropy can be calculated for a random variable as the average level of information, or surprise, or uncertainty over possible outcomes.

- **Low Probability Event** (*surprising*): More information.
- **High Probability Event** (*unsurprising*): Less information.

Information *h(x)* can be calculated for an event *x*, given the probability of the event *P(x)* as follows:

- h(x) = -log(P(x))

Entropy is the number of bits required to transmit a randomly selected event from a probability distribution. A skewed distribution has a low entropy, whereas a distribution where events have equal probability has a larger entropy.

A skewed probability distribution has less "surprise" and in turn a low entropy because likely events dominate. Balanced distribution are more surprising and turn have higher entropy because events are equally likely.

- **Skewed Probability Distribution** (*unsurprising*): Low entropy.
- **Balanced Probability Distribution** (*surprising*): High entropy.

Entropy *H(x)* can be calculated for a random variable with a set of *x* in *X* discrete states discrete states and their probability *P(x)* as follows:

- H(X) = – sum x in X P(x) * log(P(x))

If you would like to know more about calculating information for events and entropy for distributions see this tutorial:

- A Gentle Introduction to Information Entropy

Cross-entropy builds upon the idea of entropy from information theory and calculates the number of bits required to represent or transmit an average event from one distribution compared to another distribution.

> *… the cross entropy is the average number of bits needed to encode data coming from a source with distribution p when we use model q …*

– See Chapter 2, Machine Learning: A Probabilistic Perspective, 2012.

The intuition for this definition comes if we consider a target or underlying probability distribution P and an approximation of the target distribution Q, then the cross-entropy of Q from P is the number of additional bits to represent an event using Q instead of P.

The cross-entropy between two probability distribution

P, Q)

Where H() is the cross-entropy function, P may be the he target distribution.

entropy can be calculated using the probabilitie

- H(P, Q) = – sum x in X P(x) * log(Q(x))

P(x) is the probability of the event x in P, Q(x) is the probability of event x in Q and log is the base-2 logarithm, meaning that the results are in bits. If the base-e or natural logarithm is used instead, the result will have the units called nats.

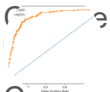
This calculation is for discrete probability distributions, although a similar calculation can be used for continuous probability distributions using the integral across the events instead of the sum.

The result will be a positive number measured in bits and will be equal to the entropy of the distribution if the two probability distributions are identical.

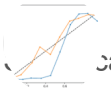
Note: this >> SEE WHAT'S INSIDE ıe joint probability, or more specifically, the joint entropy between P and Q. This is misleading as we are scoring the difference between probability distributions with cross-entropy. Whereas, joint entropy is a different concept that uses the same notation and instead calculates the uncertainty across two (or more) random variables.

Cross-Entropy Versus KL Divergence

Cross-entropy is not KL Divergence.


How to Use ROC Curves and Precision-Recall Curves for Classification in Python

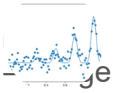
Cross-entropy is related to divergence measures, such as the Kullback-Leibler, or KL, Divergence that quantifies how much one distribution differs from another.


How and When to Use a Calibrated Classification Model with scikit-learn

Specifically, the KL divergence measures a very simila ge number of extra bits required to represent a message

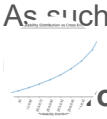

How to Calculate the KL Divergence for Machine Learning

In other words, the KL divergence is the avera data, due to the fact that we used distribution p.


How to Implement Bayesian Optimization from Scratch in Python

– ge 58, Machine Learning: A Probabilistic Perspe

As such, the KL divergence is often referred to as the


A Gentle Introduction to Cross-Entropy for Machine Learning

oss-Entropy: Average number of total bits to represent an event from Q instead of P.

- **Relative Entropy** (*KL Divergence*): Average number of extra bits to represent an event from Q instead of P.

KL divergence can be calculated as the negative sum of probability of each event in P multiples by the log of the probability of the event in Q over the probability of the event in P. Typically, log base-2 so that the result is measured in bits.

- KL(P || Q) = – sum x in X P(x) * log(Q(x) / P(x))

The value ergence for a given event.

As such, we can calculate the cross-entropy by adding the entropy of the distribution plus the additional entropy calculated by the KL divergence. This is intuitive, given the definition of both calculations; for example:

- H(P, Q) = H(P) + KL(P || Q)

Where H(P, Q) is the cross-entropy of Q from P, H(P) is the entropy of P and KL(P || Q) is the divergence of Q from P.

Entropy can be calculated for a probability distribution as the negative sum of the probability for each event multiplied by the log of the probability for the event, wh

- H(P) = – sum x on X p(x) * log(p(x))

Like KL divergence, cross-entropy is not symmetrical, meaning that:

- H(P, Q) != H(Q, P)

As we will see later, both cross-entropy and KL divergence calculate the same quantity when they are used as loss functions for optimizing a classification predictive model. It is under this context that you might sometimes see that cross-entropy and KL divergence are the same.

For a lot more detail on the KL Divergence, see the tutorial:

How to Calculate Cross-Entropy

In this section, we will make the calculation of cross-entropy concrete with worked examples.

Two Discrete Probability Distributions

Consider a random variable with three discrete events as different colors: red, green, and blue.

We may have two different probability distributions for this variable, as follows:

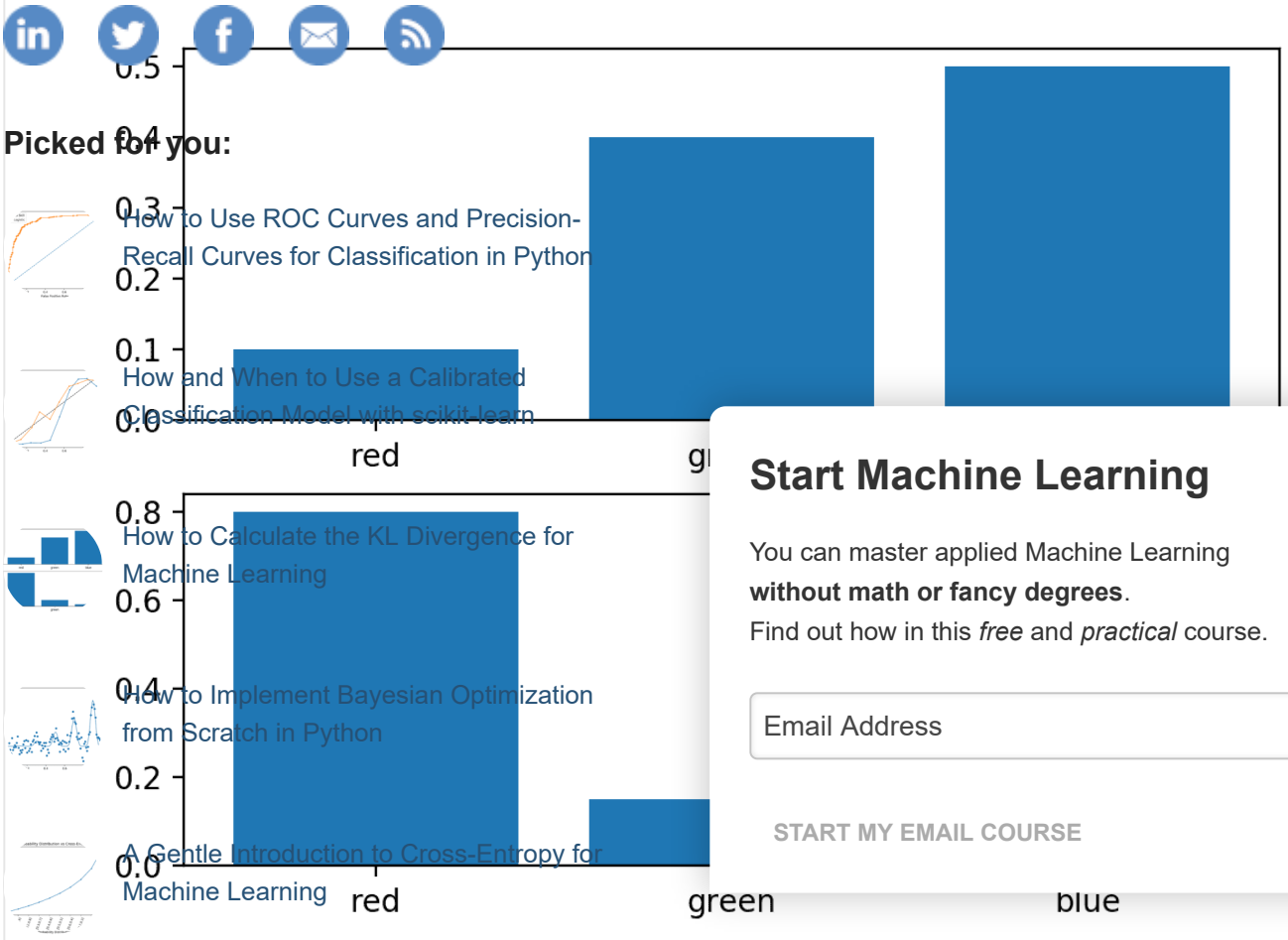

```
...
# define distributions
events = ['red', 'green', 'blue']
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
```

We can plot a bar chart of these probabilities to compare them directly as probability histograms.


```
# plot of distributions
from matplotlib import pyplot
# define distributions
events = ['red', 'green', 'blue']
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
print('P=%.3f Q=%.3f' % (sum(p), sum(q)))
# plot first distribution
pyplot.subplot(2,1,1)
pyplot.bar(events, p)
# plot second distribution
pyplot.subplot(2,1,2)
pyplot.bar(events, q)
# show the plot
pyplot.show()
```

Running the example creates a histogram for each probability distribution, allowing the probabilities for each event to be directly compared.

We can see that indeed the distributions are different.



Histogram of Two Different Probability Distributions for the Same Random Variable

Calculate Cross-Entropy Between Distributions

Next, we can develop a function to calculate the cross-entropy between the two distributions.

We will use log base-2 to ensure the result has units in bits.

```
# calculate cross entropy
def cross_entropy(p, q):
    return -sum([p[i]*log2(q[i]) for i in range(len(p))])
```

We can then use this function to calculate the cross-entropy of P from Q, as well as the reverse, Q from P.

```
...
# calculate cross entropy H(P, Q)
ce_pq = cross_entropy(p, q)
print('H(P, Q): %.3f bits' % ce_pq)
# calculate cross entropy H(Q, P)
ce_qp = cross_entropy(q, p)
print('H(Q, P): %.3f bits' % ce_qp)
```

Tying this all together, the complete example is listed below.

```
# example of calculating cross entropy
```

```
from math import log2
# calculate cross entropy
def cross_entropy(p, q):
	return -sum([p[i]*log2(q[i]) for i in range(len(p))])

# define data
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
# calculate cross entropy H(P, Q)
ce_pq = cross_entropy(p, q)
print('H(P, Q): %.3f bits' % ce_pq)
# calculate cross entropy H(Q, P)
ce_qp = cross_entropy(q, p)
print('H(Q, P): %.3f bits' % ce_qp)
```


g the example first calculates the cross-entropy of Q from P as just over 3 bits, then P from Q as just under 3 bits.

```
H(P, Q): 3.288 bits
H(Q, P): 2.906 bits
```


ulate Cross-Entropy Between a D

If two probability distributions are the same, then the c the distribution.

demonstrate this by calculating the cross-entropy of P vs P and Q vs Q.

The complete example is listed below.

```
# example of calculating cross entropy for identical distributions
from math import log2

# calculate cross entropy
def cross_entropy(p, q):
	return -sum([p[i]*log2(q[i]) for i in range(len(p))])
# define data
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
# calculate cross entropy H(P, P)
ce_pp = cross_entropy(p, p)
print('H(P, P): %.3f bits' % ce_pp)
# calculate cross entropy H(Q, Q)
ce_qq = cross_entropy(q, q)
print('H(Q, Q): %.3f bits' % ce_qq)
```


Running the example first calculates the cross-entropy of Q vs Q which is calculated as the entropy for Q, and P vs P which is calculated as the entropy for P.

```
H(P, P): 1.361 bits
H(Q, Q): 0.884 bits
```

Calculate Cross-Entropy Using KL Divergence

We can also calculate the cross-entropy using the KL divergence.

The cross-entropy calculated with KL divergence should be identical, and it may be interesting to calculate the KL divergence between the distributions as well to see the relative entropy or additional bits required instead of the total bits calculated by the cross-entropy.

We can define a function to calculate the KL divergence between the distributions using log base-2 to ensure the result is also in bits.

```
# calculate the kl divergence KL(P || Q)
def kl_divergence(p, q):
    return sum(p[i] * log2(p[i]/q[i]) for i in
```

Next, we can define a function to calculate the entropy

```
# calculate entropy H(P)
def entropy(p):
    return -sum([p[i] * log2(p[i]) for i in ra
```

Finally, we can calculate the cross-entropy using the e

```
# calculate cross entropy H(P, Q)
def cross_entropy(p, q):
    return entropy(p) + kl_divergence(p, q)
```

With our worked example, we can compare the cross-entropy for H(P, Q) to the KL divergence KL(P || Q) and the entropy H(P).

The complete example is listed below.

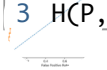
```
# example of calculating cross entropy with kl divergence
from math import log2

# calculate the kl divergence KL(P || Q)
def kl_divergence(p, q):
    return sum(p[i] * log2(p[i]/q[i]) for i in range(len(p)))

# calculate entropy H(P)
def entropy(p):
    return -sum([p[i] * log2(p[i]) for i in range(len(p))])

# calculate cross entropy H(P, Q)
def cross_entropy(p, q):
    return entropy(p) + kl_divergence(p, q)

# define data
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
# calculate H(P)
en_p = entropy(p)
print('H(P): %.3f bits' % en_p)
# calculate kl divergence KL(P || Q)
kl_pq = kl_divergence(p, q)
print('KL(P || Q): %.3f bits' % kl_pq)
# calculate cross entropy H(P, Q)
ce_pq = cross_entropy(p, q)
```

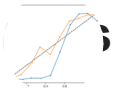
```
print('H(P, Q): %.3f bits' % ce_pq)
```


Running the example, we can see that the cross-entropy score of 3.288 bits is comprised of the entropy of [illegible] bits calculated by the KL divergence.

This is a useful example that clearly illustrates the relationship between all three calculations.


```
H(P): 1.361 bits
KL(P || Q): 1.927 bits
H(P, Q): 3.288 bits
```

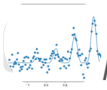




ss-Entropy as a Loss Function

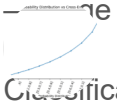
Cross-entropy is widely used as a loss function when

amples that you may encounter include the log
alg rithm), and artificial neural networks that can be u



... using the cross-entropy error function instea
problem leads to faster training as well as impr

– page 235, Pattern Recognition and Machine Learn



Classification problems are those that involve one or more input variables and the prediction of a class label.

Classification tasks that have just two labels for the output variable are referred to as binary classification problems, whereas those problems with more than two labels are referred to as categorical or multi-class classification problems.

- **Binary Classification**: Task of predicting one of two class labels for a given example.
- **Multi-Class Classification**: Task of predicting one of more than two class labels for a given example.

We can see that the idea of cross-entropy may be useful for optimizing a classification model.

Each example has a known class label with a probability of 1.0, and a probability of 0.0 for all other labels. A model can estimate the probability of an example belonging to each class label. Cross-entropy can then be used to calculate the difference between the two probability distributions.

As such, we can map the classification of one example onto the idea of a random variable with a probability distribution as follows:

- **Random Variable**: The example for which we require a predicted class label.
- **Events**: Each class label that could be predicted.

In classification tasks, we know the target probability distribution P for an input as the class label 0 or 1 interpreted as probabilities as "*impossible*" or "*certain*" respectively. These probabilities have no surprise at [illegible] have zero information content or zero entropy.

Our model seeks to approximate the target probability distribution Q.

In the language of classification, these are the actual and the predicted probabilities, or *y* and *yhat*.

Actual Probability (*y*): The known probability of each class label for an example in the dataset (P).

- **Predicted Probability** (*yhat*): The probability of each class label an example predicted by the model (Q).

[illegible], therefore, estimate the cross-entropy for a sin[illegible] described above; for example.

CE(P, Q) = -sum x in X P(x) * log(Q(x))

Where each *x* in *X* is a class label that could be assig[illegible]n label and 0 for all other labels.

[illegible]ss entropy for a single example in a binary cla[illegible] operation as follows:

CE(P, Q) = -(P(class0) * log(Q(class0)) + P(class1[illegible]

You may see this form of calculating cross-entropy cited in textbooks.

If there are just two class labels, the probability is modeled as the Bernoulli distribution for the positive class label. This means that the probability for class 1 is predicted by the model directly, and the probability for class 0 is given as one minus the predicted probability, for example:

- **Predicted P(class 0)** = 1 - yhat
- **Predicted P(class 1)** = yhat

When cal[illegible] classification tasks, the base-e or natural logarithm is used. This means that the units are in nats, not bits.

We are often interested in minimizing the cross-entropy for the model across the entire training dataset. This is calculated by calculating the average cross-entropy across all training examples.

Calculate Entropy for Class Labels

Recall that when two distributions are identical, the cross-entropy between them is equal to the entropy for the probability distribution.

Class labels are encoded using the values 0 and 1 when preparing data for classification tasks.

For example, if a classification problem has three classes, and an example has a label for the first class, then the probability distribution will be [1, 0, 0]. If an example has a label for the second class, it will have a probability distribution of [0, 1, 0] for the three events as [0, 1, 0]. This is called a one hot encoding.

This probability distribution has no information as the outcome is certain. We know the class. Therefore the entropy for this variable is zero.

This is an important concept and we can demonstrate it with a worked example.

Pretend with have a classification problem with 3 classes, and we have one example that belongs to each class. We can represent each example as a discrete probability distribution with a 1.0 probability for the class which the example belongs and a 0.0 probability for all other classes.

We can calculate the entropy of the probability distribu

The complete example is listed below.

```
# entropy of examples from a classification t
from math import log2
from numpy import asarray

# calculate entropy
def entropy(p):
    return -sum([p[i] * log2(p[i]) for i in r

# class 1
p = asarray([1,0,0]) + 1e-15
print(entropy(p))
# class 2
p = asarray([0,1,0]) + 1e-15
print(entropy(p))
# class 3
p = asarray([0,0,1]) + 1e-15
print(entropy(p))
```


Running the example calculates the entropy for each random variable.

We can see that in each case, the entropy is 0.0 (actually a number very close to zero).

Note that ll value to the 0.0 values to avoid the *log()* from blowing up, as we cannot calculate the log of 0.0.

```
9.805612959471341e-14
9.805612959471341e-14
9.805612959471341e-14
```

As such, the entropy of a known class label is always 0.0.

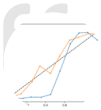
This means that the cross entropy of two distributions (real and predicted) that have the same probability distribution for a class label, will also always be 0.0.

Recall that when evaluating a model using cross-entropy on a training dataset that we average the cross-entropy across all examples in the dataset.

Therefore, a cross-entropy of 0.0 when training a model indicates that the predicted class probabilities are identical to the probabilities in the training dataset, e.g. zero loss.

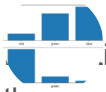
Recall that the KL divergence is the extra bits required to transmit one variable compared to another. It is the cross-entropy without the entropy of the class label, which we know would be zero anyway.

, minimizing the KL divergence and the cross entropy for a classification task are identical.

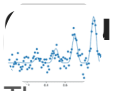


Minimizing this KL divergence corresponds exactly to minimizing the cross-entropy between the distributions.

— Page 132, Deep Learning, 2016.

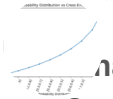


ice, a cross-entropy loss of 0.0 often indicates that is another story.



ılate Cross-Entropy Between Cla

The use of cross-entropy for classification often gives classes, mirroring the name of the classification task;



nary Cross-Entropy: Cross-entropy as a loss function for a binary classification task.

- **Categorical Cross-Entropy**: Cross-entropy as a loss function for a multi-class classification task.

We can make the use of cross-entropy as a loss function concrete with a worked example.


```
.. where you'll find the Really Good stuff.
# define classification data
p = [1, 1, 1, 1, 1, 0, 0, 0, 0, 0]
q = [0.8, 0.9, 0.9, 0.6, 0.8, 0.1, 0.4, 0.2, 0.1, 0.3]
```

Consider a two-class classification task with the following 10 actual class labels (P) and predicted class labels (Q).

We can enumerate these probabilities and calculate the cross-entropy for each using the cross-entropy function developed in the previous section using *log()* (natural logarithm) instead of *log2()*.

```
# calculate cross entropy
def cross_entropy(p, q):
    return -sum([p[i]*log(q[i]) for i in range(len(p))])
```

For each actual and predicted probability, we must convert the prediction into a distribution of probabilities across each event, in this case, the classes {0, 1} as 1 minus the probability for class 0 and probability for class 1.

We can then calculate the cross-entropy and repeat the process for all examples

```
...
# calculate cross entropy for each example
results = list()
for i in range(len(p)):
    # create the distribution for each event {0, 1}
    expected = [1.0 - p[i], p[i]]
    predicted = [1.0 - q[i], q[i]]
    # calculate cross entropy for the two events
    ce = cross_entropy(expected, predicted)
    print('>[y=%.1f, yhat=%.1f] ce: %.3f nats' % (p[i], q[i], ce))
    results.append(ce)
```

Finally, we can calculate the average cross-entropy across the dataset and report it as the cross-entropy loss for the model on the dataset.

```
...
# calculate the average cross entropy
mean_ce = mean(results)
print('Average Cross Entropy: %.3f nats' % mean_ce)
```

Tying this all together, the complete example is listed below.

```
# calculate cross entropy for classification problem
from math import log
from numpy import mean

# calculate cross entropy
def cross_entropy(p, q):
    return -sum([p[i]*log(q[i]) for i in range(len(p))])

# define classification data
p = [1, 1, 1, 1, 1, 0, 0, 0, 0, 0]
q = [0.8, 0.9, 0.9, 0.6, 0.8, 0.1, 0.4, 0.2, 0.1, 0.3]
# calculate cross entropy for each example
results = list()
for i in range(len(p)):
    # create the distribution for each event {0, 1}
    expected = [1.0 - p[i], p[i]]
    predicted = [1.0 - q[i], q[i]]
    # calculate cross entropy for the two events
    ce = cross_entropy(expected, predicted)
    print('>[y=%.1f, yhat=%.1f] ce: %.3f nats' % (p[i], q[i], ce))
    results.append(ce)

# calculate the average cross entropy
mean_ce = mean(results)
print('Average Cross Entropy: %.3f nats' % mean_ce)
```

Running the example prints the actual and predicted probabilities for each example and the cross-entropy in nats.

The final average cross-entropy loss across all examples is reported, in this case, as 0.247 nats.

```
>[y=1.0, yhat=0.8] ce: 0.223 nats
>[y=1.0, yhat=0.9] ce: 0.105 nats
>[y=1.0, yhat=0.9] ce: 0.105 nats
>[y=1.0, yhat=0.6] ce: 0.511 nats
>[y=1.0, yhat=0.8] ce: 0.223 nats
>[y=0.0, yhat=0.1] ce: 0.105 nats
>[y=0.0, yhat=0.4] ce: 0.511 nats
>[y=0.0, yhat=0.2] ce: 0.223 nats
```

```
>[y=0.0, yhat=0.1] ce: 0.105 nats
>[y=0.0, yhat=0.3] ce: 0.357 nats
Average Cross Entropy: 0.247 nats
```

is the cross-entropy loss calculated when optimizing a logistic regression model or a neural network model under a cross-entropy loss function.

Calculate Cross-Entropy Using Keras

We can confirm the same calculation by using the *binary_crossentropy()* function from the Keras deep learning API to calculate the cross-entropy loss for our small dataset.

The complete example is listed below.

Note: This example assumes that you have the Keras configured with a backend library such as TensorFlow example.

```
# calculate cross entropy with keras
from numpy import asarray
from keras import backend
from keras.losses import binary_crossentropy
# prepare data in Python
p = asarray([1, 1, 1, 1, 1, 0, 0, 0, 0, 0])
q = asarray([0.8, 0.9, 0.9, 0.6, 0.8, 0.1, 0.
# convert to keras variables
y_true = backend.variable(p)
y_pred = backend.variable(q)
# calculate the average cross-entropy
mean_ce = backend.eval(binary_crossentropy(y_true, y_pred))
print('Average Cross Entropy: %.3f nats' % mean_ce)
```

Running the example, we can see that the same average cross-entropy loss of 0.247 nats is reported.


```
Average Cross Entropy: 0.247 nats
```

Intuition for Cross-Entropy on Predicted Probabilities

We can further develop the intuition for the cross-entropy for predicted class probabilities.

For example, given that an average cross-entropy loss of 0.0 is a perfect model, what do average cross-entropy values greater than zero mean exactly?

We can explore this question no a binary classification problem where the class labels as 0 and 1. This is a discrete probability distribution with two events and a certain probability for one event and an impossible probability for the other event.

We can then calculate the cross entropy for different "predicted" probability distributions transitioning from a perfect match of the target distribution to the exact opp

We would expect that as the predicted probability distribution diverges further from the target distribution that the cross-entropy calculated will increase.

This example below implements this and plots the cross-entropy result for the predicted probability distribution compared to the target of [0, 1] for two events as we would see for the cross-entropy in a binary classification task.

```
# cross-entropy for predicted probability distribution vs label
from math import log
from matplotlib import pyplot

# calculate cross-entropy
def cross_entropy(p, q, ets=1e-15):
	return -sum([p[i]*log(q[i]+ets) for i in range(len(p))])

# define the target distribution for two even
target = [0.0, 1.0]
# define probabilities for the first event
probs = [1.0, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0
# create probability distributions for the tw
dists = [[1.0 - p, p] for p in probs]
# calculate cross-entropy for each distributi
ents = [cross_entropy(target, d) for d in dis
# plot probability distribution vs cross-entr
pyplot.plot([1-p for p in probs], ents, marke
pyplot.title('Probability Distribution vs Cro
pyplot.xticks([1-p for p in probs], ['[%.1f,%
pyplot.subplots_adjust(bottom=0.2)
pyplot.xlabel('Probability Distribution')
pyplot.ylabel('Cross-Entropy (nats)')
pyplot.show()
```

Running the example calculates the cross-entropy score for each probability distribution then plots the results as a line plot.

We can see that as expected, cross-entropy starts at 0.0 (far left point) when the predicted probability distribution matches the target distribution, then steadily increases as the predicted probability distribution diverges.

We can also see a dramatic leap in cross-entropy when the predicted probability distribution is the exact opposite of the target distribution, that is, [1, 0] compared to the target of [0, 1].

Line Plot of Probability Distribution vs Cross-Entropy for a Binary Classification Task

We are not going to have a model that predicts the exact opposite probability distribution for all cases on a binary classification task.

As such, we can remove this case and re-calculate the plot.

The upda listed below.

```
# cross-entropy for predicted probability distribution vs label
from math import log
from matplotlib import pyplot

# calculate cross-entropy
def cross_entropy(p, q, ets=1e-15):
    return -sum([p[i]*log(q[i]+ets) for i in range(len(p))])

# define the target distribution for two events
target = [0.0, 1.0]
# define probabilities for the first event
probs = [1.0, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1]
# create probability distributions for the two events
dists = [[1.0 - p, p] for p in probs]
# calculate cross-entropy for each distributi
ents = [cross_entropy(target, d) for d in dis
```

```
# plot probability distribution vs cross-entropy
pyplot.plot([1-p for p in probs], ents, marker='.')
pyplot.title('Probability Distribution vs Cross-Entropy')
pyplot.xticks([1-p for p in probs], ['[%.1f,%.1f]'%(d[0],d[1]) for d in dists], rotation=70)
pyplot.subplots_adjust(bottom=0.2)
pyplot.xlabel('Probability Distribution')
pyplot.ylabel('Cross-Entropy (nats)')
pyplot.show()
```

Running the example gives a much better idea of the relationship between the divergence in probability distribution and the calculated cross-entropy.

Line Plot of Probability Distribution vs Cross-Entropy for a Binary Classification Task With Extreme Case Removed

A plot like this can be used as a guide for interpreting the average cross-entropy reported for a model for a binary classification dataset.

For example, you can use these cross-entropy values to interpret the mean cross-entropy reported by Keras for a neural network model on a binary classification task, or a binary classification model in scikit-learn evaluated using the logloss metric.

You can use it to answer the general question:

What is a good cross-entropy score?

If you are working in nats (and you usually are) and you are getting mean cross-entropy less than 0.2, you are off to a good start, and less than 0.1 or 0.05 is even better.

On the other hand, if you are getting mean cross-entropy greater than 0.2 or 0.3 you can probably improve, and if you are getting a mean cross-entropy greater than 1.0, then something is going on and you're making poor probability predictions on many examples in your dataset.

I summarise these intuitions for the mean cross

- **Cross-Entropy = 0.00**: Perfect probabilities.
- **Cross-Entropy < 0.02**: Great probabilities.
- **Cross-Entropy < 0.05**: On the right track.
- **Cross-Entropy < 0.20**: Fine.
- **Cross-Entropy > 0.30**: Not great.
- **Cross-Entropy > 1.00**: Terrible.
- **Cross-Entropy > 2.00** Something is broken.

This listing will provide a useful guide when interpretin
ion model, or your artificial neural network mod

You can also calculate separate mean cross-entropy scores per-class and help tease out on which classes you're model has good probabilities, and which it might be messing up.

Cross-Entropy Versus Log Loss

Cross-Entropy is not Log Loss, but they calculate the same quantity when used as loss functions for classification problems.

Log Lo Log Likelihood

Logistic loss refers to the loss function commonly used to optimize a logistic regression model.

It may also be referred to as logarithmic loss (which is confusing) or simply log loss.

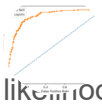
Many models are optimized under a probabilistic framework called the maximum likelihood estimation, or MLE, that involves finding a set of parameters that best explain the observed data.

This involves selecting a likelihood function that defines how likely a set of observations (data) are given model parameters. When a log likelihood function is used (which is common), it is often referred to as optimizing the log likelihood for the model. Because it is more common to minimize a function than to

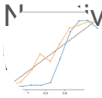
maximize it in practice, the log likelihood function is inverted by adding a negative sign to the front. This transforms it into a Negative Log Likelihood function or NLL for short.

In deriving the log likelihood function under a framework of maximum likelihood estimation for Bernoulli probability distribution functions (two classes), the calculation comes out to be:

- negative log-likelihood(P, Q) = -(P(class0) * log(Q(class0)) + P(class1) * log(Q(class1)))



antity can be averaged over all training examples by calculating the average of the log of the likelihood function.



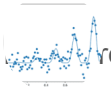
Negative log-likelihood for binary classification problems is often shortened to simply “log loss” as the loss is derived for logistic regression.

- log loss = negative log-likelihood, under a Bernou

sure that the negative log-likelihood is the sam

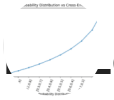
Bernoulli probability distribution functions (two events

Multinoulli distributions (multi-class classification) also



re on log loss and the negative log likelihood, s

- A Gentle Introduction to Logistic Regression With



Loss and Cross Entropy Calculate the Same Thing

For classification problems, “*log loss*“, “*cross-entropy*” and “*negative log-likelihood*” are used interchangeably.

More generally, the terms “*cross-entropy*” and “*negative log-likelihood*” are used interchangeably in the context of loss functions for classification models.

> *The negative log-likelihood for logistic regression is given by […] This is also called the cross-er*

— Page 246, Machine Learning: A Probabilistic Perspective, 2012.

Therefore, calculating log loss will give the same quantity as calculating the cross-entropy for Bernoulli probability distribution. We can confirm this by calculating the log loss using the log_loss() function from the scikit-learn API.

Calculating the average log loss on the same set of actual and predicted probabilities from the previous section should give the same result as calculating the average cross-entropy.

The complete example is listed below.

```
1  # calculate log loss for classification probl
```

```
from sklearn.metrics import log_loss
from numpy import asarray
# define classification data
p = [1, 1, 1, 1, 1, 0, 0, 0, 0, 0]
q = [0.8, 0.9, 0.9, 0.6, 0.8, 0.1, 0.4, 0.2, 0.1, 0.3]
# define data as expected, e.g. probability for each event {0, 1}
y_true = asarray([[1-v, v] for v in p])
y_pred = asarray([[1-v, v] for v in q])
# calculate the average log loss
ll = log_loss(y_true, y_pred)
print('Average Log Loss: %.3f' % ll)
```

Running the example gives the expected result of 0.247 log loss, which matches 0.247 nats when calculated using the average cross-entropy.

```
Average Log Loss: 0.247
```

This does not mean that log loss calculates cross-entr

, they are different quantities, arrived at from d

ting a loss function for a classification task, res ally,

a cross-entropy loss function is equivalent to a maxim ulli

probability distribution.

emonstrates a connection between the study of

theory for discrete probability distributions.

limited to discrete probability distributions, and ear

it ne first time.

Specifically, a linear regression optimized under the maximum likelihood estimation framework assumes a Gaussian continuous probability distribution for the target variable and involves minimizing the mean squared error function. This is equivalent to the cross-entropy for a random variable with a Gaussian probability distribution.

> *Any loss consisting of a negative log-likelihood is a cross-entropy between the empirical distribution defined by the training set and the probability distribution defined by model. For example, mean squared error is the cross-entropy between the empirical distribution and a Gaussian model.*

— Page 132, Deep Learning, 2016.

This is a little mind blowing, and comes from the field of differential entropy for continuous random variables.

It means that if you calculate the mean squared error between two Gaussian random variables that cover the same events (have the same mean and standard deviation), then you are calculating the cross-entropy between the variables.

It also means that if you are using mean squared error loss to optimize your neural network model for a regression problem, you are in effect using a cross entropy loss.

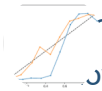
Further Reading

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

ials

How to Use ROC Curves and Precision-Recall Curves for Classification in Python

- A Gentle Introduction to Information Entropy
- How to Calculate the KL Divergence for Machine Learning

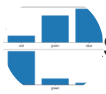


How and When to Use a Calibrated Classification Model with scikit-learn

gentle Introduction to Logistic Regression With Maximum Likelihood Estimation

ow to Choose Loss Functions When Training De

- Loss and Loss Functions for Training Deep Learn



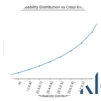
How to Calculate the KL Divergence for Machine Learning

s

- Machine Learning: A Probabilistic Perspective, 20
- Pattern Recognition and Machine Learning, 2006
- ep Learning, 2016.

How to Implement Bayesian Optimization from Scratch in Python

API



A Gentle Introduction to Cross-Entropy for Machine Learning

age of loss functions, Keras API.

klearn.metrics.log_loss API.

Articles

- Kullback-Leibler divergence, Wikipedia.
- Cross entropy, Wikipedia.
- Joint Entropy, Wikipedia.
- Loss functions for classification, Wikipedia.
- Differential entropy, Wikipedia.

Summary

In this tutorial, you discovered cross-entropy for machine learning.

Specifically, you learned:

- How to calculate cross-entropy from scratch and using standard machine learning libraries.
- Cross-entropy can be used as a loss function when optimizing classification models like logistic regression and artificial neural networks.
- Cross-entropy is different from KL divergence but can be calculated using KL divergence, and is different from log loss but calculates the same quantity when used as a loss function.

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

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ownlee

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

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‹ Naive Bayes Classifier From Scratch in Python

A Gentle Introduction to Maximum Likelihood Estimation for Machine Learning ›

49 Responses to *A Gentle Introduction t* *g*

Markus October 22, 2019 at 6:57 am #

REPLY

Hi

Thanks for this blog post.

What confuses me a bit is the fact that we interpret the labels 0 and 1 in the example as the probability values for calculating the cross entropy between the target distribution and the predicted distribution!

What if the labels were 4 and 7 instead of 0 and 1?!

Jason Brownlee October 22, 2019 at 1:44 pm

Thanks.

Good question. For binary classification we map th

I recommend reading about the Bernoulli distributi

https://machinelearningmastery.com/discrete-proba

sharpblade4 October 22, 2019 at 5:35 pm #

Hi Jason,

A small fix suggestion: in the beginning of the article in section “What Is Cross-Entropy?” you’ve mentioned that “The result will be a positive number measured in bits and 0 if the two probability distributions are identical.”.

However, I would suggest to mention that the same probability-distributions H(P,P) is the entropy for the probability-distribution H(P), opposed to KL divergence of the same probability-distribution which would indeed outcome zero.

Thanks,

Ron U

Jason Brownlee October 23, 2019 at 6:34 am #

REPLY

Thanks Ron!

I’ll schedule time to update the post and give an example of exactly what you’re referring to. E.g.:

```
# example of calculating cross entropy
from math import log2

# calculate cross entropy
def cross_entropy(p, q):
    return -sum([p[i]*log2(q[i]) for i
```

```
# define data
p = [0.10, 0.40, 0.50]
q = [0.80, 0.15, 0.05]
# calculate cross entropy H(P, P)
ce_pp = cross_entropy(p, p)
print('H(P, P): %.3f bits' % ce_pp)
# calculate cross entropy H(Q, Q)
ce_qq = cross_entropy(q, q)
print('H(Q, Q): %.3f bits' % ce_qq)
```

H(P, P): 1.361 bits
H(Q, Q): 0.884 bits

Update: I have updated the post to correctly discus

Thanks Again!

Hugh Brown October 26, 2019 at 4:39 pm #

Why not use zip?

```
# calculate cross entropy
def cross_entropy(p, q):
	return -sum(pp*log2(qq) for pp, qq in zip(p, q))
```

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Jason Brownlee October 27, 2019 at 5:43 am #

REPLY

Thanks for the tip Hugh, that is a much cleaner approach!

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Anthony The Koala October 28, 2019 at 3:48 am #

REPLY

Dear Dr Jason,

In the last few lines under the subheading “How to Calculate Cross-Entropy”, you had the simple example with the following outputs:

```
H(P): 1.361 bits          #entropy
KL(P || Q): 1.927 bits #kl divergence
H(P, Q): 3.288 bits     #cross entropy = entropy + kl divergence
```

What is the interpretation of these figures in ‘plain English’ please.

For example if the above example produced the follow

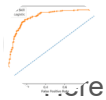
```
H(P): 0.361 bits          #entropy
KL(P || Q): 2.927 bits #kl divergence
H(P, Q): 3.288 bits     #cross entropy = entropy + kl divergence
```

Ne

r if ad

```
H(P): 1.927 bits          #entropy
KL(P || Q): 0.361 bits #kl divergence
H(P, Q): 3.288 bits     #cross entropy = entropy + kl divergence
```

Pic

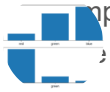


How to Use ROC Curves and Precision-Recall Curves for Classification in Python

re is another example of made up figures.

```
H(P) = 0.05 bits        #entropy
KL(P||Q) = 0.2 bits  #kl diverengence
H(P,Q) = 0.25 bits      #cross entropy = entrop
```

Classification Model with scikit-learn

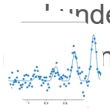


How to Calculate the KL Divergence for Machine Learning

mpare the calculated KL Divergence for figures' doe predictable model?

Also:

nderstand that a bit is a base 2 number. Eg 1 = 1(ba number of bits in a base 2 system is an integer. W



How to Implement Bayesian Optimization from Scratch in Python

Anthony of Sydney

A Gentle Introduction to Cross-Entropy for Machine Learning

Jason Brownlee October 28, 2019 at 6:10 am #

REPLY

Typically we use cross-entropy to evaluate a model, e.g. true classes vs probability predictions.

In that case, we would compare the average cross-entropy calculated across all examples and a lower value would represent a better fit. Interpreting the specific figures is often not useful.

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ɔala October 28, 2019 at 6:18 am #

REPLY

Dear Dr Jason,

Thank you for response.

The other question please:

How can you have a fraction of a bit. For example entropy = 3.2285 bits. What is 0.2285 bits.

Thank you,

Anthony of Sydney

Jason Brownlee October 28, 2019 at 7:00 am #

REPLY

Recall, it is an average over a dis

Think of it more of a measure and less like the crisp bits in a computer.

REPLY

Farhan October 28, 2019 at 6:32 pm #

Great Article, Hope to see more more content on machine learning and AI.

REPLY

Jason Brownlee October 29, 2019 at 5:21 am #

Thanks!

REPLY

Confused October 31, 2019 at 1:26 pm #

Hi,

d you provide an example of this sentence “The er

ures of these values will equal 0.0.”?

Does this mean a distribution with a mixture of these v

=0) = 0.6 has entropy zero? But this should not be

.

Thank you!

Loving the Tutorials?

REPLY

Jason Brownlee October 31, 2019 at 1:46 pm #

Good question.

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Sorry that is confusing.

I m >> SEE WHAT'S INSIDE ibution for a class label will always be zero.

I have updated the tutorial to be clearer and given a worked example.

REPLY

Xin November 13, 2019 at 9:35 am #

Hi Jason! This is the best article I’ve ever seen on cross entropy and KL-divergence! Finally I can understand them 😉 Thank you so much for the comprehensive article.

I have one small question: in the secion “Intuition for Cross-Entropy on Predicted Probabilities”, in the first code block to plot the visualization, the code is as follows:

```
# define the target distribution for two events
target = [0.0, 0.1]
# define probabilities for the first event
probs = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
# create probability distributions for the two events
dists = [[p, 1.0 - p] for p in probs]
# calculate cross-entropy for each distribution
ce = [cross_entropy(target, d) for d in dists]
```

not quite understand why the target probability for the two events are [0.0, 0.1]? Could you explain a bit more? Thank you!

Jason Brownlee November 13, 2019 at 1:45

Thanks! I worked really hard on it and I'm

Yes, looks like a typo. I'll fix it ASAP. It should be [0

Update: I have updated the code and re-generated

Scott November 14, 2019 at 8:54 am #

Jason, I so appreciate all your various posts on ML topics. If I may add one comment regarding what I've found helpful in the past:

One point that I didn't see really emphasized here that I've seen in other treatments (e.g., https://tdhopper.com/blog/cross-entropy-and-kl-divergence/) is that cross-entropy and KL difference "differ by a constant", i.e. in your expression

$$H(P, Q) = H(P) + KL(P \,||\, Q)$$

the H(P) is constant with respect to Q. In most ML tasks, P is usually fixed as the "true" distribution" and Q is the dist ying to refine until it matches P.

"In many of these situations, p is treated as the 'true' distribution, and q as the model that we're trying to optimize…. Because p is fixed, $H(p)$ doesn't change with the parameters of the model, and can be disregarded in the loss function." (https://stats.stackexchange.com/questions/265966/why-do-we-use-kullback-leibler-divergence-rather-than-cross-entropy-in-the-t-sne/265989)

You do get to this when you say "As such, minimizing the KL divergence and the cross entropy for a classification task are identical."

And yet for me at least, knowing that the two "differ by a constant" makes it intuitively obvious why minimizing one is the same as minimizing the other, even if they're actually intended to measure different things.

…Thus I think this "differ by a constant" is another reason that people get mixed up about cross-entropy vs KL divergence, and why guides like yours are so helpfi

December 15, 2019 at 6:01 am #

REPLY

Thanks for your note Scott.

Yes, H(P) is the entropy of the distribution. This becomes 0 when class labels are 0 and 1. I outline this at the end of the post when we talk about class labels.

A constant of 0 in that case means using KL divergence and cross entropy result in the same numbers, e.g. the kl divergence.

Arij February 11, 2020 at 6:52 am #

thanks for a grate article!

what confused me that in your article you have me

”

The result will be a positive number measured in bits a

probability distributions are identical.”

then again mentioned

“If two probability distributions are the same, then the c

bution.”

then

“This means that the cross entropy of two distributions (real and predicted) that have the same probability distribution for a class label, will also always be 0.0.”

“Therefore, a cross-entropy of 0.0 when training a model indicates that the predicted class probabilities are identical to the probabilities in the training dataset, e.g. zero loss.”

Am I missing something?

Jason Brownlee February 11, 2020 at 1:42 pm #

REPLY

The statements are correct.

The cross-entropy will be the entropy between the distributions if the distributions are identical.

In this case, if we are working with class labels like 0 and 1, then the entropy for two identical distributions will be zero.

We demonstrate this with a worked example in the above tutorial.

Does that help?

Arij February 11, 2020 at 5:36 pm #

REPLY

t w ot a ex es, they were understandable, thanks.

Just I could not imagine and understand them numerically.

Reading them again I understand that when the values of any distribution are only one or zero then entropy, cross-entropy, KL all will be zero.

will have values in case they have values between 0 and 1 also

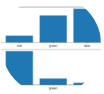
How to Use ROC Curves and Precision-Recall Curves for Classification in Python

How and When to Use a Calibrated Classification Model with scikit-learn

Jason Brownlee February 12, 2020 at 5:43 am #

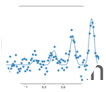
REPLY

Exactly!



How to Calculate the KL Divergence for Machine Learning

Grzegorz Kępisty April 17, 2020 at 4:23 pm #



How to Implement Bayesian Optimization from Scratch in Python

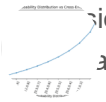
Good morning Jason!

nk you for great post!

Question on KL Divergence: In its definition we have lo

sion error is it a probable issue in real applications

ards!



A Gentle Introduction to Cross-Entropy for Machine Learning

Jason Brownlee April 18, 2020 at 5:41 am #

REPLY

Good question, no problem as probabilities are always greater than zero, so log never blows

PP

More on kl divergence here too:

htt .com/divergence-between-probability-distributions/

Allan April 27, 2020 at 2:25 am #

REPLY

Is it possible to use KL divergence as a classification criterion?

Jason Brownlee April 27, 2020 at 5:37 am #

REPLY

Probably, it would be the same as log loss and cross entropy when using class labels instead of probabilities.

Alla April 2[illegible]020 at 12:46 pm #

REPLY

Thanks for your reply. So let say the final calculation result is “Average Log Loss”, what does this value implies meaning?

Jason Brownlee April 28, 2020 at 6:39 am #

REPLY

Average difference between the probability distributions of expected and predicted values in bits.

Gledson April 29, 2020 at 6:21 am #

Hello Jason, Congratulations on the explanati[illegible]t on my crossentropy. Should I replace -Inf with som[illegible] Gledson.

Jason Brownlee April 29, 2020 at 6:36 am #

REPLY

You cannot log a zero. It is a good idea to always add a tiny value to anything to log, e.g. log(value + 1e-8)

Zeinab May 13, 2020 at 3:47 am #

REPLY

Thanks for all your great post, I’ve read some of them.

I’m working on traffic classification and I’ve converted my data to string of bits, I want to use cross-entropy on bytes.

Assume below lists:

p = [1, 0, 1, 1, 0, 0, 1, 0]
q = [1, 1, 1, 0, 1, 0, 0, 1]

When I use `-sum([p[i] * log2(q[i]) for i in range(len(p))])`, I encounter this error :ValueError: math domain error. S

Would you please tell me what I'm doing wrong here and how can I implement cross-entropy on a list of bits?

test

Jason Brownlee May 13, 2020 at 6:43 am #

REPLY

Can't calculate log of 0.0. Try adding a tiny value to the equation, e.g. 1e-8 or 1e-15

Zeinab May 13, 2020 at 11:03 pm #

I've converted the traffic to string of bi
any value.

TuanVu May 13, 2020 at 7:58 pm #

Why we use log function for cross entropy?

Jason Brownlee May 14, 2020 at 5:46 am #

REPLY

Good question, perhaps start here:
https://machinelearningmastery.com/what-is-information-entropy/

TuanVu May 14, 2020 at 9:22 am #

REPLY

Jason Brownlee May 14, 2020 at 1:25 pm #

REPLY

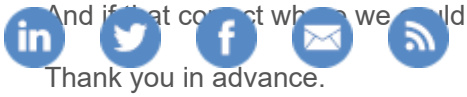
You're welcome.

Zahir May 29, 2020 at 3:36 pm #

REPLY

Hello Jason,
Thank you so much for all your great posts.

I have a quesion, if we have conditional entropy H(y|x)=-sum P(x,y) log(P(y|x)
could we say that it is equal to cross-entropy H(x,y) = – sum y log y^?
And if that correct when we could say that? i.e., under what assumptions.
Thank you in advance.



Jason Brownlee May 30, 2020 at 5:52 am # REPLY

I think you're asking me if the conditional entropy is the same as the cross entropy. I don't think it is off the cuff, but perhaps confirm with a good textbook.

Zahir May 30, 2020 at 10:23 am #

Thank you so much for your replay,
I found it in "Privacy-Preserving Adversarial Ne
as a cost function, but when they implement th
why?

Jason Brownlee May 31, 2020 at 6

Fascinating.

Perhaps email the authors directly.

BARURI SAI AVINASH November 1, 2020 at 4:22 pm # REPLY

How can be Number of bits per charecter in text generation is equal to loss ???

Jason Brownlee November 2, 2020 at 6:38 am # REPLY

Perhaps try re-reading the above tutorial that lays it all out.

Eric Orr December 22, 2020 at 11:05 am # REPLY

This is excellent Introduction to Cross-Entropy. It seems that one of the following sentences may have a typo in the stated notion of "surprise". My first impression is that the second sentence should have said "are less surprising". Is that true?

"Low probability events are more surprising therefore have a larger amount of information. Whereas probability distributions where the events are equally likely are more surprising and have larger entropy."

Jason Brownlee December 22, 2020 at 1:34 pm #

REPLY

Thanks.

Yes it could be clearer. Information is about events, entropy is about distributions, cross-entropy is about comparing distributions.

Surprise means something different when talking about information/events as compared to entropy/distributions.

I mixed the discussion of the two at the start of the

Also see this:
https://machinelearningmastery.com/what-is-inform

Does that help?

Eric Orr December 22, 2020 at 11:48 am #

After additional consideration, it appears that

lows.

"In probability distributions where the events are equally likely, no events have larger or smaller likelihood (smaller or larger surprise, respectively), and the distribution has larger entropy."

Sorry for belabouring this. It is a good point but sometimes confusing.

stefani January 6, 2021 at 11:19 pm #

REPLY

nderstood a concept when you can describe it with very simple words and I feel that is the case here. Wonderful job!

Jason Brownlee January 7, 2021 at 6:18 am #

REPLY

Thanks!

Aaron February 20, 2021 at 8:52 am #

REPLY

“Relative Entropy (KL Divergence): Average number of extra bits to represent an event from Q instead of P.”

Souldn’t it rather say: Relative Entropy (KL Divergence): Average number of extra bits to represent an event om sing ste f P

Since the expectation is over P(x)*[…]

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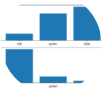
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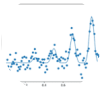
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