Lab : Predicting Online Ad Click-Through with Logistic Regression

In this chapter, we will be continuing our journey of tackling the billion-dollar worth problem of advertising click-through prediction. We will be focusing on learning a very (probably the most) scalable classification model—logistic regression. We will be exploring what logistic function is, how to train a logistic regression model, adding regularization to the model, and variants of logistic regression that are applicable to very large datasets. Besides the application in classification, we will also be discussing how logistic regression and random forest are used in picking significant features. Again, you won't get bored as there will be lots of implementations from scratch, and with scikit-learn and TensorFlow.

In this chapter, we will cover the following topics:

- Categorical feature encoding
- Logistic function
- What is logistic regression
- Training a logistic regression model via gradient descent
- Training a logistic regression model via stochastic gradient descent
- The implementations of logistic regression with scikit-learn
- Click-through prediction with logistic regression
- Logistic regression with L1 and L2 regularization
- Logistic regression for feature selection
- Online learning
- Another way to select features—random forest

Pre-reqs:

- Docker

Lab Environment

We will run Jupyter Notebook as a Docker container. This setup will take some time because of the size of the image. Run the following commands one by one:

`docker run -d --user root -p 8888:8888 --name jupyter -e GRANT_SUDO=yes jupyter/tensorflow-notebook:2ce7c06a61a1 start-notebook.sh`

`docker exec -it jupyter bash -c 'cd /home/jovyan/work && git clone https://github.com/athertahir/python-machine-learning-by-example.git && sudo && chmod +x ~/work/prepareContainer.sh && ~/prepareContainer.sh'`

`docker restart jupyter`

Note: After completing these steps, jupyter notebook will be accessible at port 8888 of the host machine.

All Notebooks are present in `work` folder.

Login

When the container is running, execute this statement:
`docker logs jupyter 2>&1 | grep -v "HEAD"`

This will show something like:

```
Copy/paste this URL into your browser when you connect for the first time, to login with a token:
    http://localhost:8888/?token=f89b02dd78479d52470b3c3a797408b20cc5a11e067e94b8
```

```
    THIS IS NOT YOUR TOKEN.  YOU HAVE TO SEARCH THE LOGS TO GET YOUR TOKEN
```

The token is the value behind `/?token=`. You need that for logging in.

Note: You can also run follow ing command to get token directly:
`docker exec -it jupyter bash -c 'jupyter notebook list' | cut -d'=' -f 2 | cut -d' ' -f 1`

Converting categorical features to numerical – one-hot encoding and ordinal encoding

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In the previous chapter, *Predicting Online Ads Click-through with Tree-Based Algorithms*, w e mentioned how **one-hot encoding** transforms categorical features to numerical features in order to be used in the tree algorithms in scikit-learn and TensorFlow. This w ill not limit our choice to tree-based algorithms if w e can adopt one-hot encoding to any other algorithms that only take in numerical features.

The simplest solution w e can think of in terms of transforming a categorical feature w ith *k* possible values is to map it to a numerical feature w ith values from 1 to *k*. For example, [*Tech*, *Fashion*, *Fashion*, *Sports*, *Tech*, *Tech*, *Sports*] becomes [1, 2, 2, 3, 1, 1, 3]. How ever, this w ill impose an ordinal characteristic, such as *Sports* being greater than *Tech*, and a distance property, such as *Sports* being closer to *Fashion* than to *Tech*.

Instead, one-hot encoding converts the categorical feature to *k* binary features. Each binary feature indicates the presence or absence of a corresponding possible value. Hence, the preceding example becomes the follow ing:

User interest
Tech
Fashion
Fashion
Sports
Tech
Tech
Sports

Interest: tech	Interest: fashion	Interest: sports
1	0	0
0	1	0
0	1	0
0	0	1
1	0	0
1	0	0
0	0	1

Previously, we have used `OneHotEncoder` from scikit-learn to convert a matrix of string into a binary matrix, but here, let's take a look at another module, `DictVectorizer`, which also provides an efficient conversion. It transforms dictionary objects (categorical feature: value) into one-hot encoded vectors.

For example, take a look at the following codes:

```
>>> from sklearn.feature_extraction import DictVectorizer
>>> X_dict = [{'interest': 'tech', 'occupation': 'professional'},
...           {'interest': 'fashion', 'occupation': 'student'},
...           {'interest': 'fashion','occupation':'professional'},
...           {'interest': 'sports', 'occupation': 'student'},
...           {'interest': 'tech', 'occupation': 'student'},
...           {'interest': 'tech', 'occupation': 'retired'},
...           {'interest': 'sports','occupation': 'professional'}]
>>> dict_one_hot_encoder = DictVectorizer(sparse=False)
>>> X_encoded = dict_one_hot_encoder.fit_transform(X_dict)
>>> print(X_encoded)
[[ 0.  0. 1. 1.  0. 0.]
 [ 1.  0. 0. 0.  0. 1.]
 [ 1.  0. 0. 1.  0. 0.]
 [ 0.  1. 0. 0.  0. 1.]
 [ 0.  0. 1. 0.  0. 1.]
 [ 0.  0. 1. 0.  1. 0.]
 [ 0.  1. 0. 1.  0. 0.]]
```

We can also see the mapping by executing the following:

```
>>> print(dict_one_hot_encoder.vocabulary_)
```

```
{'interest=fashion': 0, 'interest=sports': 1,
'occupation=professional': 3, 'interest=tech': 2,
'occupation=retired': 4, 'occupation=student': 5}
```

When it comes to new data, we can transform it by:

```
>>> new_dict = [{'interest': 'sports', 'occupation': 'retired'}]
>>> new_encoded = dict_one_hot_encoder.transform(new_dict)
>>> print(new_encoded)
[[ 0. 1. 0. 0. 1. 0.]]
```

We can inversely transform the encoded features back to the original features by:

```
>>> print(dict_one_hot_encoder.inverse_transform(new_encoded))
[{'interest=sports': 1.0, 'occupation=retired': 1.0}]
```

One important thing to note is that if a new (not seen in training data) category is encountered in new data, it should be ignored. `DictVectorizer` handles this implicitly (while `OneHotEncoder` needs to specify parameter `ignore`):

```
>>> new_dict = [{'interest': 'unknown_interest',
               'occupation': 'retired'},
...             {'interest': 'tech', 'occupation':
               'unseen_occupation'}]
>>> new_encoded = dict_one_hot_encoder.transform(new_dict)
>>> print(new_encoded)
[[ 0.  0. 0. 0.  1. 0.]
 [ 0.  0. 1. 0.  0. 0.]]
```

Sometimes, we do prefer transforming a categorical feature with *k* possible values into a numerical feature with values ranging from *1* to *k*. We conduct **ordinal encoding** in order to employ ordinal or ranking knowledge in our learning; for example, *large*, *medium*, and *small* become 3, 2, and 1 respectively, *good* and *bad* become 1 and 0, while one-hot encoding fails to preserve such useful information. We can realize ordinal encoding easily through the use of `pandas`, for example:

```
>>> import pandas as pd
>>> df = pd.DataFrame({'score': ['low',
...                              'high',
...                              'medium',
...                              'medium',
...                              'low']})
>>> print(df)
   score
0     low
1    high
2  medium
3  medium
4     low
>>> mapping = {'low':1, 'medium':2, 'high':3}
>>> df['score'] = df['score'].replace(mapping)
>>> print(df)
  score
```

```
0      1
1      3
2      2
3      2
4      1
```

We convert the string feature into ordinal values based on the mapping we define.

We can run the code now. Run `cat python-machine-learning-by-example/Chapter07/encoding.py` to view file.

Run Code

Now, run the python code by running: `python encoding.py` {{execute}}

Classifying data with logistic regression

As seen in the last chapter, we trained the tree-based models only based on the first 300,000 samples out of 40 million. We did so simply because training a tree on a large dataset is extremely computationally expensive and time-consuming. Since we are now not limited to algorithms directly taking in categorical features thanks to one-hot encoding, we should turn to a new algorithm with high scalability to large datasets. Logistic regression is one of the most, or perhaps the most, scalable classification algorithms.

Getting started with the logistic function

Let's start with an introduction to the **logistic function** (which is more commonly referred to as the **sigmoidfunction**) as the algorithm core before we dive into the algorithm itself. It basically maps an input to an output of a value between *0* and *1*, and is defined as follows:

$$y(z) = \frac{1}{1 + exp(-z)}$$

We can visualize what it looks like by performing the following steps:

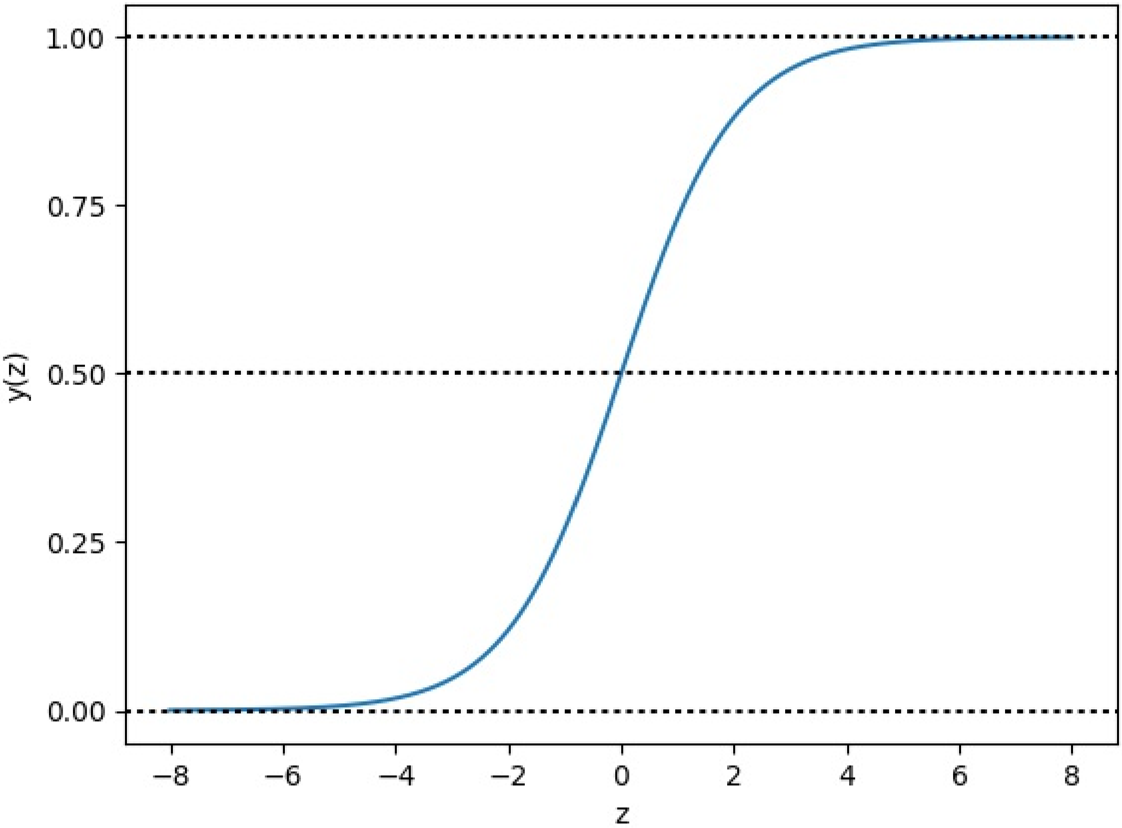
1. Define the logistic function:

```
>>> import numpy as np
>>> def sigmoid(input):
...     return 1.0 / (1 + np.exp(-input))
```

2. Input variables from `-8` to `8`, and the corresponding output, as follow s:

```
>>> z = np.linspace(-8, 8, 1000)
>>> y = sigmoid(z)
>>> import matplotlib.pyplot as plt
>>> plt.plot(z, y)
>>> plt.axhline(y=0, ls='dotted', color='k')
>>> plt.axhline(y=0.5, ls='dotted', color='k')
>>> plt.axhline(y=1, ls='dotted', color='k')
>>> plt.yticks([0.0, 0.25, 0.5, 0.75, 1.0])
>>> plt.xlabel('z')
>>> plt.ylabel('y(z)')
>>> plt.show()
```

Refer to the follow ing screenshot for the end result:



In the S-shaped curve, all inputs are transformed into the range from 0 to 1. For positive inputs, a greater value results in an output closer to 1; for negative inputs, a smaller value generates an output closer to 0; w hen the input is 0, the output is the midpoint, 0.5.

Jumping from the logistic function to logistic regression

Now that w e have some know ledge of the logistic function, it is easy to map it to the algorithm that stems from it. In logistic regression, the function input *z* becomes the w eighted sum of features. Given a data sample *x* w ith *n* features, *x~1~, x~2~, …, x~n~* (*x* represents a feature vector and ***x*** = (x~1~, x~2~, …, x~n~)), and **weights** (also called **coefficients**) of the model ***w*** (***w*** represents a vector (w_1, w_2, …, w_n)), *z* is expressed as follows:

$$z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = w^T x$$

Also, occasionally, the model comes with an **intercept** (also called **bias**), w_0. In this instance, the preceding linear relationship becomes:

$$z = w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = w^T x$$

As for the output *y(z)* in the range of 0 to 1, in the algorithm, it becomes the probability of the target being *1* or the positive class:

$$\hat{y} = P(y = 1|x) = \frac{1}{1 + exp(-w^T x)}$$

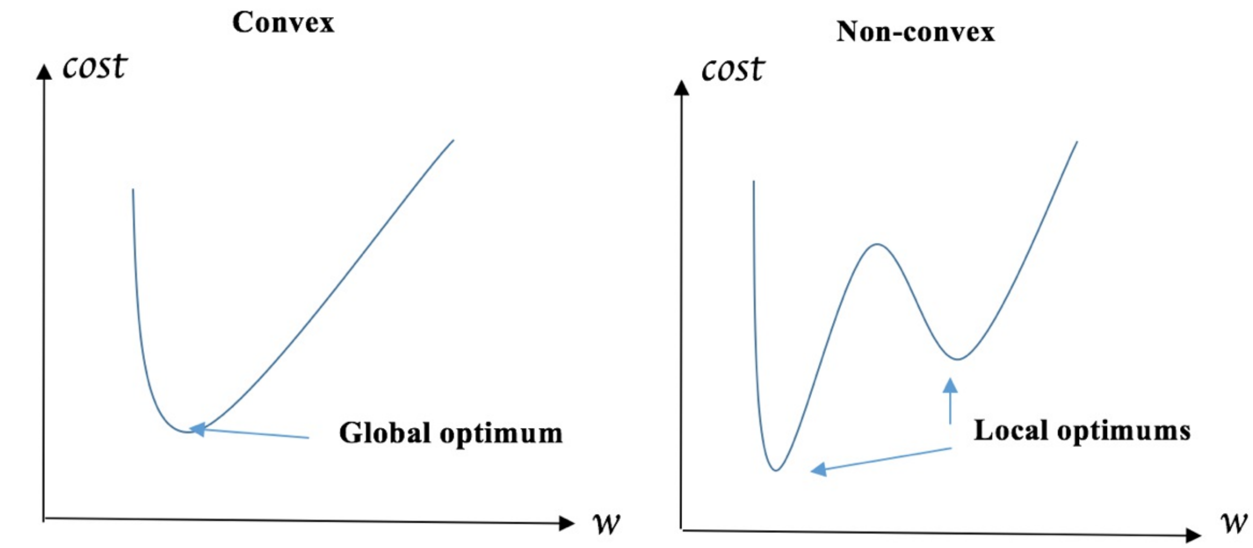
Hence, logistic regression is a probabilistic classifier, similar to the Naïve Bayes classifier.

A logistic regression model or, more specifically, its weight vector ***w*** is learned from the training data, with the goal of predicting a positive sample as close to *1* as possible and predicting a negative sample as close to 0 as possible. In mathematical language, the weights are trained so as to minimize the cost defined as the **mean squared error** (**MSE**), which measures the average of squares of difference between the truth and the prediction. Given *m* training samples, ($x^{(1)}$, $y^{(1)}$), ($x^{(2)}$,$y^{(2)}$), … ($x^{(i)}$, $y^{(i)}$)…, ($x^{(m)}$, $y^{(m)}$), where $y^{(i)}$ is either *1* (positive class) or *0* (negative class), the cost function *J(w)* regarding the weights to be optimized is expressed as follows:

$$J(w) = \frac{1}{m} \sum_{i=1}^{m} \frac{1}{2} \left(\hat{y}(x^{(i)}) - y^{(i)}\right)^2$$

However, the preceding cost function is **non-convex**, which means that, when searching for the optimal ***w***, many local (suboptimal) optimums are found and the function does not converge to a global optimum.

Examples of the **convex** and **non-convex** functions are plotted respectively below:



To overcome this, the cost function in practice is defined as follows:

$$J(w) = \frac{1}{m}\sum_{i=1}^{m} -\left[y^{(i)}log\big(\hat{y}(x^{(i)})\big) + (1-y^{(i)})log\big(1-\hat{y}(x^{(i)})\big)\right]$$

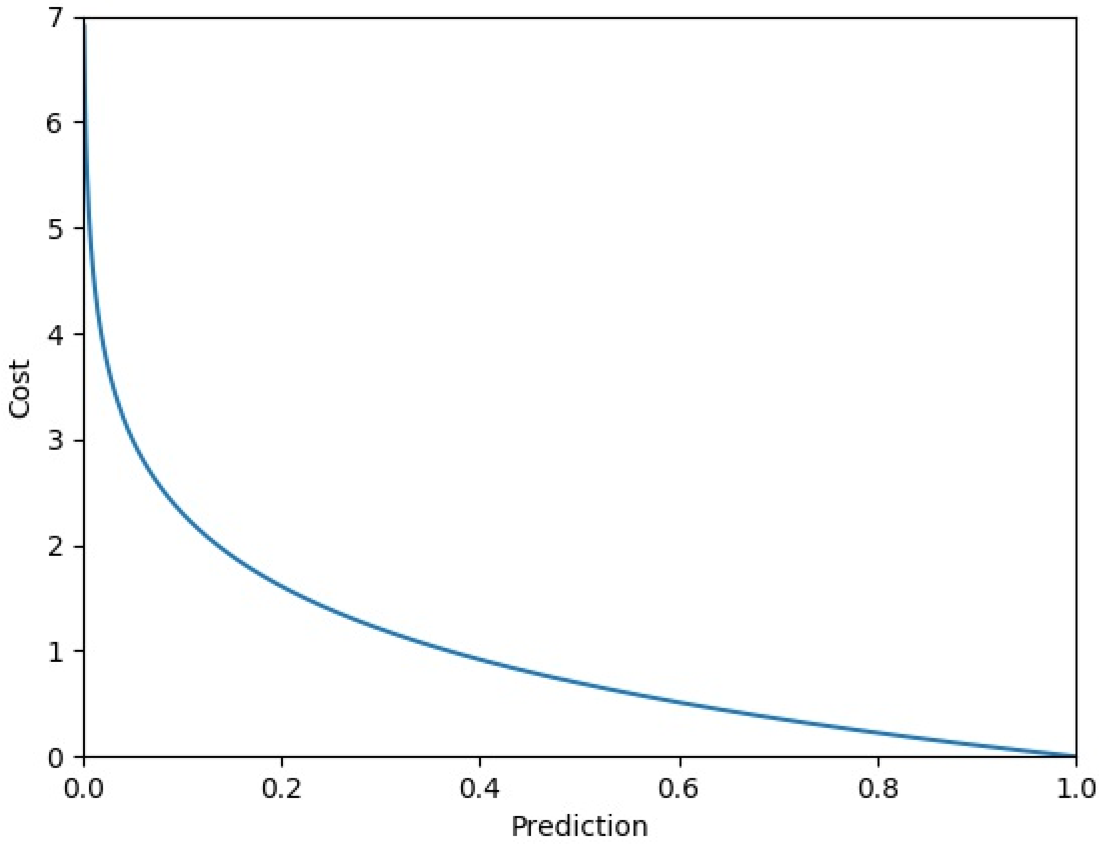
We can take a closer look at the cost of a single training sample:

$$\begin{aligned} j(w) &= -y^{(i)}log\big(\hat{y}(x^{(i)})\big) - (1-y^{(i)})log\big(1-\hat{y}(x^{(i)})\big) \\ &= \begin{cases} -log\big(\hat{y}(x^{(i)})\big), & if\ y^{(i)} = 1 \\ -log\big(1-\hat{y}(x^{(i)})\big), & if\ y^{(i)} = 0 \end{cases} \end{aligned}$$

If *y^(i)*^=1, when it predicts correctly (positive class in 100% probability), the sample cost *j* is *0*; the cost keeps increasing when it is less likely to be the positive class; when it incorrectly predicts that there is no chance to be the positive class, the cost is infinitely high. We can visualize it as follows:

```
>>> y_hat = np.linspace(0, 1, 1000)
>>> cost = -np.log(y_hat)
>>> plt.plot(y_hat, cost)
>>> plt.xlabel('Prediction')
>>> plt.ylabel('Cost')
>>> plt.xlim(0, 1)
>>> plt.ylim(0, 7)
>>> plt.show()
```

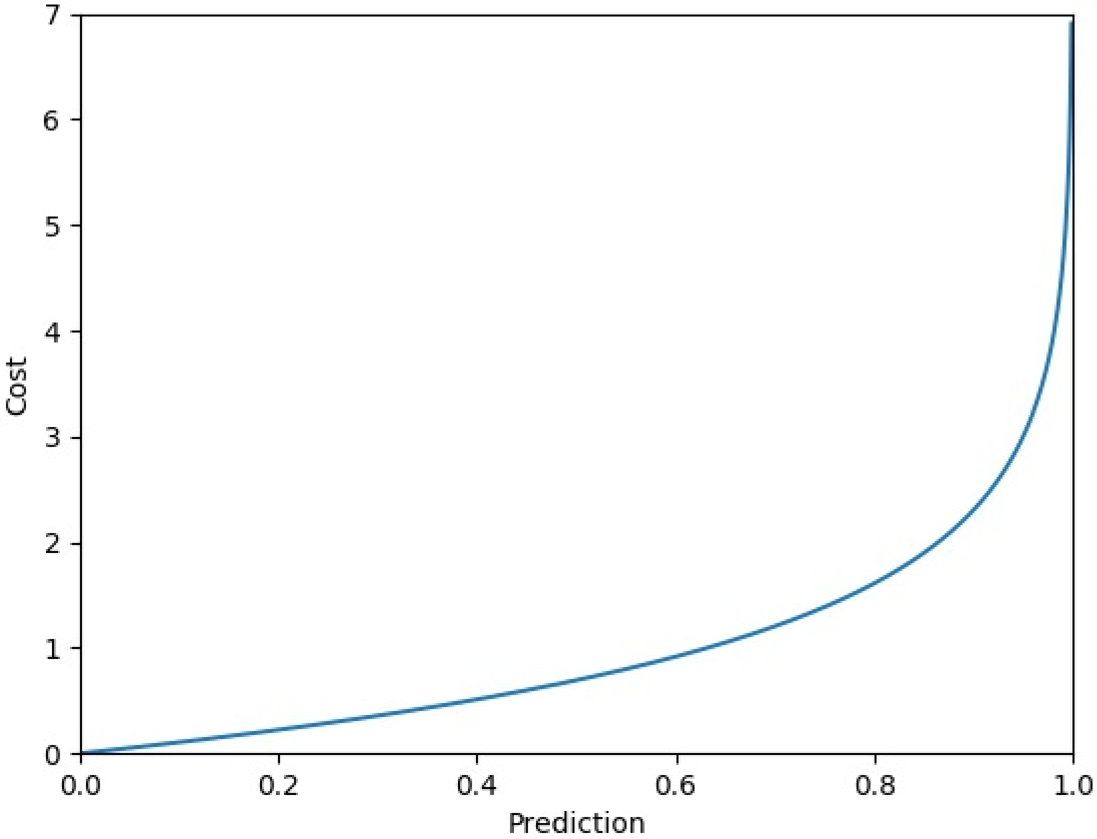
Refer to the following screenshot for the end result:



On the contrary, if *y^(i)^=0*, w hen it predicts correctly (positive class in *0* probability, or negative class in 100% probability), the sample cost *j* is *0*; the cost keeps increasing w hen it is more likely to be the positive class; w hen it incorrectly predicts that there is no chance to be the negative class, the cost goes infinitely high. We can visualize it using the follow ing codes:

```
>>> y_hat = np.linspace(0, 1, 1000)
>>> cost = -np.log(1 - y_hat)
>>> plt.plot(y_hat, cost)
>>> plt.xlabel('Prediction')
>>> plt.ylabel('Cost')
>>> plt.xlim(0, 1)
>>> plt.ylim(0, 7)
>>> plt.show()
```

The follow ing screenshot is the resultant output:



Minimizing this alternative cost function is actually equivalent to minimizing the MSE-based cost function. The advantages of choosing it over the other one include the follow ing:

- Obviously, being convex, so that the optimal model w eights can be found
- A summation of the logarithms of prediction

$$\hat{y}(x^{(i)})$$

~~or~~

$$1 - \hat{y}(x^{(i)})$$

simplifies the calculation of its derivative with respect to the weights, which we will talk about later

Due to the logarithmic function, the cost function

$$J(w) = \frac{1}{m} \sum_{i=1}^{m} -\left[y^{(i)} log\left(\hat{y}(x^{(i)})\right) + (1 - y^{(i)}) log\left(1 - \hat{y}(x^{(i)})\right)\right]$$

is also called **logarithmic loss**, or simply **log loss.**

We can run the code now. Run `cat python-machine-learning-by-example/Chapter07/logistic_function.py` to view file.

Run Code

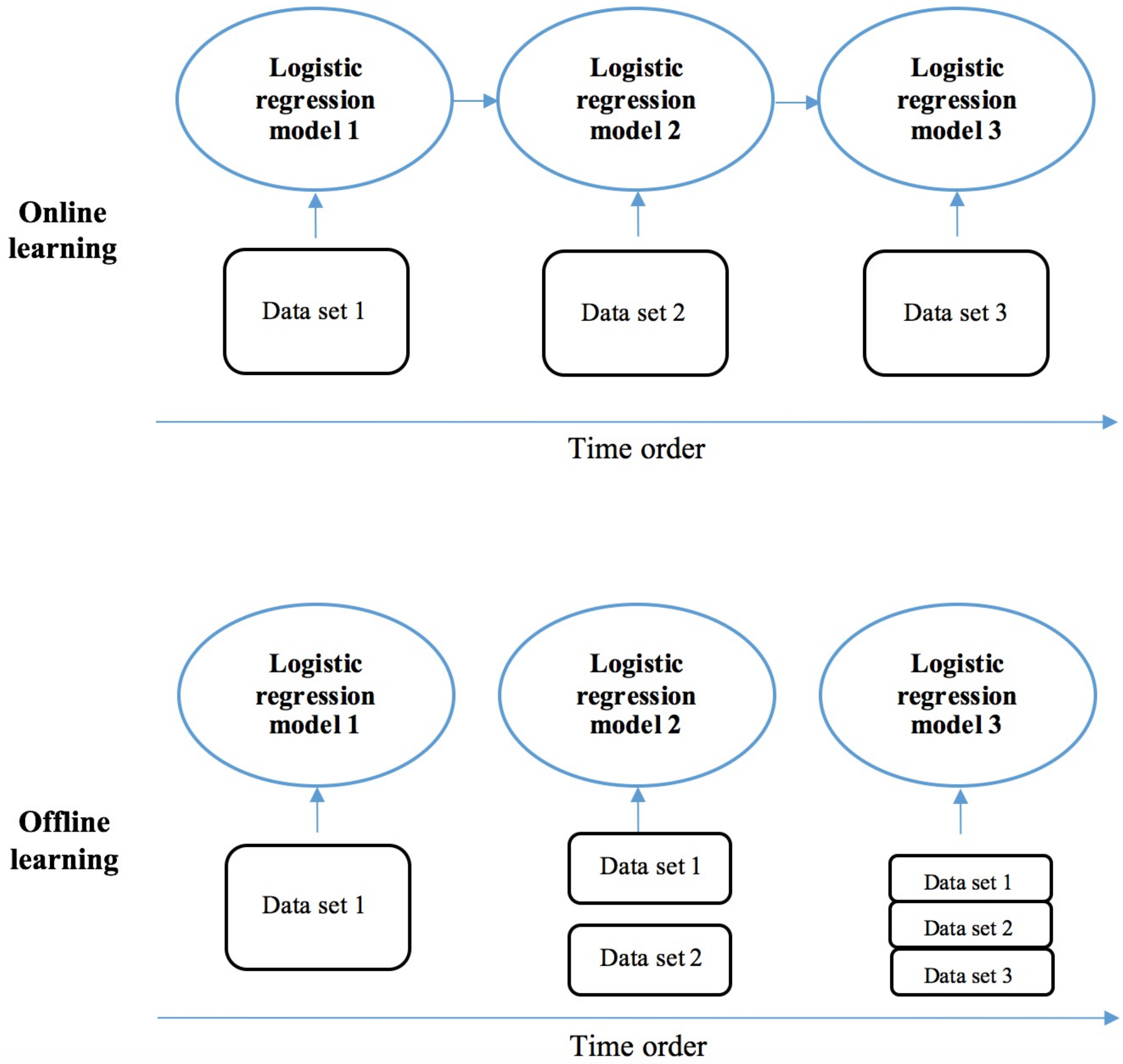
Now, run the python code by running: `python logistic_function.py` {{execute}}

Training on large datasets with online learning

So far, we have trained our model on no more than 300,000 samples. If we go beyond this figure, memory might be overloaded since it holds too much data, and the program will crash. In this section, we will be presenting how to train on a large-scale dataset with **online learning**.

Stochastic gradient descent grows from gradient descent by sequentially updating the model with individual training samples one at a time, instead of the complete training set at once. We can scale up stochastic gradient descent further with online learning techniques. In online learning, new data for training is available in a sequential order or in real time, as opposed to all at once in an **offline learning** environment. A relatively small chunk of data is loaded and preprocessed for training at a time, which releases the memory used to hold the entire large dataset. Besides better computational feasibility, online learning is also used because of its adaptability to cases where new data is generated in real time and needed in modernizing the model. For instance, stock price prediction models are updated in an online learning manner with timely market data; click-through prediction models need to include the most recent data reflecting users' latest behaviors and tastes; spam email detectors have to be reactive to the ever-changing spammers by considering new features that are dynamically generated.

The existing model trained by previous datasets is now updated based on the most recently available dataset only, instead of rebuilt from scratch based on previous and recent datasets together, as in offline learning:



The `SGDClassifier` module in scikit-learn implements online learning with the `partial_fit` method (while the `fit` method is applied in offline learning, as we have seen). We train the model with 1,000,000 samples, where we feed in 100,000 samples at one time to simulate an online learning environment. And we will test the trained model on the next 100,000 samples as follows:

```
>>> n_rows = 100000 * 11
>>> df = pd.read_csv("train", nrows=n_rows)
>>> X = df.drop(['click', 'id', 'hour', 'device_id', 'device_ip'],
                                                      axis=1).values
>>> Y = df['click'].values
>>> n_train = 100000 * 10
>>> X_train = X[:n_train]
>>> Y_train = Y[:n_train]
>>> X_test = X[n_train:]
>>> Y_test = Y[n_train:]
```

Fit the encoder on the w hole training set as follow s:

```
>>> enc = OneHotEncoder(handle_unknown='ignore')
>>> enc.fit(X_train)
```

Initialize an SGD logistic regression model w here w e set the number of iterations to `1` in order to partially fit the model and enable online learning:

```
>>> sgd_lr_online = SGDClassifier(loss='log', penalty=None,
                                fit_intercept=True, n_iter=1,
                                learning_rate='constant', eta0=0.01)
```

Loop over every `100000` samples and partially fit the model:

```
>>> start_time = timeit.default_timer()
>>> for i in range(10):
... x_train = X_train[i*100000:(i+1)*100000]
... y_train = Y_train[i*100000:(i+1)*100000]
... x_train_enc = enc.transform(x_train)
... sgd_lr_online.partial_fit(x_train_enc.toarray(), y_train,
                                                    classes=[0, 1])
```

Again, w e use the `partial_fit` method for online learning. Also, w e specify the `classes` parameter, w hich is required in online learning:

```
>>> print("--- %0.3fs seconds ---" % (timeit.default_timer() -
                                                     start_time))
--- 167.399s seconds ---
```

Apply the trained model on the testing set, the next 100,000 samples, as follow s:

```
>>> x_test_enc = enc.transform(X_test)
>>> pred = sgd_lr_online.predict_proba(x_test_enc.toarray())[:, 1]
>>> print('Training samples: {0}, AUC on testing set:
          {1:.3f}'.format(n_train * 10, roc_auc_score(Y_test, pred)))
Training samples: 10000000, AUC on testing set: 0.761
```

With online learning, training based on a total of 1 million samples only takes 167 seconds and yields better accuracy.

Handling multiclass classification

One last thing w orth noting is how logistic regression algorithms deal w ith multiclass classification. Although w e interact w ith the scikit-learn classifiers in multiclass cases the same w ay as in binary cases, it is encouraging to understand how logistic regression w orks in multiclass classification.

Logistic regression for more than two classes is also called **multinomial logistic regression**, or better known latterly as **softmax regression**. As we have seen in the binary case, the model is represented by one weight vector ***w***, the probability of the target being *1* or the positive class is written as follows:

$$\hat{y} = P(y = 1|x) = \frac{1}{1 + exp\,(-w^T x)}$$

In the *K* class case, the model is represented by *K* weight vectors, *w~1~, w~2~, …, w~K~*, and the probability of the target being class *k* is written as follows:

$$\widehat{y_k} = P(y = k|x) = \frac{exp\,(w_k^T x)}{\sum_{j=1}^{K} exp\,(w_j^T x)}$$

Note that the term ~~

$$\sum_{j=1}^{K} exp(w_j^T x)$$

normalizes probabilities ~~

$$\widehat{y_k}$$

(*k* from *1* to *K*) so that they total *1*. The cost function in the binary case is expressed as follows:

$$J(w) = \frac{1}{m}\sum_{i=1}^{m} -\left[y^{(i)}log\big(\hat{y}(x^{(i)})\big) + (1-y^{(i)})log\big(1-\hat{y}(x^{(i)})\big)\right] + \alpha\|w\|^q$$

Similarly, the cost function in the multiclass case becomes the following:

$$J(w) = \frac{1}{m}\sum_{i=1}^{m} -\left[\sum_{j=1}^{K} 1\{y^{(i)} = j\}log\big(\widehat{y_k}(x^{(i)})\big)\right]$$

Here, function *1{y^(i)^=j}* is *1* only if *y^(i)^=j* is true, otherwise *0*.

With the cost function defined, we obtain the step *Δw~j~*, for the *j* weight vector in the same way we derived the step *Δw* in the binary case:

$$\Delta w_j = \frac{1}{m}\sum_{i=1}^{m}\big(-1\{y^{(i)} = j\} + \widehat{y_k}(x^{(i)})\big)x^{(i)}$$

In a similar manner, all *K* weight vectors are updated in each iteration. After sufficient iterations, the learned weight vectors *w~1~, w~2~, …, w~K~* are then used to classify a new sample *x'* by means of the following equation:

$$y' = \underset{k}{argmax}\,\widehat{y_k} = \underset{k}{argmax}\,P(y = k|x')$$

To have a better sense, we experiment on it with a classic dataset, the handwritten digits for classification:

```
>>> from sklearn import datasets
>>> digits = datasets.load_digits()
>>> n_samples = len(digits.images)
```

As the image data is stored in 8*8 matrices, we need to flatten them, as follows:

```
>>> X = digits.images.reshape((n_samples, -1))
>>> Y = digits.target
```

We then split the data as follows:

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
                                    test_size=0.2, random_state=42)
```

We then combine grid search and cross-validation to find the optimal multiclass logistic regression model as follow s:

```
>>> from sklearn.model_selection import GridSearchCV
>>> parameters = {'penalty': ['l2', None],
...               'alpha': [1e-07, 1e-06, 1e-05, 1e-04],
...               'eta0': [0.01, 0.1, 1, 10]}
>>> sgd_lr = SGDClassifier(loss='log', learning_rate='constant',
                          eta0=0.01, fit_intercept=True, n_iter=10)
>>> grid_search = GridSearchCV(sgd_lr, parameters,
                               n_jobs=-1, cv=3)
>>> grid_search.fit(term_docs_train, label_train)
>>> print(grid_search.best_params_)
{'alpha': 1e-07, 'eta0': 0.1, 'penalty': None}
```

To predict using the optimal model, w e apply the follow ing:

```
>>> sgd_lr_best = grid_search.best_estimator_
>>> accuracy = sgd_lr_best.score(term_docs_test, label_test)
>>> print('The accuracy on testing set is:
                              {0:.1f}%'.format(accuracy*100))
The accuracy on testing set is: 94.2%
```

It doesn't look much different from the previous example, since `SGDClassifier` handles multiclass internally.

We can run the code now. Run `cat python-machine-learning-by-example/Chapter07/scikit_logistic_regression.py` to view file.

Run Code

Now, run the python code by running: `python scikit_logistic_regression.py` {{execute}}

Feature selection using random forest

We have seen how feature selection w orks w ith L1-regularized logistic regression in one of the previous sections, w here w eights of unimportant features are compressed to close to, or exactly, 0. Besides L1-regularized logistic regression, random forest is another frequently used feature selection technique.

To recap, random forest is bagging over a set of individual decision trees. Each tree considers a random subset of the features w hen searching for the best splitting point at each node. And, as an essence of the decision tree algorithm, only those significant features (along w ith their splitting values) are used to constitute tree nodes. Consider the forest as a w hole: the more frequently a feature is used in a tree node, the more important it is. In other w ords, w e can rank the importance of features based on their occurrences in nodes among all trees, and select the top most important ones.

A trained `RandomForestClassifier`{.literal} module in scikit-learn comes w ith an attribute, `feature_importances_`{.literal}, indicating the feature importance, w hich are calculated as the proportions of occurrences in tree nodes. Again, w e examine feature selection w ith random forest on the dataset w ith 100,000 ad click samples:

```
>>> from sklearn.ensemble import RandomForestClassifier
>>> random_forest = RandomForestClassifier(n_estimators=100,
                   criterion='gini', min_samples_split=30, n_jobs=-1)
>>> random_forest.fit(X_train_enc.toarray(), Y_train)
```

After fitting the random forest model, w e obtain the feature importance scores by:

```
>>> feature_imp = random_forest.feature_importances_
>>> print(feature_imp)
[1.60540750e-05 1.71248082e-03 9.64485853e-04 ... 5.41025913e-04
 7.78878273e-04 8.24041944e-03]
```

Take a look at the bottom 10 feature scores and the corresponding 10 least important features:

```
>>> feature_names = enc.get_feature_names()
>>> print(np.sort(feature_imp)[:10])
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
>>> bottom_10 = np.argsort(feature_imp)[:10]
>>> print('10 least important features are:\n', feature_names[bottom_10])
10 least important features are:
 ['x8_ea4912eb' 'x8_c2d34e02' 'x6_2d332391' 'x2_ca9b09d0'
'x2_0273c5ad' 'x8_92bed2f3' 'x8_eb3f4b48' 'x3_535444a1' 'x8_8741c65a'
'x8_46cb77e5']
```

And now, take a look at the top 10 feature scores and the corresponding 10 most important features:

```
>>> print(np.sort(feature_imp)[-10:])
[0.00809279 0.00824042 0.00885188 0.00897925 0.01080301 0.01088246
 0.01270395 0.01392431 0.01532718 0.01810339]
>>> top_10 = np.argsort(feature_imp)[-10:]
>>> print('10 most important features are:\n', feature_names[top_10])
10 most important features are:
 ['x17_-1' 'x18_157' 'x12_300' 'x13_250' 'x3_98572c79' 'x8_8a4875bd'
 'x14_1993' 'x15_2' 'x2_d9750ee7' 'x18_33']
```

We can run the code now. Run `cat python-machine-learning-by-example/Chapter07/random_forest_feature_selection.py` to view file.

Run Code

Now, run the python code by running: `python random_forest_feature_selection.py` {{execute}}