Machine Learning

Innovative Assignment

Developed By:

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Sample Dataset:

```csv
0,235.47,12.22,0.271,25.2,45.6,25.28
0,235.47,12.22,0.271,25.2,45.6,25.28
0,235.66,12.22,1.061,25.2,45.6,25.28
0,235.66,12.11,1.061,25.2,45.6,25.28
0,235.66,12.06,1.341,25.2,45.6,25.28
0,236.04,12.01,0.411,25.2,45.6,25.28
0,236.04,12.06,0.411,25.2,45.6,25.28
0,235.7,12.01,0.941,25.2,45.6,25.28
0,235.7,12.1,0.941,25.2,45.6,25.28
0,235.7,12.1,0.941,25.2,45.6,25.28
0,236.23,12.1,0.381,25.2,45.6,25.28
1,229.98,11.77,1.281,22.7,39,28.67
1,229.98,11.77,1.281,22.7,39,28.67
1,230.95,11.77,0.541,22.7,39,28.67
1,230.95,11.82,0.541,22.7,39,28.67
1,230.95,11.82,0.541,22.7,39,28.67
1,230.95,11.82,0.601,22.7,39,28.77
1,230.38,11.82,0.601,22.7,39,28.77
1,230.38,11.88,0.601,22.7,39,28.77
1,230.38,11.88,0.601,22.7,39,28.77
```

First attribute : Class value **0** or **1**

2nd attribute onwards - select one to work for **features**

Use this other attributes as input to Neural Network and classify the tuple.

Tweak

In general, activation function at output layer yields exact class value
i.e. 0 or 1 but out put should be probabilistic which we get before classifying it to 0 or 1

References for Visulization

- https://nbviewer.jupyter.org/urls/gist.github.com/fonnesbeck/5850463/raw/a29d9ffb863bfab09ff6c1fc853e1d5bf69fe3e4/3.+Plotting+and+Visualization.ipynb (https://nbviewer.jupyter.org/urls/gist.github.com/fonnesbeck/5850463/raw/a29d9ffb863bfab09ff6c1fc853e1d5bf69fe3e4/3.+Plotting+and+Visualization.ipynb)

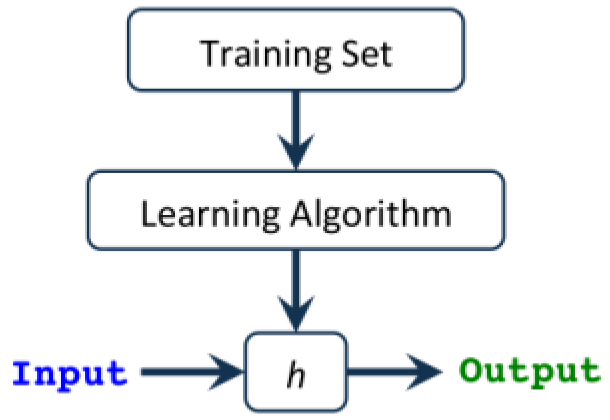
In [1]:

```python
"""
Implementing Classifier with Neural Network and Regression for given dataset
"""
__author__ = ["Gahan Saraiya", "Priyanka Bhati"]
```

Introduction

A hypothesis `h(x)` , takes an *input* and gives us the *estimated output value*.

This hypothesis can be a as simple as a one variable linear equation, .. up to a very complicated and long multivariate equation with respect to the type of the algorithm we're using (*i.e. linear regression, logistic regression..etc*).

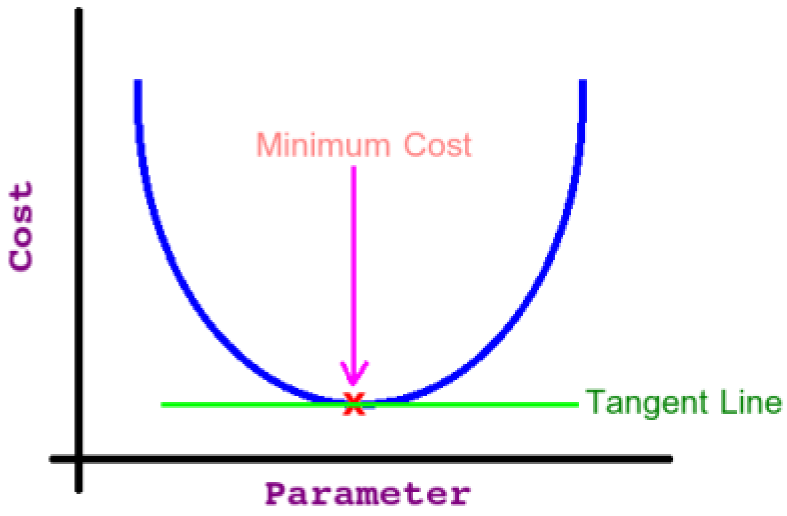


[(https://i.stack.imgur.com/i8OO5.png)](https://i.stack.imgur.com/i8OO5.png)

Our task is to find the ***best Parameters*** (a.k.a Thetas or Weights) that give us the ***least error*** in predicting the output. We call this error a ***Cost or Loss Function*** and apparently our goal is to ***minimize*** it in order to get the best predicted output!

One more thing to recall, that the relation between the parameter value and its effect on the cost function (i.e. the error) looks like a ***bell curve*** (i.e. **Quadratic**; recall this because it's very important) .

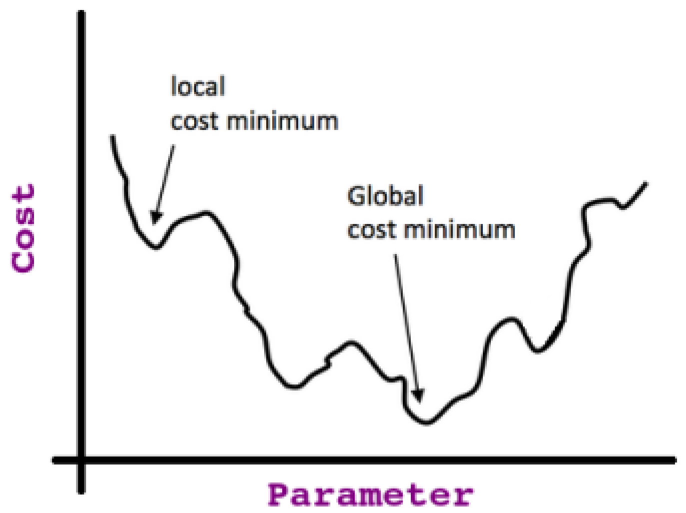
So if we start at any point in that curve and if we keep taking the derivative (i.e. tangent line) of each point we stop at, we will end up at what so called the **Global Optima** as shown in this image:



[(https://i.stack.imgur.com/mZ9UU.png)](https://i.stack.imgur.com/mZ9UU.png)

If we take the partial derivative at minimum cost point (i.e. global optima) we find the ***slope*** of the tangent line = **0** (then we know that we reached our target).

That's valid only if we have *Convex* Cost Function, but if we don't, we may end up stuck at what so called ***Local Optima***; consider this non-convex function:



[(https://i.stack.imgur.com/WYEux.png)](https://i.stack.imgur.com/WYEux.png)

Now you should have the intuition about the hack relationship between what we are doing and the terms: *Deravative*, *Tangent Line*, *Cost Function*, *Hypothesis* ..etc.

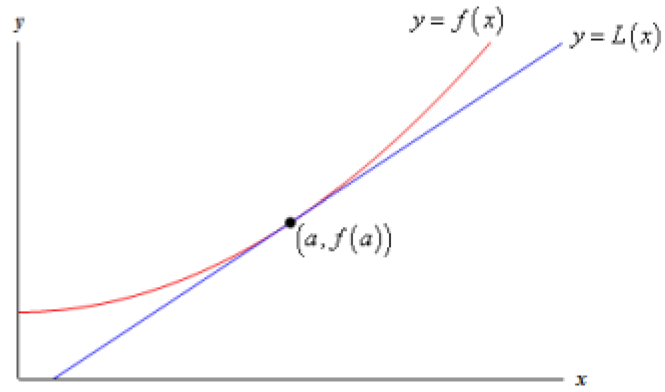
Side Note: The above mentioned intuition also related to the Gradient Descent Algorithm (see later).

Background

Linear Approximation:

Given a function, `f(x)` , we can find its tangent at `x=a` . The equation of the tangent line L(x) is: `L(x)=f(a)+f′(a)(x−a)` .

Take a look at the following graph of a function and its tangent line:



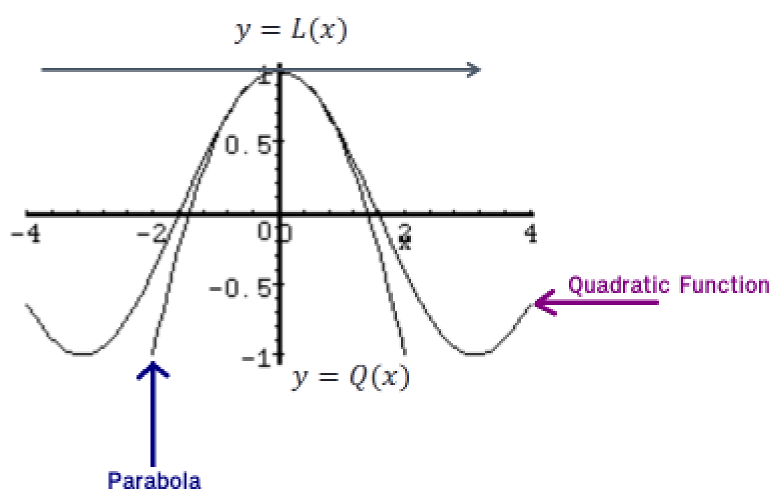
[(https://i.stack.imgur.com/u0vU0.png)](https://i.stack.imgur.com/u0vU0.png)

From this graph we can see that near `x=a`, the tangent line and the function have nearly the same graph. On occasion we will use the tangent line, `L(x)`, as an approximation to the function, `f(x)`, near `x=a`. In these cases we call the tangent line the linear approximation to the function at `x=a`.

Quadratic Approximation:

Same like linear approximation but this time we are dealing with a curve but we **cannot** find the point near to **0** by using the tangent line.

Instead, we use a **parabola** (*which is a curve where any point is at an equal distance from a fixed point or a fixed straight line*), like this:



[(https://i.stack.imgur.com/Yd2mE.png)](https://i.stack.imgur.com/Yd2mE.png)

And in order to fit a good parabola, both parabola and quadratic function should have same value, same first derivative, AND second derivative, ... the formula will be (*just out of curiosity*): `Qa(x) = f(a) + f'(a)(x-a) + f''(a)(x-a)2/2`

Now we should be ready to do the comparison in details.

In [2]:
```
# Import built-in modules
import os
import numpy as np # linear algebra
import itertools
from subprocess import check_output
from collections import Counter

def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
```

In [3]:
```
# Import 3rd party Python packages
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt #for plotting
from sklearn import linear_model, exceptions
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
# dividing into train and test
from sklearn.model_selection import train_test_split
import seaborn as sns
# print(check_output(["ls", "input"]).decode("utf8"))
# %matplotlib inline
```

In [4]:
```
WORKING_DIR = os.getcwd()
DATASET_DIR = os.path.join(WORKING_DIR, "dataset")
DATA_PATH_B = os.path.join(DATASET_DIR, "B.csv")
DATA_PATH_navy = os.path.join(DATASET_DIR, "navy_svm.csv")
```

In [5]:
```
# read data frame
# bdf = pd.read_csv(DATA_PATH_B)
navyData = pd.read_csv(DATA_PATH_navy)
navyData.head()
```

Out[5]:

	class	a1	a2	a3	a4	a5	a6
0	0	235.47	12.22	0.271	25.2	45.6	25.28
1	0	235.47	12.22	0.271	25.2	45.6	25.28
2	0	235.66	12.22	1.061	25.2	45.6	25.28
3	0	235.66	12.11	1.061	25.2	45.6	25.28
4	0	235.66	12.06	1.341	25.2	45.6	25.28

In [6]:
```
navyData.describe()
```

Out[6]:

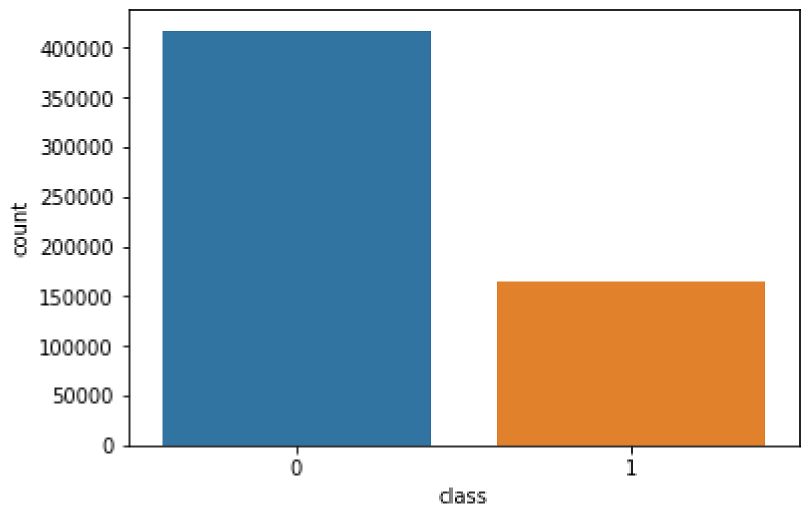
	class	a1	a2	a3	a4	a5	a6
count	582905.000000	582905.000000	582905.000000	582905.000000	582905.000000	582905.000000	582905.000000
mean	0.283895	232.478022	11.897178	0.784452	21.182873	38.854022	27.888130
std	0.450887	4.017430	0.372777	0.410430	3.781182	4.108154	1.400513
min	0.000000	217.590000	0.160000	0.031000	16.400000	27.900000	-11.550000
25%	0.000000	229.670000	11.640000	0.451000	18.400000	36.800000	26.880000
50%	0.000000	233.740000	11.860000	0.681000	20.100000	39.100000	27.540000
75%	1.000000	235.700000	12.080000	1.051000	22.700000	40.600000	28.670000
max	1.000000	244.600000	16.330000	5.781000	39.300000	52.700000	37.130000

In [7]:
```
navyData.groupby('class').mean()
```

Out[7]:

	a1	a2	a3	a4	a5	a6
class						
0	232.752346	11.800671	0.747009	19.535520	39.021003	27.171677
1	231.786060	12.140608	0.878898	25.338199	38.432825	29.695329

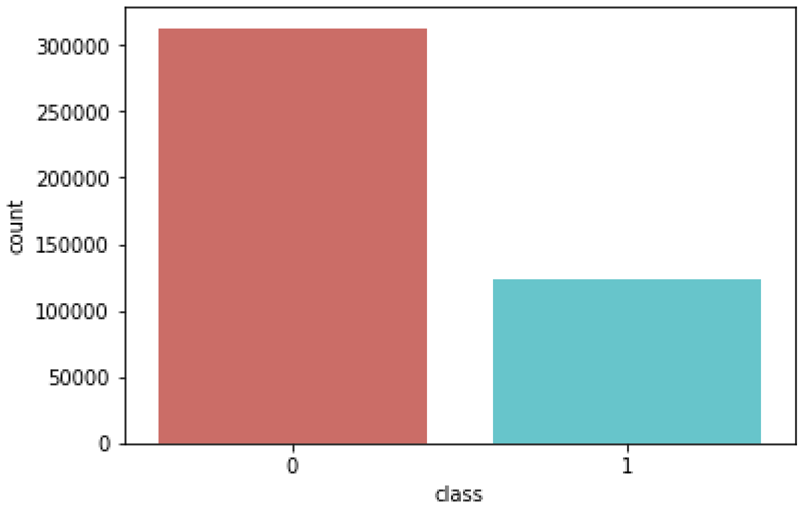
In [8]:
```
sns.countplot(navyData['class']);
```



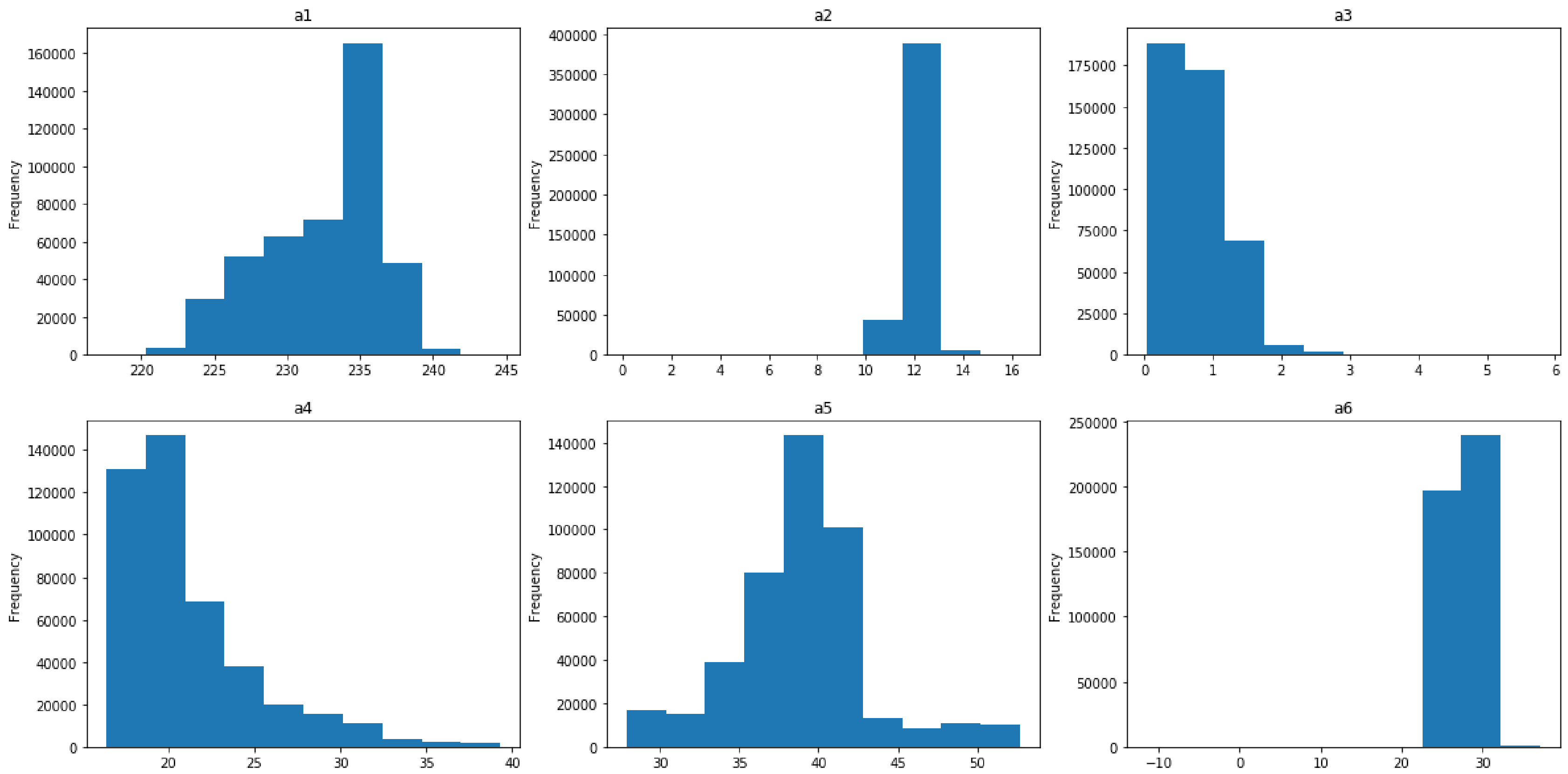
In [9]:
```
##Saperating attributes and labels
navy_data_attrib = navyData.iloc[:, 1:]
# preserves column header rather than converting to series navyData['class']
navy_data_class = navyData.iloc[:, [0]]

attrib_train, attrib_test, class_train, class_test = train_test_split(
            navy_data_attrib,
            navy_data_class,
        #     train_size=0.171556,  # Exact 100000 for train size 0.171556
        #     test_size=0.4,
            shuffle=True, # boolean, optional
            stratify=None # array-like or None: If not None,
                        #data is split in a stratified fashion, using this as the class labels.
)
```

In [10]:
```python
sns.countplot(x='class', data=class_train, palette='hls');
```



In [11]:
```python
# attrib_train.a1.plot(kind='hist', subplots=True, layout=(1,2));
# attrib_train.a2.plot(kind='hist', subplots=True, layout=(1,2));
# attrib_train.a2.hist(subplots=True, layout=(1,2));
r, c = 2, 3 # row x col
fig, axes = plt.subplots(nrows=r, ncols=c, figsize=(20, 10))
cols = ['a1','a2','a3', 'a4', 'a5', 'a6']
for i, var in enumerate(cols):
    attrib_train[var].plot(kind='hist', ax=axes[i//c, i%3], title=var)
```



Comparison between the methods

1. Newton's Method

Recall the motivation for gradient descent step at x: we minimize the quadratic function (i.e. Cost Function).

Newton's method uses in a sense a ***better*** quadratic function minimisation. A better because it uses the quadratic approximation (i.e. first AND *second* partial derivatives).

You can imagine it as a twisted Gradient Descent with The Hessian (*The Hessian is a square matrix of second-order partial derivatives of order nxn*).

Moreover, the geometric interpretation of Newton's method is that at each iteration one approximates `f(x)` by a quadratic function around `xn`, and then takes a step towards the maximum/minimum of that quadratic function (in higher dimensions, this may also be a saddle point). Note that if `f(x)` happens to be a quadratic function, then the exact extremum is found in one step.

Drawbacks:

1. It's computationally ***expensive*** because of The Hessian Matrix (i.e. second partial derivatives calculations).
2. It attracts to ***Saddle Points*** which are common in multivariable optimization (i.e. a point its partial derivatives disagree over whether this input should be a maximum or a minimum point!).

2. Limited-memory Broyden–Fletcher–Goldfarb–Shanno Algorithm:

In a nutshell, it is analogue of the Newton's Method but here the Hessian matrix is ***approximated*** using updates specified by gradient evaluations (or approximate gradient evaluations). In other words, using an estimation to the inverse Hessian matrix.

The term Limited-memory simply means it stores only a few vectors that represent the approximation implicitly.

If I dare say that when dataset is ***small***, L-BFGS relatively performs the best compared to other methods especially it saves a lot of memory, however there are some "*serious*" drawbacks such that if it is unsafeguarded, it may not converge to anything.

3. A Library for Large Linear Classification:

It's a linear classification that supports logistic regression and linear support vector machines (*A linear classifier achieves this by making a classification decision based on the value of a linear combination of the characteristics i.e feature value*).

The solver uses a coordinate descent (CD) algorithm that solves optimization problems by successively performing approximate minimization along coordinate directions or coordinate hyperplanes.

`LIBLINEAR` is the winner of ICML 2008 large-scale learning challenge. It applies *Automatic parameter selection* (a.k.a L1 Regularization) and it's recommended when you have high dimension dataset (*recommended for solving large-scale classification problems*)

Drawbacks:

1. It may get stuck at a *non-stationary point* (i.e. non-optima) if the level curves of a function are not smooth.
2. Also cannot run in parallel.
3. It cannot learn a true multinomial (multiclass) model; instead, the optimization problem is decomposed in a "one-vs-rest" fashion so separate binary classifiers are trained for all classes.

Side note: According to Scikit Documentation: The "liblinear" solver is used by default for historical reasons.

4. Stochastic Average Gradient:

SAG method optimizes the sum of a finite number of smooth convex functions. Like stochastic gradient (SG) methods, the SAG method's iteration cost is independent of the number of terms in the sum. However, by ***incorporating a memory of previous gradient values the SAG method achieves a faster convergence rate*** than black-box SG methods.

It is **faster** than other solvers for *large* datasets, when both the number of samples and the number of features are large.

Drawbacks:

1. It only supports L2 penalization.
2. Its memory cost of `O(N)`, which can make it impractical for large N (*because it remembers the most recently computed values for approx. all gradients*).

5. SAGA:

The SAGA solver is a *variant* of SAG that also supports the non-smooth *penalty=l1* option (i.e. L1 Regularization). This is therefore the solver of choice for ***sparse*** multinomial logistic regression and it's also suitable ***very Large*** dataset.

Side note: According to Scikit Documentation: The SAGA solver is often the best choice.

Summary

The following table is taken from [Scikit Documentation (http://scikit-learn.org/stable/modules/linear_model.html)](http://scikit-learn.org/stable/modules/linear_model.html)

Case	Solver
L1 penalty	"liblinear" or "saga"
Multinomial loss	"lbfgs", "sag", "saga" or "newton-cg"
Very Large dataset (n_samples)	"sag" or "saga"

[(https://i.stack.imgur.com/K568D.png)](https://i.stack.imgur.com/K568D.png)

In [12]:
```
if False:
    iterations = 1e5
    solvers = ["liblinear", "lbfgs", "sag", "newton-cg"]
    print("Applying Logistic Regression.../`-`\`|")
    print("{:<20}\t{:<20}".format("Classifier", "Accuracy"))
    print("{:<20}\t{:<20}".format("-"*20, "-"*20))
    for solver in solvers:
        print("{:<20}\t{:<20}".format("-"*20, "-"*20))
        logistic_reg_hypothesis = linear_model.LogisticRegression(
                                    C=iterations, # number of iterations
                                    multi_class="ovr",
                                    solver=solver  # solver
                                )
        logistic_reg_hypothesis.fit(attrib_train, class_train.values.ravel())
        y_pred = logistic_reg_hypothesis.predict(attrib_test)
        print("{:<20}\t{:<20}".format(solver, accuracy_score(class_test['class'], y_pred)))
```

In [13]:
```
# # and plot the result
# plt.figure(1, figsize=(4, 3))
# plt.clf()
# plt.scatter(navy_data_attrib.ravel(), navy_data_class, color='black', zorder=20)
# # X_test = np.linspace(-5, 10, 300)
```

With Technique for Classification multinomial

In [14]:
```
# iterations = 1e2
solvers = ["liblinear", "lbfgs", "sag", "newton-cg"][:3]
print("Applying Logistic Regression.../`-`\`|")
print("{:<10}\t{:<20}\t{:<20}".format("Classifier", "No. of Iterations", "Accuracy"))
# print("{:<20}\t{:<20}".format("-"*20, "-"*20))
for i in range(1, 8):
    print("="*50)
    iterations = 10**i
    for solver in solvers:
#         print("{:<20}\t{:<20}".format("-"*20, "-"*20))
        print("{:<10}\t{:<20}".format(solver, iterations), end="")
        logistic_reg_hypothesis = linear_model.LogisticRegression(
                    C=iterations, # number of iterations
                    multi_class="multinomial" if solver != "liblinear" else "ovr",
                    solver=solver  # solver
                )
        logistic_reg_hypothesis.fit(attrib_train, class_train.values.ravel())
        y_pred = logistic_reg_hypothesis.predict(attrib_test)
        print("\t{:<20}".format(accuracy_score(class_test['class'], y_pred)))
    #     print('Classifier: {} having accuracy: {:.20f}'.format(solver, accuracy_score(class_test['clas
s'], y_pred)))
```

```
Applying Logistic Regression.../`-`\`|
Classifier      No. of Iterations       Accuracy
==================================================
liblinear       10                      0.9573929333616968
lbfgs           10                      0.9650305022404908
sag             10                      0.9570978610689852
==================================================
liblinear       100                     0.9573929333616968
lbfgs           100                     0.9659843405820473
sag             100                     0.9570704124836166
==================================================
liblinear       1000                    0.9605083478010252
lbfgs           1000                    0.9671371811675256
sag             1000                    0.9574684169714603
==================================================
liblinear       10000                   0.9604534506302882
lbfgs           10000                   0.9658539598015468
sag             10000                   0.9575439005812239
==================================================
liblinear       100000                  0.9568096509226156
lbfgs           100000                  0.9657853383381254
sag             100000                  0.9575919356056187
==================================================
liblinear       1000000                 0.9573929333616968
lbfgs           1000000                 0.9657304411673884
sag             1000000                 0.9570841367763009
==================================================
liblinear       10000000                0.9573929333616968
lbfgs           10000000                0.9657235790210462
sag             10000000                0.9574890034104867
```

In [15]:

```python
# iterations = 1e2
RUN_NEWTON_METHOD = False
if RUN_NEWTON_METHOD:
    solvers = ["newton-cg"]
    print("Applying Logistic Regression.../`-`\`|")
    print("{:<10}\t{:<20}\t{:<20}".format("Classifier", "No. of Iterations", "Accuracy"))
    # print("{:<20}\t{:<20}".format("-"*20, "-"*20))
    for i in range(1, 8):
        print("="*50)
        iterations = 10**i
        for solver in solvers:
    #        print("{:<20}\t{:<20}".format("-"*20, "-"*20))
            print("{:<10}\t{:<20}".format(solver, iterations), end="")
            logistic_reg_hypothesis = linear_model.LogisticRegression(
                                    C=iterations, # number of iterations
                                    multi_class="ovr",
                                    solver=solver  # solver
                                )
            logistic_reg_hypothesis.fit(attrib_train, class_train.values.ravel())
            y_pred = logistic_reg_hypothesis.predict(attrib_test)
            print("\t{:<20}".format(accuracy_score(class_test['class'], y_pred)))
```

With Technique for Classification One v/s All

In [16]:

```python
# iterations = 1e2
solvers = ["liblinear", "lbfgs", "sag", "saga", "newton-cg"][:4]
print("Applying Logistic Regression.../`-`\`|")
print("{:<10}\t{:<20}\t{:<20}".format("Classifier", "No. of Iterations", "Accuracy"))
# print("{:<20}\t{:<20}".format("-"*20, "-"*20))
for i in range(1, 7):
    print("="*50)
    iterations = 10**i
    for solver in solvers:
#        print("{:<20}\t{:<20}".format("-"*20, "-"*20))
        print("{:<10}\t{:<20}".format(solver, iterations), end="")
        logistic_reg_hypothesis = linear_model.LogisticRegression(
                                    C=iterations, # number of iterations
                                    multi_class="ovr",
                                    solver=solver  # solver
                                )
        logistic_reg_hypothesis.fit(attrib_train, class_train.values.ravel())
        y_pred = logistic_reg_hypothesis.predict(attrib_test)
        print("\t{:<20}".format(accuracy_score(class_test['class'], y_pred)))
```

```
Applying Logistic Regression.../`-`\`|
Classifier      No. of Iterations       Accuracy
==================================================
liblinear       10                      0.9573929333616968
lbfgs           10                      0.9665538987284443
sag             10                      0.9565557515079567
saga            10                      0.9565969243860094
==================================================
liblinear       100                     0.9573929333616968
lbfgs           100                     0.9671028704358149
sag             100                     0.956521440776246
saga            100                     0.9566106486786937
==================================================
liblinear       1000                    0.9605083478010252
lbfgs           1000                    0.9672881483870525
sag             1000                    0.9565832000933252
saga            1000                    0.9566037865323516
==================================================
liblinear       10000                   0.9604534506302882
lbfgs           10000                   0.9667048659479712
sag             10000                   0.9565694758006409
saga            10000                   0.9565969243860094
==================================================
liblinear       100000                  0.9568096509226156
lbfgs           100000                  0.9670891461431307
sag             100000                  0.9565694758006409
saga            100000                  0.9566037865323516
==================================================
liblinear       1000000                 0.9573929333616968
lbfgs           1000000                 0.9669381789236037
sag             1000000                 0.9566449594104044
saga            1000000                 0.9566106486786937
```