Project4

December 8, 2021

[123]:
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import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets

#Problem 1
def gradient_descent(X, Y, alpha, T):
    m, n = X.shape # examples m and features n
    loss_f = np.zeros(T) # track loss
    theta = np.zeros(n)
    for i in range(T):
        loss_f[i] = 1/(2*m)*np.linalg.norm(X.dot(theta) - Y)**2 # compute␣
↪steepest ascent at f(theta)
        gradient = (1/m)*np.transpose(X).dot(X.dot(theta) - Y)
        theta = theta - alpha*gradient
    return theta, loss_f
```

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#Problem 2
#Based on the sigmoid function h(x) = 1/(1+e^(theta*x^i)), there are m␣
↪observations.
# First, apply log on the both sides of h(x), we got -log(1+e^(-theta*x))
# Transform log(1+e^-theta*x) into -theta*x^i-log(1+e^(-theta*x^i))
#loss function is  f(theta) = 1/m * (sum from 1 to m(yi*log(h(xi))+(1-yi) *␣
↪log(1-h(xi))).
# Plug log(h(xi)) and log(1-h(xi)) into loss function
#After simplified, it becomes -1/m * (sum from 1 to m(yi*theta*xi -␣
↪log(1+e^(theta*xi)))
# By using log property, theta*xi - log(1+e^(theta*xi)) is equalt to␣
↪-log(1+e^(theta*xi))
#Compute the partial derivative theta j, of yi*theta*xi
#The answer is yi * x^i j
#The partial derivative theta j of log(1+e^(theta*xi))
#The answer is x^ij*h theta(x^i)
```

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# The partial derivative theta j of f(theta) is sum from 1 to m(yi - h␣
↪theta(xi))*xi
#theta j = theta j - alpha * derivative theta j of f(theta)
#theta j = theta j - alpha * (sum from 1 to m(h theta(xi)-yi)*xi)
```

[134]:
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#Problem 3
def log_gradient_descent(X, y, alpha, T):
    m, n = X.shape  # examples m and features n
    loss_of_f = np.zeros(T) #track loss
    y = np.array(y)
    theta = np.zeros(n)
    for i in range(T):
            h = float(1)/(1+np.exp(-np.dot(X,theta)))
            loss_of_f[i] = -(y * np.log(h) + (1-y) * np.log(1-h)).mean()
            gradient = np.transpose(X).dot(h-y)/m
            theta = theta - alpha*gradient
    return theta, loss_of_f
```

[135]:
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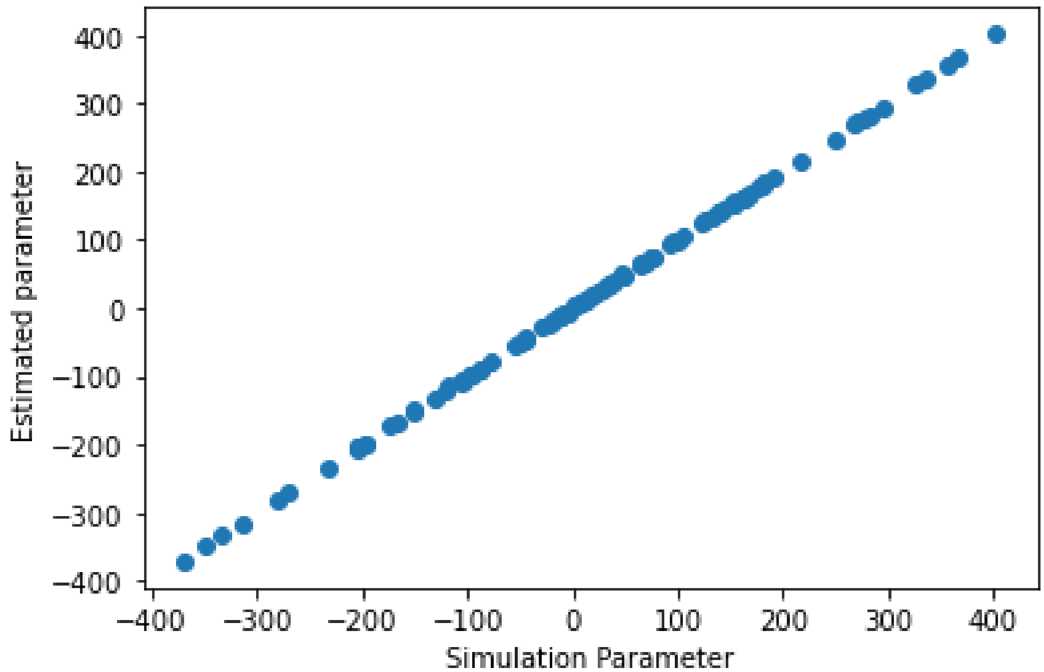
#Problem 4
gen_data_x, gen_data_y = sklearn.datasets.make_regression(n_samples=100,
n_features=20, noise = 1.5)
T = 300
alpha = 0.1
theta, loss = gradient_descent(gen_data_x, gen_data_y, alpha, T)
y_h = gen_data_x*theta
y_h = np.sum(y_h, axis=1)
plt.scatter(x=gen_data_y, y=y_h)
plt.xlabel("Simulation Parameter")
plt.ylabel("Estimated parameter")
plt.show()
```



[136]:
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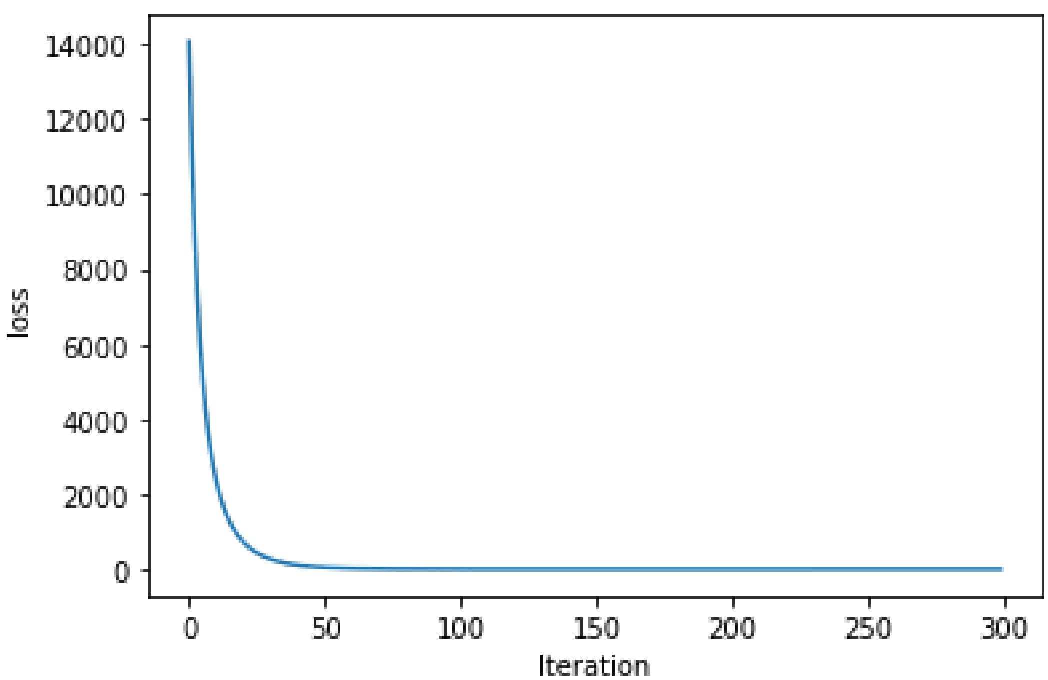
plt.xlabel("Iteration")
plt.ylabel("loss")
plt.plot(np.arange(T), loss)
```

[136]: `[<matplotlib.lines.Line2D at 0x40804c1790>]`



[137]:
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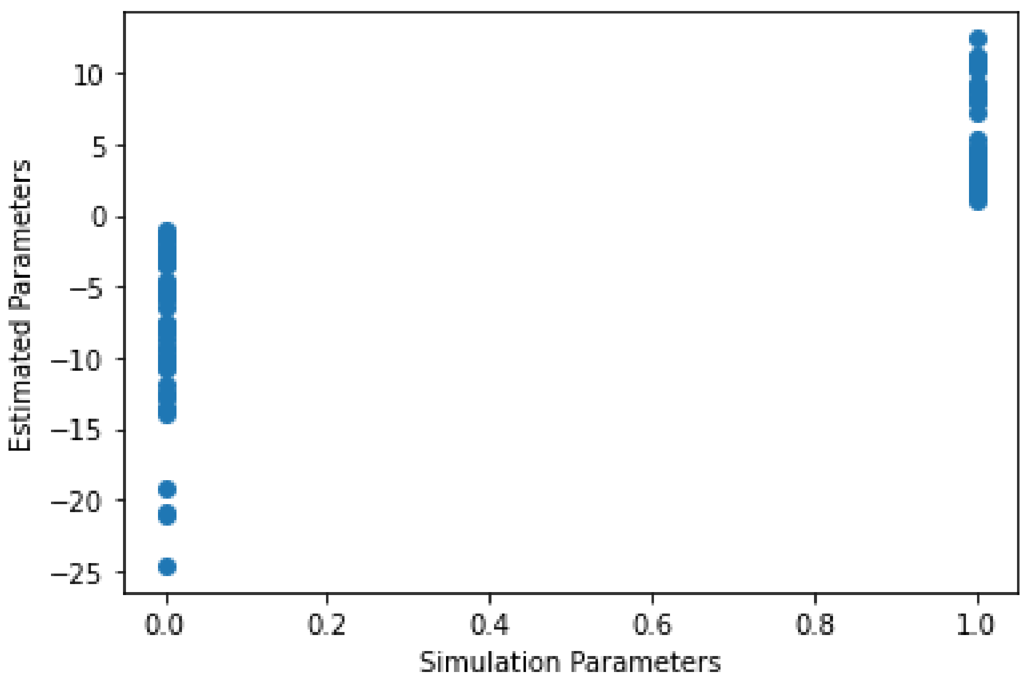
#The first plot shows that the predictions fit the simiuation well.
#From the second plot, we can find that the loss decreases as the iteration␣
↪increases.
```

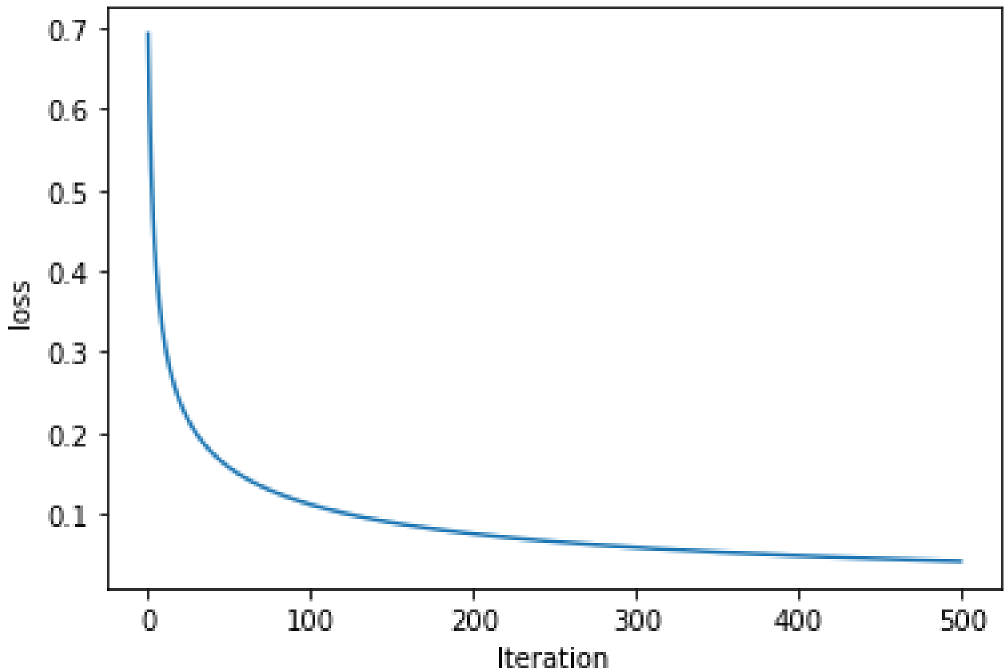
[138]:
```
#simulate data for logistic regression.
log_gen_data_x, dump_y = sklearn.datasets.make_regression(n_samples=100,␣
↪n_features=20, noise = 1.5)
log_gen_data_y = [0 if i>0 else 1 for i in dump_y]
T = 500
alpha = 0.5
log_theta, log_loss = log_gradient_descent(log_gen_data_x, log_gen_data_y,␣
↪alpha, T)
y_h = np.zeros(len(log_gen_data_y))
for i in range(len(log_gen_data_x[0])):
    y_h += log_gen_data_x[:,i]*log_theta[i]
plt.xlabel("Simulation Parameters")
plt.ylabel("Estimated Parameters")
plt.scatter(x=log_gen_data_y, y=y_h)
```

[138]: <matplotlib.collections.PathCollection at 0x4081454d90>



[139]:
```python
plt.xlabel("Iteration")
plt.ylabel("loss")
plt.plot(np.arange(T), log_loss)
```

[139]: [<matplotlib.lines.Line2D at 0x409321a550>]



[152]:
```python
# I am going to use the iris dataset from the sklearn module.
# According to the length and width, I would predict whether
#an iris is an iris setosa(numeric 0) or an iris versicolour (numeric 1).
# I am going to use classification tree and k-NN classification algorithms.
iris = datasets.load_iris()
X = iris.data[:,:2] # Choose the first 2 features
Y = [0 if i>0.5 else 1 for i in iris.target] #convert 3 labels to 2 labels
DataX = pd.DataFrame(X)
Datay = pd.DataFrame(Y)
```

[153]:
```python
from sklearn.base import BaseEstimator
from sklearn.base import RegressorMixin

class Logreg_model(BaseEstimator, RegressorMixin):

    def __init__(self, T, alpha):
        super().__init__()
        self.params_ = None
        self.loss_ = None
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        self.T = T
        self.alpha = alpha

    def fit(self, X, y):
        theta, loss = log_gradient_descent(X, y, self.alpha,self.T)
        self.params_ = theta
        self.loss_ = loss
        return self

    def predict(self, X):
        log_y_hat = np.sum(X * self.params_, axis = 1)
        log_y_hat = [0 if i<0 else 1 for i in log_y_hat]
        return log_y_hat
```

[154]:
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cv = KFold(n_splits=10, random_state=1, shuffle=True)
T=500
alpha =0.5
model = Logreg_model(T, alpha ).fit(X,Y)
Poly_SVC_scores = cross_val_score(model, X, Y, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)
print('Accuracy: mean: %.3f (std: %.3f)' % (np.mean(Poly_SVC_scores), np.
 ↪std(Poly_SVC_scores)))
```

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Accuracy: mean: 0.993 (std: 0.020)
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[155]:
```
#Using knn

from scipy import stats
from sklearn.model_selection import *
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
model = KNeighborsClassifier()
cv = KFold(n_splits = 10,shuffle=True, random_state = 2)
KNN_scores = cross_val_score(model, X, Y, scoring='accuracy', cv=cv)
print("Average 10-fold score:" +str(KNN_scores.mean()))
```

```
Average 10-fold score:0.9933333333333334
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[156]:
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# Using Classification tree
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
cv = KFold(n_splits = 10,shuffle=True, random_state = 2)
svm_scores = cross_val_score(model, X, Y, scoring='accuracy', cv=cv)
print("Average 10-fold score:" +str(svm_scores.mean()))
```

```
Average 10-fold score:0.9800000000000001
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[157]:
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#According to the average 10fold score, the prediction performance of ␣
↪Logreg_model
# is better.
```