In [178]:
```
# Import relevant packages
import numpy as np
import cvxpy as cp
import matplotlib.pyplot as plt
import pandas as pd
```

In [179]:
```
# Load the data
data = pd.read_csv('data.csv')
# Process the data
for i in range(len(data)):
    if data.iloc[i, 1] == 'M':
        data.iloc[i, 1] = 1
    else:
        data.iloc[i, 1] = 0
# Take a look at the data
data.head()
```

Out[179]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_me
0	842302	1	17.99	10.38	122.80	1001.0	0.118
1	842517	1	20.57	17.77	132.90	1326.0	0.084
2	84300903	1	19.69	21.25	130.00	1203.0	0.109
3	84348301	1	11.42	20.38	77.58	386.1	0.142
4	84358402	1	20.29	14.34	135.10	1297.0	0.100

5 rows × 33 columns

In [180]:
```
# Divide the dataset into training and test set
X = np.array(data.iloc[:350, 2:32])
Y = np.array(data.iloc[:350, 1])
X_test = np.array(data.iloc[350:, 2:32])
Y_test = np.array(data.iloc[350:, 1])

# Dimension of training set, 350 observations and 30 independent variabl
es
m = 30
n = 350
# Number of lambdas
N = 100
```

Logistic Regression

In [181]:

```
# Formulate the optimization problem
def logistic(Y, X, m, n, lamb):
    # Define variables
    beta = cp.Variable(m)
    s = cp.Variable(m)
    # Log-likelihood function
    log_likelihood = cp.sum(
        cp.multiply(Y, X @ beta) - cp.logistic(X @ beta)
    )
    # Minimize the negate of the log-likelihood
    objective = cp.Minimize(-log_likelihood/m + lamb * cp.sum(s))
    # Constraints for slack variable
    constraints = [beta <= s, beta >= -s, s >= 0]
    # Formulate the problem
    problem = cp.Problem(objective, constraints)

    # Get the optimal value
    return problem.solve(), beta.value
```

In [182]:

```
# Predict the labels
def pred(beta, X):
    # Product between X and beta
    ls = X @ beta
    for i in range(len(ls)):
        # Benign if negative
        if ls[i] <= 0:
            ls[i] = 0
        # Malignant if positive
        else:
            ls[i] = 1
    return ls

# Error test
def regression_error(pred, actual):
    # If prediction is wrong, the difference between it and actual label
is either -1 or 1
    # Get the percentage of wrong predictions
    return np.sum(np.abs(pred - actual)) / float(np.size(actual))
```

In [194]:
```
# Simulation with different lambdas
def logistic_sim(m, n, N, X, Y, X_test, Y_test):
    # Store the results
    error_train = []
    error_test = []
    lambda_ = np.logspace(-2, 0, N)
    beta_vals = []
    outcome_ls = []
    for i in range(N):
        # Run logistic regression
        outcome, beta = logistic(Y, X, m, n, lambda_[i])
        beta_vals.append(beta)
        outcome_ls.append(outcome)
        # Run predictions
        predict_train = pred(beta, X)
        predict_test = pred(beta, X_test)
        # Run accuracy test
        train_err = regression_error(predict_train, Y)
        error_train.append(train_err)
        test_err = regression_error(predict_test, Y_test)
        error_test.append(test_err)
    return beta_vals, outcome_ls, error_train, error_test
```

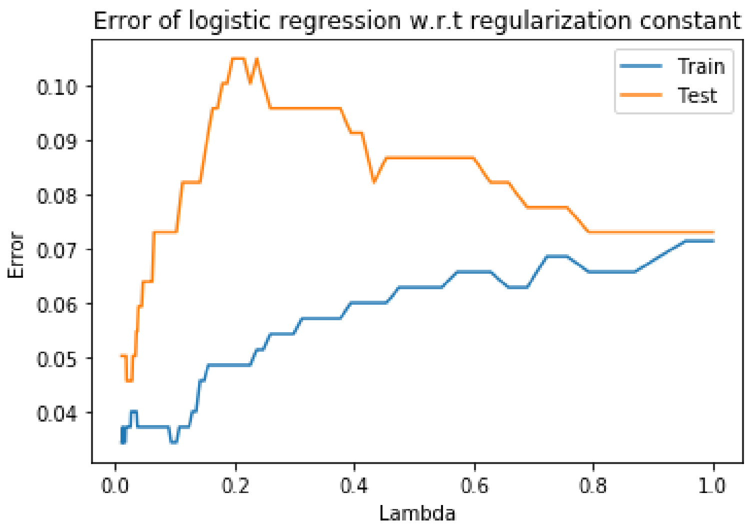
In [195]:
```
beta_vals_log, outcome_ls_log, error_train_log, error_test_log = logisti
c_sim(m, n, N, X, Y, X_test, Y_test)
```

In [185]:
```
print('Training error for the first 20 lambdas: {}'.format(error_train_l
og[:20]))
print('Test error for the first 20 lambdas: {}'.format(error_test_log[:2
0]))
```

```
Training error for the first 20 lambdas is [0.03428571428571429, 0.0342
8571428571429, 0.03428571428571429, 0.03428571428571429, 0.037142857142
857144, 0.037142857142857144, 0.03428571428571429, 0.03428571428571429,
0.03428571428571429, 0.03428571428571429, 0.03428571428571429, 0.034285
71428571429, 0.037142857142857144, 0.037142857142857144, 0.037142857142
857144, 0.037142857142857144, 0.037142857142857144, 0.03714285714285714
4, 0.037142857142857144, 0.037142857142857144]
Test error for the first 20 lambdas is [0.0502283105022831, 0.050228310
5022831, 0.0502283105022831, 0.0502283105022831, 0.0502283105022831, 0.
0502283105022831, 0.0502283105022831, 0.0502283105022831, 0.05022831050
22831, 0.0502283105022831, 0.0502283105022831, 0.0502283105022831, 0.05
02283105022831, 0.0502283105022831, 0.045662100456621, 0.04566210045662
1, 0.045662100456621, 0.045662100456621, 0.045662100456621, 0.045662100
456621]
```

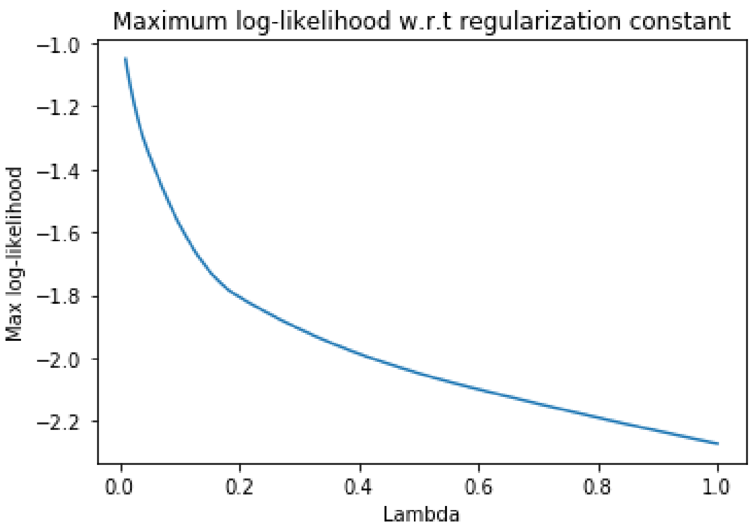
In [196]:
```
# Error plot w.r.t lambda
lambda_ls = np.logspace(-2, 0, N)
plt.figure()
plt.plot(lambda_ls, error_train_log, label='Train')
plt.plot(lambda_ls, error_test_log, label='Test')
plt.title('Error of logistic regression w.r.t regularization constant')
plt.xlabel('Lambda')
plt.ylabel('Error')
plt.legend()
```

Out[196]: <matplotlib.legend.Legend at 0x822154710>



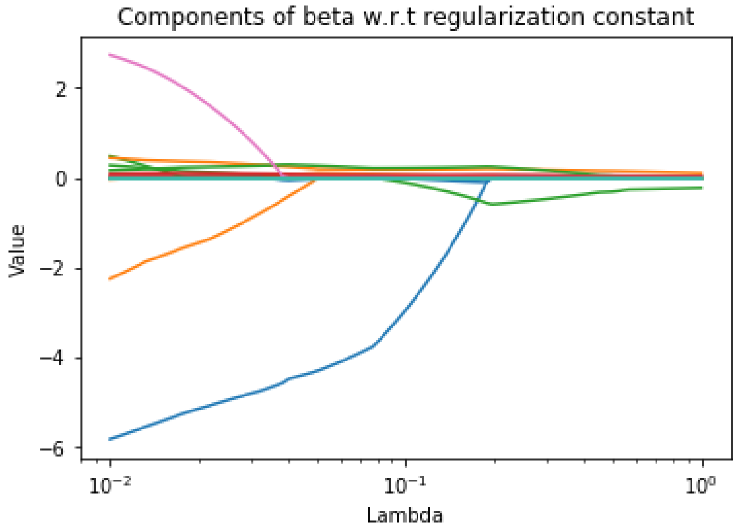
In [201]:
```
# Maximum log-likelihood w.r.t lambda
plt.figure()
plt.plot(lambda_ls, -np.array(outcome_ls_log))
plt.title('Maximum log-likelihood w.r.t regularization constant')
plt.xlabel('Lambda')
plt.ylabel('Max log-likelihood')
```

Out[201]: Text(0,0.5,'Max log-likelihood')



In [193]:
```
# Beta values w.r.t lambda
plt.figure()
for i in range(m):
    plt.plot(lambda_ls, [each[i] for each in beta_vals_log])
plt.title('Components of beta w.r.t regularization constant')
plt.xscale('log')
plt.xlabel('Lambda')
plt.ylabel('Value')
```

Out[193]: Text(0,0.5,'Value')



SVM

In [202]:
```
# Formulate the optimization problem
def svm(Y, X, m, n, lamb):
    # Define the variables
    beta = cp.Variable((m,1))
    v = cp.Variable()
    s = cp.Variable((m, 1))
    # Loss function
    loss = cp.sum(cp.pos(1 - cp.multiply(Y, X*beta - v)))
    # Minimize loss
    objective = cp.Minimize(loss/n + lamb*cp.sum(s))
    # Constraints for slack variable
    constraints = [beta <= s, beta >= -s, s >= 0]
    # Formulate the problem
    problem = cp.Problem(objective, constraints)
    # Get optimal values
    return problem.solve(), beta.value, v.value
```

In [203]:
```
# Predict the labels
def pred_svm(beta, X, v):
    f = X @ beta
    ls = np.array([each[0] for each in f]) - v
    for i in range(len(ls)):
        # Benign if negative
        if ls[i] <= 0:
            ls[i] = -1
        # Malignant if positive
        else:
            ls[i] = 1
    return ls

# Error of SVM
def svm_error(pred, actual):
    actual = [each[0] for each in actual]
    # -1 and 1 are indicators, hence if predict and actual are differen
t, their sum is zero
    return len(np.where(pred + actual == 0)[0]) / float(np.size(actual))
```

In [204]:
```
# Simulate SVM with different lambdas
def svm_sim(m, n, N, X, Y, X_test, Y_test):
    # Process data
    for i in range(len(Y_test)):
        if Y_test[i] == 0:
            Y_test[i] = -1
    Y_test = np.array([[each] for each in Y_test])
    for i in range(len(Y)):
        if Y[i] == 0:
            Y[i] = -1
    Y = np.array([[each] for each in Y])

    # Store the outcomes
    error_train = []
    error_test = []
    lambda_ = np.logspace(-2, 0, N)
    beta_vals = []
    v_vals = []
    outcome_ls = []
    for i in range(N):
        # Run SVM
        outcome, beta, v = svm(Y, X, m, n, lambda_[i])
        beta_vals.append(beta)
        v_vals.append(v)
        outcome_ls.append(outcome)
        # Run predictions
        predict_train = pred_svm(beta, X, v)
        predict_test = pred_svm(beta, X_test, v)
        # Run error test
        train_err = svm_error(predict_train, Y)
        error_train.append(train_err)
        test_err = svm_error(predict_test, Y_test)
        error_test.append(test_err)
#     actual = [each[0] for each in Y]
    return beta_vals, outcome_ls, error_train, error_test
```

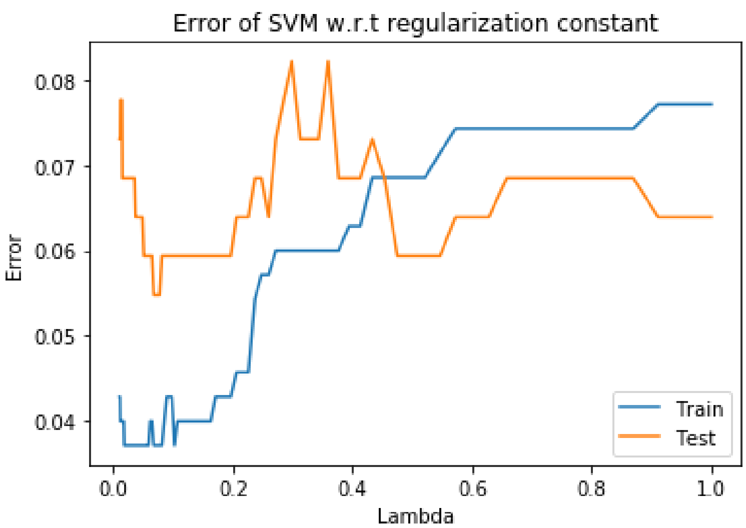
In [205]:
```
beta_vals_svm, outcome_ls_svm, error_train_svm, error_test_svm = svm_sim
(m, n, 100, X, Y, X_test, Y_test)
```

In [206]:
```
print('Training error for the first 20 lambdas: {}'.format(error_train_s
vm[:20]))
print('Test error for the first 20 lambdas: {}'.format(error_test_svm[:2
0]))
```

```
Training error for the first 20 lambdas: [0.04285714285714286, 0.042857
14285714286, 0.04285714285714286, 0.04, 0.04, 0.04, 0.04, 0.04, 0.04,
0.04, 0.04, 0.04, 0.04, 0.037142857142857144, 0.037142857142857144, 0.0
37142857142857144, 0.037142857142857144, 0.037142857142857144, 0.037142
857142857144, 0.037142857142857144]
Test error for the first 20 lambdas: [0.0730593607305936, 0.07305936073
05936, 0.0730593607305936, 0.0776255707762557, 0.0776255707762557, 0.07
76255707762557, 0.0776255707762557, 0.0776255707762557, 0.0776255707762
557, 0.0684931506849315, 0.0684931506849315, 0.0684931506849315, 0.0684
931506849315, 0.0684931506849315, 0.0684931506849315, 0.068493150684931
5, 0.0684931506849315, 0.0684931506849315, 0.0684931506849315, 0.068493
1506849315]
```

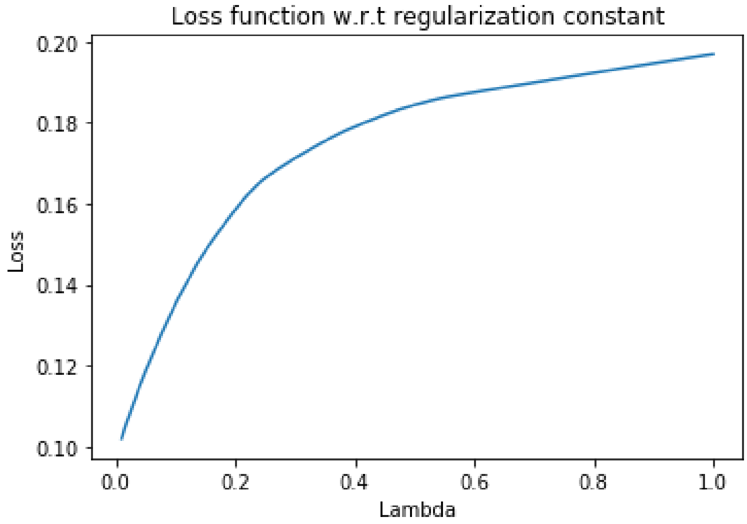
In [207]:
```
# Error plot w.r.t lambda
lambda_ls = np.logspace(-2, 0, N)
plt.figure()
plt.plot(lambda_ls, error_train_svm, label='Train')
plt.plot(lambda_ls, error_test_svm, label='Test')
plt.title('Error of SVM w.r.t regularization constant')
plt.xlabel('Lambda')
plt.ylabel('Error')
plt.legend()
```

Out[207]: <matplotlib.legend.Legend at 0x822637080>



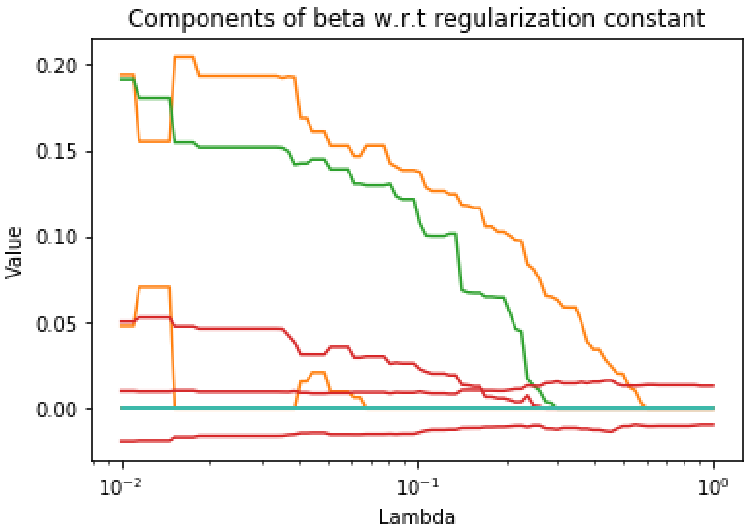
In [209]:
```
# Loss function w.r.t lambda
plt.figure()
plt.plot(lambda_ls, outcome_ls_svm)
plt.title('Loss function w.r.t regularization constant')
plt.xlabel('Lambda')
plt.ylabel('Loss')
```

Out[209]:
```
Text(0,0.5,'Loss')
```



In [210]:
```
# Beta values w.r.t lambda
plt.figure()
for i in range(m):
    plt.plot(lambda_ls, [each[i] for each in beta_vals_svm])
plt.title('Components of beta w.r.t regularization constant')
plt.xscale('log')
plt.xlabel('Lambda')
plt.ylabel('Value')
```

Out[210]:
```
Text(0,0.5,'Value')
```



In [ ]: