

# SUPPORT VECTOR MACHINES

Panagiotis Karvounaris AEM 10193

December 24, 2023

A report presented for the course of Neural Networks: Deep learning Aristotle University of Thessaloniki Faculty of Electrical and Computer Engineering

# Contents

1	Introduction	3
<b>2</b>	Code Description	4
	2.1 Load and Preprocess the CIFAR-10 dataset	4
	2.2 PCA	4
	2.3 Options For Gamma Parameters and RBF Kernel SVC	4
	2.4 Save Data to File	5
	2.5 Training SVM Models	5
	2.6 No PCA, 5000 Samples	6
	2.7 No PCA, 10000 Samples	7
	2.8 No PCA, 10000 Samples	9
	2.9 PCA, 5000 Samples, Best Cases	10
	2.10 PCA, 10000 Samples, Best Cases	13
	2.11 PCA, 50000 Samples, Best Cases	16
3	Issues	19
4	Conclusion	19

# 1 Introduction

The goal of this project is to use the Support Vector Machines (SVM), from sklearn python library, to classify correctly the pictures of CIFAR-10 dataset. The dataset is consisted of pictures 32x32 pixels and coloured. We will use different SVMs and options for training in order to achieve the highest test accuracy. We start training a variety of parameters with different values for all the possible SVMs with the use of 5000 samples. This decision was made due to time limitation for these many SVMs' training. After this run, we will save the best results and run again for 10000 samples. We save the results of this run too. Then, we do the 10000 samples run again but we are using PCA to preprocess the training and test data. At the end, we get the parameters that gave us the best results from the above and use this train cases to train the SVM to 50000 samples (the whole dataset).

# 2 Code Description

In order to test multiple SVMs and a great variety of parameters, we used COTS SVMs from sklearn library. The code analysis is explained below.

# 2.1 Load and Preprocess the CIFAR-10 dataset

We use the 'tensorflow.keras.datasets' library to load the CIFAR-10 dataset. First of all, we load the data for training and testing, then we reshape the image data and scales the pixel values dividing by 255. We reshape the original image data from a 4D array to a 2D array. It uses information about the number of samples, image height, image width, and the number of channels. So, each image has a total of 32x32x3 = 3072 features. Furthermore, we shuffle the data in order to have better results in the training for 5000 and 10000 samples.

```
import tensorflow as tf
from sklearn.utils import shuffle

(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

x_train = x_train.reshape((-1, 3072)) / 255.0

x_test = x_test.reshape((-1, 3072)) / 255.0

y_train = y_train.ravel()

y_test = y_test.ravel()

x_train, y_train = shuffle(x_train, y_train, random_state=0)
```

### 2.2 PCA

For most of the training instances we use Primary Component Analysis (PCA), in order to speed up the training process. PCA is a linear dimensionality reduction technique and we use to to reduce the every image dimension from 3072 to about 100 dimensions, while keeping at least 90 percent of the initial information of the image. The speed of the training is improving, thus we can use more training samples, so we end up training a bigger potion of the dataset at the same time, that increases the performance of the SVM.

```
from sklearn.decomposition import PCA
pca = PCA(0.9).fit(x_train)
pca_train_data = pca.transform(x_train)
pca_test_data = pca.transform(x_test)
```

# 2.3 Options For Gamma Parameters and RBF Kernel SVC

if gamma is equal to 'scale', which is the default option, then it uses  $1/(n_{-}features*X.var())$  as value of gamma.

if gamma is equal 'auto', gamma is uses  $1/n\_features$  if decision function shape = "ovo", whether to return a one-vs-rest ('ovr') decision function of shape (n\_samples, n\_classes) as all other classifiers, or the original one-vs-one ('ovo') decision function of libsvm which has shape (n\_samples, n\_classes \* (n\_classes - 1) / 2). However, note that internally, one-vs-one ('ovo') is always used as a multi-class strategy to train models

### 2.4 Save Data to File

In order to keep track of the results and use them afterwards to reach conclusions, we save the results of the training in a .txt file. We could use grid search in order to obtain the best combination of parameters, but we chose to run all the the SVM models and find the best combination manually. We also print the results in terminal for progress notification reasons.

```
def print_and_log(text, log_file):
    print(text)
    log_file.write(text + '\n')

with open("svm_log.txt", "w") as log_file:
    print_and_log('data to be saved', log_file)
```

# 2.5 Training SVM Models

1) Linear Kernel, 6 values for C

$$C = [0.1, 1, 10, 50, 100, 1000]$$

2) Polynomial Kernel, 2 values for degree, 6 values for C and 7 values for gamma

$$degree = \begin{bmatrix} 2, 3 \end{bmatrix}$$
 
$$C = \begin{bmatrix} 0.1, 1, 10, 50, 100, 1000 \end{bmatrix}$$
 
$$qamma = \begin{bmatrix} 'scale', 'auto', 0.1, 0.5, 1, 10, 20 \end{bmatrix}$$

3) Sigmoid Kernel, 6 values for C and 7 values for gamma

$$C = \begin{bmatrix} 0.1, 1, 10, 50, 100, 1000 \end{bmatrix}$$

$$gamma = \left['scale', 'auto', 0.1, 0.5, 1, 10, 20\right]$$

4) Radial Basis Function (RBF) Kernel, 6 values for  ${\bf C}$  and 7 values for gamma

$$C = [0.1, 1, 10, 50, 100, 1000]$$

$$gamma = \left[ 'scale', 'auto', 0.1, 0.5, 1, 10, 20 \right]$$

# 2.6 No PCA, 5000 Samples

```
for C in [0.1, 1, 10, 50, 100, 1000]:
    start_time = time()
    linearSVM = SVC(kernel='linear', C=C)
    linearSVM.fit(x_train[:5000], y_train[:5000])
    output = "Linear Kernel, C = " + str(C) + "\n"
    output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(linearSVM.score(x_train[:5000], y_train[:5000])) + '
    output += "Test accuracy = " + str(linearSVM.score(x_test, y_test)) + "\n"
    print_and_log(output, log_file)
for degree in [2, 3]:
    for C in [0.1, 1, 10, 50, 100, 1000]:
        for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
            start_time = time()
            polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma)
            polySVM.fit(x_train[:5000], y_train[:5000])
            output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", C
            output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
            output += "Elapsed time: " + str(time() - start_time) + "\n"
            output += "Train accuracy = " + str(polySVM.score(x_train[:5000], y_train[:5000]
            output += "Test accuracy = " + str(polySVM.score(x_test, y_test)) + "\n"
            print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        sigmoidSVM = SVC(kernel='sigmoid', C=C, gamma=gamma)
        sigmoidSVM.fit(x_train[:5000], y_train[:5000])
        output = "Sigmoid Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(sigmoidSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
        output += "Train accuracy = " + str(sigmoidSVM.score(x_train[:5000], y_train[:5000])
        output += "Test accuracy = " + str(sigmoidSVM.score(x_test, y_test)) + "\n"
        print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
        rbfSVM.fit(x_train[:5000], y_train[:5000])
        output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
```

```
output += "Train accuracy = " + str(rbfSVM.score(x_train[:5000], y_train[:5000])) +
        output += "Test accuracy = " + str(rbfSVM.score(x_test, y_test)) + "\n"
        print_and_log(output, log_file)
  Best results are below:
  - RBF Kernel, C = 10, Gamma = scale
Number of support vectors = [466\ 473\ 486\ 527\ 470\ 543\ 480\ 483\ 433\ 501]
Elapsed time: 48.928696155548096
Train accuracy = 0.997
Test accuracy = 0.4462
   - RBF Kernel, C = 50, Gamma = scale
Number of support vectors = [470\ 473\ 486\ 527\ 470\ 542\ 482\ 484\ 429\ 501]
Elapsed time: 48.48292779922485
Train accuracy = 1.0
Test accuracy = 0.4414
   - RBF Kernel, C = 100, Gamma = scale
Number of support vectors = [470 \ 473 \ 487 \ 527 \ 470 \ 542 \ 482 \ 484 \ 429 \ 501] //
Elapsed time: 47.37176752090454
Train accuracy = 1.0
Test accuracy = 0.4414
   - RBF Kernel, C = 1000, Gamma = scale
Number of support vectors = [470 \ 473 \ 487 \ 527 \ 470 \ 542 \ 482 \ 484 \ 429 \ 501]
Elapsed time: 45.42233157157898
Train accuracy = 1.0
Test accuracy = 0.4414
    No PCA, 10000 Samples
for C in [0.1, 1, 10, 50, 100, 1000]:
    start_time = time()
    linearSVM = SVC(kernel='linear', C=C)
    linearSVM.fit(x_train[:10000], y_train[:10000])
    output = "Linear Kernel, C = " + str(C) + "\n"
    output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(linearSVM.score(x_train[:10000], y_train[:10000])) .
    output += "Test accuracy = " + str(linearSVM.score(x_test, y_test)) + "\n"
    print_and_log(output, log_file)
for degree in [2, 3]:
    for C in [0.1, 1, 10, 50, 100, 1000]:
        for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
             start_time = time()
             polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma)
             polySVM.fit(x_train[:10000], y_train[:10000])
             output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", C
```

```
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
            output += "Elapsed time: " + str(time() - start_time) + "\n"
            output += "Train accuracy = " + str(polySVM.score(x_train[:10000], y_train[:1000
            output += "Test accuracy = " + str(polySVM.score(x_test, y_test)) + "\n"
            print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        sigmoidSVM = SVC(kernel='sigmoid', C=C, gamma=gamma)
        sigmoidSVM.fit(x_train[:10000], y_train[:10000])
        output = "Sigmoid Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(sigmoidSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
        output += "Train accuracy = " + str(sigmoidSVM.score(x_train[:10000], y_train[:10000
        output += "Test accuracy = " + str(sigmoidSVM.score(x_test, y_test)) + "\n"
        print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
        rbfSVM.fit(x_train[:10000], y_train[:10000])
        output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
        output += "Train accuracy = " + str(rbfSVM.score(x_train[:10000], y_train[:10000]))
        output += "Test accuracy = " + str(rbfSVM.score(x_test, y_test)) + "\n"
        print_and_log(output, log_file)
   Best results are below:
  - Polynomial Kernel, Degree = 3, C = 1000, Gamma = auto
Number of support vectors = [815\ 871\ 979\ 997\ 939\ 955\ 890\ 857\ 756\ 908]
Elapsed time: 88.35298943519592
Train accuracy = 0.8619
Test accuracy = 0.4447
   - RBF Kernel, C = 1, Gamma = scale
Number of support vectors = [898\ 940\ 1007\ 1022\ 955\ 990\ 895\ 931\ 858\ 998]
Elapsed time: 98.53359794616699
Train accuracy = 0.7101
Test accuracy = 0.4721
   - RBF Kernel, C = 10, Gamma = scale
Number of support vectors = [938\ 953\ 1005\ 1022\ 954\ 1002\ 924\ 939\ 874\ 1014]
Elapsed time: 123.72975516319275
Train accuracy = 0.9923
Test accuracy = 0.4782
```

```
- RBF Kernel, C = 100, Gamma = scale Number of support vectors = [ 940 952 1005 1022 957 1000 926 940 879 1016] Elapsed time: 123.63887023925781 Train accuracy = 1.0 Test accuracy = 0.4728
```

# 2.8 No PCA, 10000 Samples

```
pca = PCA(0.9).fit(x_train)
pca_train_data = pca.transform(x_train)
pca_test_data = pca.transform(x_test)
for C in [0.1, 1, 10, 50, 100, 1000]:
    start_time = time()
    linearSVM = SVC(kernel='linear', C=C)
    linearSVM.fit(pca_train_data[:10000], y_train[:10000])
    output = "Linear Kernel, C = " + str(C) + "\n"
    output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(linearSVM.score(pca_train_data[:5000], y_train[:5000])
    output += "Test accuracy = " + str(linearSVM.score(pca_test_data, y_test)) + "\n"
    print_and_log(output, log_file)
for degree in [2, 3]:
    for C in [0.1, 1, 10, 50, 100, 1000]:
        for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
            start_time = time()
            polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma)
            polySVM.fit(pca_train_data[:10000], y_train[:10000])
            output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", C
            output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
            output += "Elapsed time: " + str(time() - start_time) + "\n"
            output += "Train accuracy = " + str(polySVM.score(pca_train_data[:10000], y_tra:
            output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
            print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        sigmoidSVM = SVC(kernel='sigmoid', C=C, gamma=gamma)
        sigmoidSVM.fit(pca_train_data[:10000], y_train[:10000])
        output = "Sigmoid Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(sigmoidSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
        output += "Train accuracy = " + str(sigmoidSVM.score(pca_train_data[:10000], y_train_data
        output += "Test accuracy = " + str(sigmoidSVM.score(pca_test_data, y_test)) + "\n"
```

```
print_and_log(output, log_file)
for C in [0.1, 1, 10, 50, 100, 1000]:
    for gamma in ['scale', 'auto', 0.1, 0.5, 1, 10, 20]:
        start_time = time()
        rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
        rbfSVM.fit(pca_train_data[:10000], y_train[:10000])
        output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
        output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
        output += "Elapsed time: " + str(time() - start_time) + "\n"
        output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:10000], y_train[:10000])
        output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
        print_and_log(output, log_file)
  Best results are below:
   - Polynomial Kernel, Degree = 3, C = 1000, Gamma = auto
Number of support vectors = [815\ 871\ 979\ 997\ 939\ 955\ 890\ 857\ 756\ 908]
Elapsed time: 88.35298943519592
Train accuracy = 0.8619
Test accuracy = 0.4447
   - RBF Kernel, C = 1, Gamma = scale
Number of support vectors = [898\ 940\ 1007\ 1022\ 955\ 990\ 895\ 931\ 858\ 998]
Elapsed time: 98.53359794616699
Train accuracy = 0.7101
Test accuracy = 0.4721
   - RBF Kernel, C = 10, Gamma = scale
Number of support vectors = [938\ 953\ 1005\ 1022\ 954\ 1002\ 924\ 939\ 874\ 1014]
Elapsed time: 123.72975516319275
Train accuracy = 0.9923
Test accuracy = 0.4782
   - RBF Kernel, C = 100, Gamma = scale
Number of support vectors = [940\ 952\ 1005\ 1022\ 957\ 1000\ 926\ 940\ 879\ 1016]
Elapsed time: 123.63887023925781
Train accuracy = 1.0
Test accuracy = 0.4728
2.9
      PCA, 5000 Samples, Best Cases
pca = PCA(0.9).fit(x_train)
pca_train_data = pca.transform(x_train)
pca_test_data = pca.transform(x_test)
C = 0.1
start_time = time()
linearSVM = SVC(kernel='linear', C=C)
linearSVM.fit(pca_train_data[:5000], y_train[:5000])
```

```
output = "Linear Kernel, C = " + str(C) + "\n"
output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(linearSVM.score(pca_train_data[:5000], y_train[:5000]))
output += "Test accuracy = " + str(linearSVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 'scale'
degree = 2
coef0 = 0.5
start_time = time()
polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0)
polySVM.fit(pca_train_data[:5000], y_train[:5000])
output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:5000], y_train[:5000])) +
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 0.5
degree = 2
coef0 = 0.5
start_time = time()
polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0, probability = 7
polySVM.fit(pca_train_data[:5000], y_train[:5000])
output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:5000], y_train[:5000])) +
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
    rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
    rbfSVM.fit(pca_train_data[:5000], y_train[:5000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:5000], y_train[:5000])
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
    print_and_log(output, log_file)
```

```
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
    rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma, decision_function_shape = "ovo")
    rbfSVM.fit(pca_train_data[:5000], y_train[:5000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "decision_function_sl
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:5000], y_train[:5000])
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
    print_and_log(output, log_file)
   Best results are below:
   - Linear Kernel, C = 0.1
Number of support vectors = [446 \ 436 \ 477 \ 516 \ 463 \ 523 \ 441 \ 438 \ 397 \ 452]
Elapsed time: 2.4526445865631104
Train accuracy = 0.4708
Test accuracy = 0.3621
   - Polynomial Kernel, Degree = 2, C = 10, Gamma = scale, coef0 = 0.5
Number of support vectors = [406 \ 430 \ 480 \ 510 \ 463 \ 503 \ 460 \ 446 \ 385 \ 461]
Elapsed time: 1.7975034713745117
Train accuracy = 0.9206
Test accuracy = 0.4199
   - RBF Kernel, C = 1, Gamma = scale
Number of support vectors = [453\ 469\ 486\ 526\ 467\ 535\ 465\ 477\ 424\ 488]
Elapsed time: 1.495023488998413
Train accuracy = 0.6632
Test accuracy = 0.4359
   - RBF Kernel, C = 10, Gamma = scale
Number of support vectors = [454\ 468\ 485\ 525\ 469\ 533\ 472\ 470\ 421\ 493]
Elapsed time: 2.0700836181640625
Train accuracy = 0.972
Test accuracy = 0.4446
   - RBF Kernel, C = 100, Gamma = scale
Number of support vectors = [453\ 466\ 485\ 525\ 469\ 529\ 477\ 470\ 419\ 490]
Elapsed time: 2.179264545440674
Train accuracy = 1.0
Test accuracy = 0.4275
   - RBF Kernel, C = 1000, Gamma = scale
Number of support vectors = [453\ 466\ 485\ 525\ 470\ 529\ 477\ 470\ 419\ 490]
Elapsed time: 2.17147159576416
Train accuracy = 1.0
Test accuracy = 0.4276
   - RBF Kernel, C = 1, Gamma = scale, decision_function_shape = "ovo"
```

Number of support vectors =  $[453\ 469\ 486\ 526\ 467\ 535\ 465\ 477\ 424\ 488]$ 

```
Elapsed time: 1.5112762451171875
Train accuracy = 0.6632
Test accuracy = 0.4359
   - RBF Kernel, C = 10, Gamma = scale, decision_function_shape = "ovo"
Number of support vectors = [454\ 468\ 485\ 525\ 469\ 533\ 472\ 470\ 421\ 493]
Elapsed time: 2.059635639190674
Train accuracy = 0.972
Test accuracy = 0.4446
   - RBF Kernel, C = 100, Gamma = scale, decision_function_shape = "ovo"
Number of support vectors = [453\ 466\ 485\ 525\ 469\ 529\ 477\ 470\ 419\ 490]
Elapsed time: 2.1751701831817627
Train accuracy = 1.0
Test accuracy = 0.4275
   - RBF Kernel, C = 1000, Gamma = scale, decision_function_shape = "ovo"
Number of support vectors = [453\ 466\ 485\ 525\ 470\ 529\ 477\ 470\ 419\ 490]
Elapsed time: 2.183816909790039
Train accuracy = 1.0
Test accuracy = 0.4276
       PCA, 10000 Samples, Best Cases
2.10
pca = PCA(0.9).fit(x_train)
pca_train_data = pca.transform(x_train)
pca_test_data = pca.transform(x_test)
C = 0.1
start_time = time()
linearSVM = SVC(kernel='linear', C=C)
linearSVM.fit(pca_train_data[:10000], y_train[:10000])
output = "Linear Kernel, C = " + str(C) + "\n"
output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(linearSVM.score(pca_train_data[:10000], y_train[:10000])
output += "Test accuracy = " + str(linearSVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 'scale'
degree = 2
coef0 = 0.5
```

output += "Elapsed time: " + str(time() - start\_time) + "\n"

polySVM.fit(pca\_train\_data[:10000], y\_train[:10000])

polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0)

output += "Number of support vectors = " + str(polySVM.n\_support\_) + "\n"

output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s

start\_time = time()

```
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:10000], y_train[:10000]))
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 0.5
degree = 2
coef0 = 0.5
start_time = time()
polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0, probability = 7
polySVM.fit(pca_train_data[:10000], y_train[:10000])
output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:10000], y_train[:10000]))
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
    rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
    rbfSVM.fit(pca_train_data[:10000], y_train[:10000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:10000], y_train[:10000]
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
   print_and_log(output, log_file)
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
   rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma, decision_function_shape = "ovo")
    rbfSVM.fit(pca_train_data[:10000], y_train[:10000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "decision_function_sl
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:10000], y_train[:10000]
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
   print_and_log(output, log_file)
  Best results are below:
   - Linear Kernel, C = 0.1
Number of support vectors = [894\ 882\ 991\ 1009\ 948\ 973\ 839\ 856\ 827\ 899]
Elapsed time: 8.904108762741089
```

Train accuracy = 0.4403

Test accuracy = 0.3838

- Polynomial Kernel, Degree = 2, C = 10, Gamma = scale, coef0 = 0.5 Number of support vectors = [789 837 976 983 933 930 858 849 768 890]

Elapsed time: 7.057990789413452

Train accuracy = 0.8739

Test accuracy = 0.4577

- RBF Kernel, C = 1, Gamma = scale

Number of support vectors =  $[881\ 926\ 1003\ 1023\ 956\ 976\ 879\ 909\ 840\ 971]$ 

Elapsed time: 5.395939111709595

Train accuracy = 0.6554

Test accuracy = 0.4708

- RBF Kernel, C = 10, Gamma = scale

 $\mbox{Number of support vectors} = [\ 905\ 922\ 1004\ 1017\ 952\ 992\ 901\ 915\ 840\ 982]$ 

Elapsed time: 7.345630645751953

Train accuracy = 0.9614

Test accuracy = 0.4709

- RBF Kernel, C = 100, Gamma = scale

Number of support vectors =  $[920\ 919\ 1000\ 1015\ 953\ 982\ 912\ 924\ 841\ 981]$ 

Elapsed time: 8.281328201293945

Train accuracy = 0.9997

Test accuracy = 0.4556

- RBF Kernel, C = 1000, Gamma = scale

Number of support vectors =  $[920\ 919\ 999\ 1016\ 948\ 982\ 910\ 924\ 840\ 981]$ 

Elapsed time: 8.17867136001587

Train accuracy = 1.0

Test accuracy = 0.4557

- RBF Kernel, C = 1, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [  $881\ 926\ 1003\ 1023\ 956\ 976\ 879\ 909\ 840\ 971]$  Elapsed time: 5.391200542449951

Train accuracy = 0.6554

Test accuracy = 0.4708

- RBF Kernel, C = 10, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors =  $\begin{bmatrix} 905 & 922 & 1004 & 1017 & 952 & 992 & 901 & 915 & 840 & 982 \end{bmatrix}$ 

Elapsed time: 7.318029880523682

Train accuracy = 0.9614

Test accuracy = 0.4709

- RBF Kernel, C=100, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [ 920 919 1000 1015 953 982 912 924 841 981] Elapsed time: 8.248036623001099

Train accuracy = 0.9997

Test accuracy = 0.4556

- RBF Kernel, C=1000, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [ 920 919 999 1016 948 982 910 924 840 981] Elapsed time: 8.183026313781738

Train accuracy = 1.0

## 2.11 PCA, 50000 Samples, Best Cases

```
C = 0.1
start_time = time()
linearSVM = SVC(kernel='linear', C=C)
linearSVM.fit(pca_train_data[:50000], y_train[:50000])
output = "Linear Kernel, C = " + str(C) + "\n"
output += "Number of support vectors = " + str(linearSVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(linearSVM.score(pca_train_data[:50000], y_train[:50000])
output += "Test accuracy = " + str(linearSVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 'scale'
degree = 2
coef0 = 0.5
start_time = time()
polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0)
polySVM.fit(pca_train_data[:50000], y_train[:50000])
output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:50000], y_train[:50000]))
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
C = 10
gamma = 0.5
degree = 2
coef0 = 0.5
start_time = time()
polySVM = SVC(kernel='poly', C=C, degree=degree, gamma=gamma, coef0 = coef0, probability = 7
polySVM.fit(pca_train_data[:50000], y_train[:50000])
output = "Polynomial Kernel, Degree = " + str(degree) + ", C = " + str(C) + ", Gamma = " + s
output += "Number of support vectors = " + str(polySVM.n_support_) + "\n"
output += "Elapsed time: " + str(time() - start_time) + "\n"
output += "Train accuracy = " + str(polySVM.score(pca_train_data[:50000], y_train[:50000]))
output += "Test accuracy = " + str(polySVM.score(pca_test_data, y_test)) + "\n"
print_and_log(output, log_file)
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
```

```
rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma)
    rbfSVM.fit(pca_train_data[:50000], y_train[:50000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + "\n"
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:50000], y_train[:50000]
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
    print_and_log(output, log_file)
gamma = 'scale'
for C in [1, 10, 100, 1000]:
    start_time = time()
    rbfSVM = SVC(kernel='rbf', C=C, gamma=gamma, decision_function_shape = "ovo")
    rbfSVM.fit(pca_train_data[:50000], y_train[:50000])
    output = "RBF Kernel, C = " + str(C) + ", Gamma = " + str(gamma) + ", decision_function_
    output += "Number of support vectors = " + str(rbfSVM.n_support_) + "\n"
    output += "Elapsed time: " + str(time() - start_time) + "\n"
    output += "Train accuracy = " + str(rbfSVM.score(pca_train_data[:50000], y_train[:50000]
    output += "Test accuracy = " + str(rbfSVM.score(pca_test_data, y_test)) + "\n"
    print_and_log(output, log_file)
   Best results are below:
  - Linear Kernel, C = 0.1
Number of support vectors = [4497\ 4277\ 4925\ 4949\ 4892\ 4794\ 4301\ 4379\ 4164
4321
Elapsed time: 366.7933552265167
Train accuracy = 0.4206
Test accuracy = 0.4075
   - Polynomial Kernel, Degree = 2, C = 10, Gamma = scale, coef0 = 0.5
Number of support vectors = [3630\ 3496\ 4590\ 4598\ 4564\ 4370\ 3997\ 3655\ 3382
3816
Elapsed time: 290.8063061237335
Train accuracy = 0.7454
Test accuracy = 0.5421
  - RBF Kernel, C = 1, Gamma = scale
Number of support vectors = [4065 \ 4177 \ 4791 \ 4896 \ 4728 \ 4662 \ 4243 \ 4127 \ 3738]
Elapsed time: 234.4116370677948
Train accuracy = 0.65468
Test accuracy = 0.5402
   - RBF Kernel, C = 10, Gamma = scale
Number of support vectors = [4094 \ 4072 \ 4743 \ 4896 \ 4626 \ 4711 \ 4265 \ 4070 \ 3739]
4353
Elapsed time: 283.5378005504608
Train accuracy = 0.9216
Test accuracy = 0.5624
```

- RBF Kernel, C = 100, Gamma = scale

Number of support vectors =  $[4070\ 4055\ 4735\ 4836\ 4651\ 4664\ 4343\ 4065\ 3810\ 4376]$ 

Elapsed time: 378.86197662353516

Train accuracy = 0.99672Test accuracy = 0.5442

- RBF Kernel, C = 1000, Gamma = scale

Number of support vectors =  $[4038\ 4057\ 4709\ 4835\ 4636\ 4647\ 4333\ 4063\ 3804\ 4376]$ 

Elapsed time: 381.44525718688965

Train accuracy = 1.0Test accuracy = 0.5386

- RBF Kernel, C = 1, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [4065 4177 4791 4896 4728 4662 4243 4127 3738 4305]

Elapsed time: 185.95598721504211

Train accuracy = 0.65468Test accuracy = 0.5402

- RBF Kernel, C = 10, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [4094 4072 4743 4896 4626 4711 4265 4070 3739 4353]

Elapsed time: 227.3112096786499

Train accuracy = 0.9216Test accuracy = 0.5624

- RBF Kernel, C = 100, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [4070 4055 4735 4836 4651 4664 4343 4065 3810 4376]

Elapsed time: 302.2709484100342

Train accuracy = 0.99672Test accuracy = 0.5442

- RBF Kernel, C = 1000, Gamma = scale, decision\_function\_shape = "ovo" Number of support vectors = [4038 4057 4709 4835 4636 4647 4333 4063 3804 4376]

Elapsed time: 305.47143054008484

Train accuracy = 1.0Test accuracy = 0.5386

# 3 Issues

The first issue that was encountered was the size of the whole dataset. The 50.000 training data and the 10.000 test data could not be processed in order to take the full capability of every model. That's why at the start we chose to use only 5.000 samples for training and testing, that gave us a sense of the best options for the parameters of the model. But the best way to solve this issue was the use of PCA before training. This huge reduction of dimensions speed up the training process, so we can run models from 5.000 samples up to 50.000 samples in decent time and get the best result possible.

# 4 Conclusion

For the above results we can conclude that:

- CIFAR-10 dataset is a difficult dataset for classification and 3072 features needs too much computational power for 50.000 samples.
- PCA is a must methodology for preprocessing. Improves speed and accuracy.
- Sigmoid Kernel is not generally a good fit for SVM models.
- Polynomial and RBF Kernel have great results combined with PCA. The best result of every model was from a RBF Kernel SVC:

```
RBF Kernel, C=10, Gamma = scale
Train accuracy = 0.9216
Test accuracy = 0.5624
RBF Kernel, C=10, Gamma = scale, decision_function_shape = "ovo"
Train accuracy = 0.9216
Test accuracy = 0.5624
```

Of course, we can see a pretty clear overfiting situation, but we know that for this dataset 56% test accuracy is really good, so overfiting is a logic result.