PR_HW3

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1 Pattern Recognition - HW3 - Mohammad Doosti Lakhani - 98722278

Index:

1. Import Libraries
2. Loading Data
3. Pretrained Feature Extraction
4. Feature Reduction
    1. PCA
        1. 2D PCA
        2. Visualization
        3. 3D PCA
        4. Visualization
    2. TSN-E
        1. 2D TSN-E
        2. Visualization
        3. 3D TSN-E
        4. Visualization
5. Train Test Split
6. Train Models
    1. PCA
        1. SVC Linear - PCA 2D
        2. SVC Linear - PCA 3D
        3. SVC RBF - PCA 2D
        4. SVC RBF - PCA 3D
    2. TSN-E
        1. SVC Linear - TSN-E 2D
        2. SVC Linear - TSN-E 3D
        3. SVC RBF - TSN-E 2D
        4. SVC RBF - TSN-E 3D
    3. Fully Connected

1.1 1 Import Libraries

```
In [1]: %tensorflow_version 1.x

        from __future__ import print_function

        import pickle

        import seaborn as sns
        import matplotlib.pylab as plt
        import PIL
        from mpl_toolkits.mplot3d import Axes3D

        import pandas as pd
        import numpy as np

        from sklearn.svm import SVC, LinearSVC
        from sklearn.svm import base

        from sklearn.metrics import confusion_matrix
        from sklearn.decomposition import PCA
        from sklearn.manifold import TSNE

        import keras
        from keras import backend as K
        from keras.preprocessing.image import ImageDataGenerator
        from keras.optimizers import Adam
        from keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint, Learning
        from keras.layers import Dense, Conv2D, BatchNormalization, Activation
        from keras.layers import AveragePooling2D, Input, Flatten
        from keras.regularizers import l2
        from keras.models import Model
        from keras.utils import to_categorical
        from keras.applications.vgg19 import VGG19
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: FutureWarning: The skl
  warnings.warn(message, FutureWarning)
Using TensorFlow backend.
```

1.2 2 Loading Data

You need to put your data in the following structure:

```
data/train/
        /class1
        /class2
        /...
data/test/
```

```
/class1
/class2
/...
```

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
!unrar x drive/My\ Drive/IUST-PR/HW3/data.rar /content
```

In [17]:
```
# loading data
batch_size = 64
n_classes = 3
img_size = (224, 224)

datagen = ImageDataGenerator()
train_iterator = datagen.flow_from_directory('data/train/', class_mode='categorical',
                                             batch_size=batch_size, target_size=img_si
# only for NN model
test_iterator = datagen.flow_from_directory('data/test/', class_mode='categorical',
                                            batch_size=batch_size, target_size=img_si

n = 541
x = np.empty((n, img_size[0], img_size[1], n_classes))
y = np.empty((n, n_classes))
for idx in range(len(train_iterator)):
    batchx = train_iterator[idx][0]
    batchy = train_iterator[idx][1]
    if batchx.shape[0] < batch_size:
        x[idx*batch_size:] = batchx
        y[idx*batch_size:] = batchy
    else:
        x[idx*batch_size:(idx+1)*batch_size] = batchx
        y[idx*batch_size:(idx+1)*batch_size] = batchy


n_test = 31
y_test = np.empty((n_test, n_classes))
for idx in range(len(test_iterator)):
    batchy = test_iterator[idx][1]
    if batchx.shape[0] < batch_size:
        y_test[idx*batch_size:] = batchy
    else:
        y_test[idx*batch_size:(idx+1)*batch_size] = batchy


print(x.shape)
print(y.shape)
print(y_test.shape)
```

```
Found 541 images belonging to 3 classes.
```

```
Found 31 images belonging to 3 classes.
(541, 224, 224, 3)
(541, 3)
(31, 3)
```

1.3 3 Pretrained Feature Extraction

When a CNN model is trained on a large dataset that can represent images similar to our custom dataset, has features that are common in first layers and more specific in the last layers. So we remove fully connected layers and use convolutional layers as the features extracted from ImageNet dataset where it is the superset of our dataset. These features even though are in low dimensional manner w.r.t. input images, they contain much more usefull information about images.

```
In [18]: # feature extraction

         model = VGG19(include_top=False, weights='imagenet', input_tensor=None, input_shape=(
         features = model.predict_generator(train_iterator, steps=9)
         features_test = model.predict_generator(test_iterator, steps=1)
         print('NN data train shape:', features.shape)
         print('NN data test shape:', features_test.shape)
```

```
NN data train shape: (541, 7, 7, 512)
NN data test shape: (31, 7, 7, 512)
```

1.4 4 Feature Reduction

In this step, we have 77512 features to feed to our SVM models to train. But we want to reduce this info and use only 2 and 3 feature that represent our whole features.

So we use PCA and TSN-E to reduce to 2 and 3 features.

1. PCA
    1. 2D PCA
    2. Visualization
    3. 3D PCA
    4. Visualization
2. TSN-E
    1. 2D TSN-E
    2. Visualization
    3. 3D TSN-E
    4. Visualization

1.4.1 4.A PCA

1. 2D PCA
2. Visualization
3. 3D PCA
4. Visualization

4.A.a 2D PCA

```
In [33]: # 2D PCA
         pca_2d = PCA(n_components=2)
         pca_2d.fit(features.reshape(len(features), -1))
         pca_2d_features = pca_2d.transform(features.reshape(len(features), -1))
         print(pca_2d_features.shape)
```

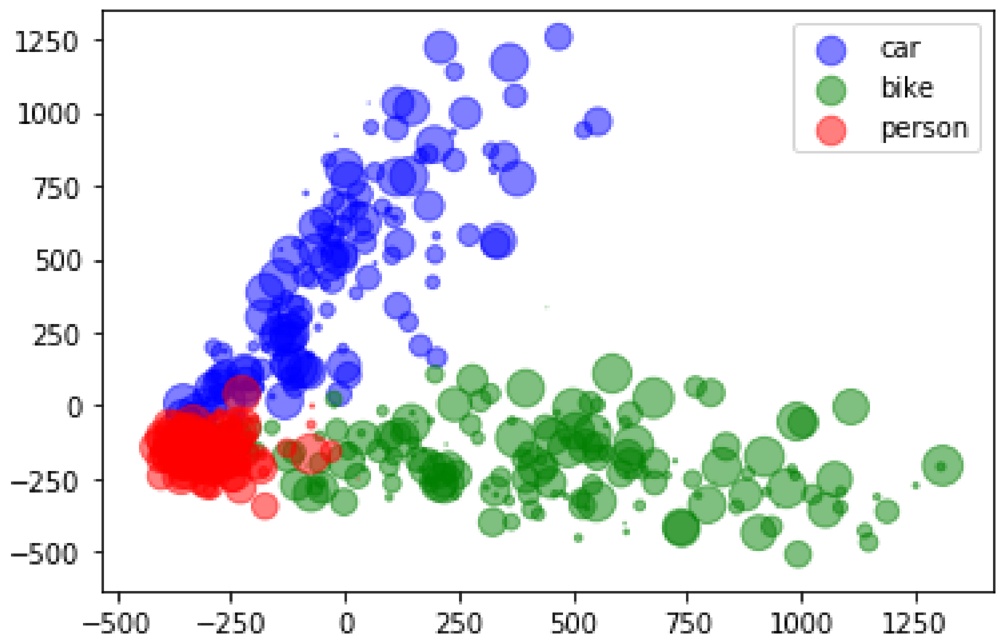
```
(541, 2)
```

4.A.b Visualization

```
In [6]: colors = np.argmax(y, axis=1)
        fig, ax = plt.subplots()
        x_ = pca_2d_features[:,0]
        y_ = pca_2d_features[:,1]
        legend_ = ['blue', 'green', 'red']
        for idx, color in enumerate(['car', 'bike', 'person']):
            area = (15 * np.random.rand(len(x)))**2
            print(x_[colors==idx].shape, y_[colors==idx].shape, colors[colors==idx].shape)
            ax.scatter(x_[colors==idx], y_[colors==idx], s=area, c=legend_[idx], alpha=0.5, la

        ax.legend()
        plt.show()
```

```
(165,) (165,) (165,)
(169,) (169,) (169,)
(207,) (207,) (207,)
```



4.A.c 3D PCA

```
In [34]: # 3D PCA
         pca_3d = PCA(n_components=3)
         pca_3d.fit(features.reshape(len(features), -1))
         pca_3d_features = pca_3d.transform(features.reshape(len(features), -1))
         print(pca_3d_features.shape)
```

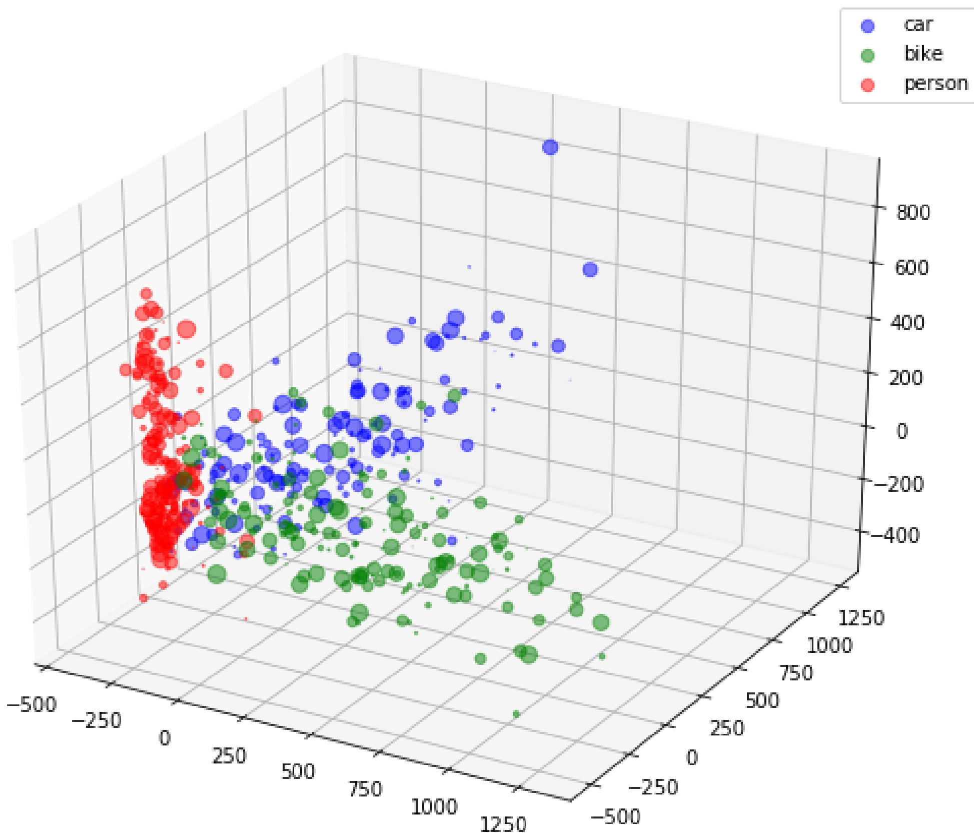
```
(541, 3)
```

4.A.d Visualization

```
In [35]: colors = np.argmax(y, axis=1)
         fig = plt.figure(figsize=(10, 8))
         ax = fig.add_subplot(111, projection='3d')
         x_ = pca_3d_features[:, 0]
         y_ = pca_3d_features[:, 1]
         z_ = pca_3d_features[:, 2]
         legend_ = ['blue', 'green', 'red']
         for idx, color in enumerate(['car', 'bike', 'person']):
             area = (9 * np.random.rand(len(x)))**2
             print(x_[colors==idx].shape, y_[colors==idx].shape, colors[colors==idx].shape)
             ax.scatter(x_[colors==idx], y_[colors==idx], z_[colors==idx], s=area, c=legend_[ic

         ax.legend()
         plt.show()
```

```
(165,) (165,) (165,)
(169,) (169,) (169,)
(207,) (207,) (207,)
```



1.4.2 4.B TSN-E

1. 2D TSN-E
2. Visualization
3. 3D TSN-E
4. Visualization

4.B.a 2D TSN-E

In [38]:
```
# TSNE 2D
tsne_2d = TSNE(n_components=2, perplexity=30, learning_rate=200)
tsne_2d_features = tsne_2d.fit_transform(features.reshape(len(features), -1))
print(tsne_2d_features.shape)
```

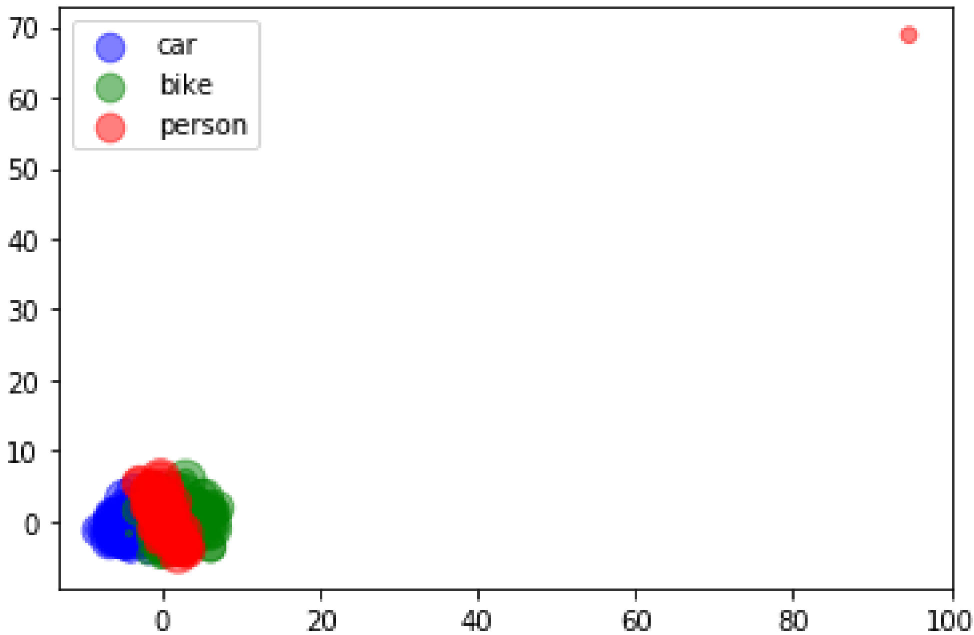
```
(541, 2)
```

4.B.b Visualization

```
In [40]: colors = np.argmax(y, axis=1)
         fig, ax = plt.subplots()
         x_ = tsne_2d_features[:,0]
         y_ = tsne_2d_features[:,1]
         legend_ = ['blue', 'green', 'red']
         for idx, color in enumerate(['car', 'bike', 'person']):
             area = (15 * np.random.rand(len(x)))**2
             print(x_[colors==idx].shape, y_[colors==idx].shape, colors[colors==idx].shape)
             ax.scatter(x_[colors==idx], y_[colors==idx], s=area, c=legend_[idx], alpha=0.5, la

         ax.legend()
         plt.show()
```

```
(165,) (165,) (165,)
(169,) (169,) (169,)
(207,) (207,) (207,)
```



4.B.c 3D TSN-E

```
In [37]: # TSNE 3D
         tsne_3d = TSNE(n_components=3, perplexity=30, learning_rate=200)
         tsne_3d_features = tsne_3d.fit_transform(features.reshape(len(features), -1))
         print(tsne_3d_features.shape)
```

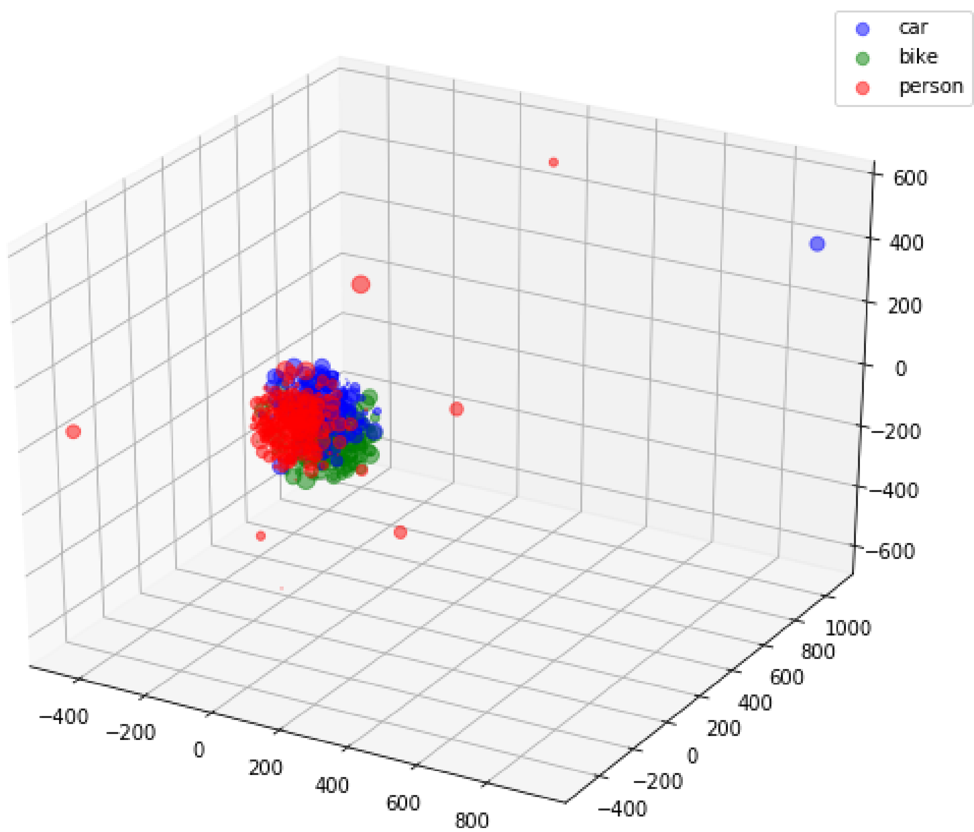
```
(541, 3)
```

4.B.d Visualization

```
In [39]: colors = np.argmax(y, axis=1)
         fig = plt.figure(figsize=(10, 8))
         ax = fig.add_subplot(111, projection='3d')
         x_ = tsne_3d_features[:, 0]
         y_ = tsne_3d_features[:, 1]
         z_ = tsne_3d_features[:, 2]
         legend_ = ['blue', 'green', 'red']
         for idx, color in enumerate(['car', 'bike', 'person']):
             area = (9 * np.random.rand(len(x)))**2
             print(x_[colors==idx].shape, y_[colors==idx].shape, colors[colors==idx].shape)
             ax.scatter(x_[colors==idx], y_[colors==idx], z_[colors==idx], s=area, c=legend_[ic

         ax.legend()
         plt.show()
```

```
(165,) (165,) (165,)
(169,) (169,) (169,)
(207,) (207,) (207,)
```



1.5 5 Train Test Split

For validating our trained model we need to separate a small proportion of our data to propose to our trained model where those have not been seen at all.

```
In [41]: # train test split
         from sklearn.model_selection import train_test_split

         pca_2d_x_train, pca_2d_x_test, pca_2d_y_train, pca_2d_y_test = train_test_split(pca_2c
                                                                                          np.arg
                                                                                          test_s
         pca_3d_x_train, pca_3d_x_test, pca_3d_y_train, pca_3d_y_test = train_test_split(pca_3c
                                                                                          np.arg
                                                                                          test_s
         tsne_2d_x_train, tsne_2d_x_test, tsne_2d_y_train, tsne_2d_y_test = train_test_split(ts
                                                                                              np
                                                                                              te
         tsne_3d_x_train, tsne_3d_x_test, tsne_3d_y_train, tsne_3d_y_test = train_test_split(ts
                                                                                              np
                                                                                              te


         print('PCA 2D features train size:',pca_2d_x_train.shape, '------','PCA 2D features te
         print('PCA 3D features train size:',pca_3d_x_train.shape, '------','PCA 3D features te
         print('TSNE 2D features train size:',tsne_2d_x_train.shape, '------','TSNE 2D features
         print('TSNE 3D features train size:',tsne_3d_x_train.shape, '------','TSNE 3D features
```

```
PCA 2D features train size: (486, 2) ------ PCA 2D features test size (55, 2)
PCA 3D features train size: (486, 3) ------ PCA 3D features test size (55, 3)
TSNE 2D features train size: (486, 2) ------ TSNE 2D features test size (55, 2)
TSNE 3D features train size: (486, 3) ------ TSNE 3D features test size (55, 3)
```

1.6 6 Train Models

1. PCA 1. SVC Linear - PCA 2D 2. SVC Linear - PCA 3D 3. SVC RBF - PCA 2D 4. SVC RBF - PCA 3D
2. TSN-E
   1. SVC Linear - TSN-E 2D
   2. SVC Linear - TSN-E 3D
   3. SVC RBF - TSN-E 2D
   4. SVC RBF - TSN-E 3D
3. Fully Connected

```
In [ ]: # SVM

        class SVM_MODELS:
            """
            Enum of possible models
```

```
    """
    SVC = 1
    LINEAR_SVC = 2


# %% functions
def build_svm(model_type: int, x: np.ndarray, y: np.ndarray, svc_kernel: str = None, sa
              path: str = None, **kwargs) -> base:
    """
    Trains a SVM model

    :param model_type: The kernel of SVM model (see `SVM_MODELS` class)
    :param svc_kernel: The possible kernels for `SVC` model (It must be one of linear,
    It will be ignored if `model_type = LINEAR_SVC`
    :param x: Features in form of numpy ndarray
    :param y: Labels in form of numpy ndarray
    :param save: Whether save trained model on disc or not
    :param path: Path to save fitted model
    :param kwargs: A dictionary of other optional arguments of models in format of {'a
    :return:A trained VSM model
    """
    if model_type == SVM_MODELS.SVC:
        model = SVC(kernel=svc_kernel, **kwargs)
    elif model_type == SVM_MODELS.LINEAR_SVC:
        model = LinearSVC(**kwargs)
    else:
        raise Exception('Model {} is not valid'.format(model_type))

    model.fit(x, y)

    if save:
        if path is None:
            path = ''
        pickle.dump(model, open(path + model.__module__ + '.model', 'wb'))
    return model
```

1.6.1 6.A PCA

1. SVC Linear - PCA 2D
2. SVC Linear - PCA 3D
3. SVC RBF - PCA 2D
4. SVC RBF - PCA 3D

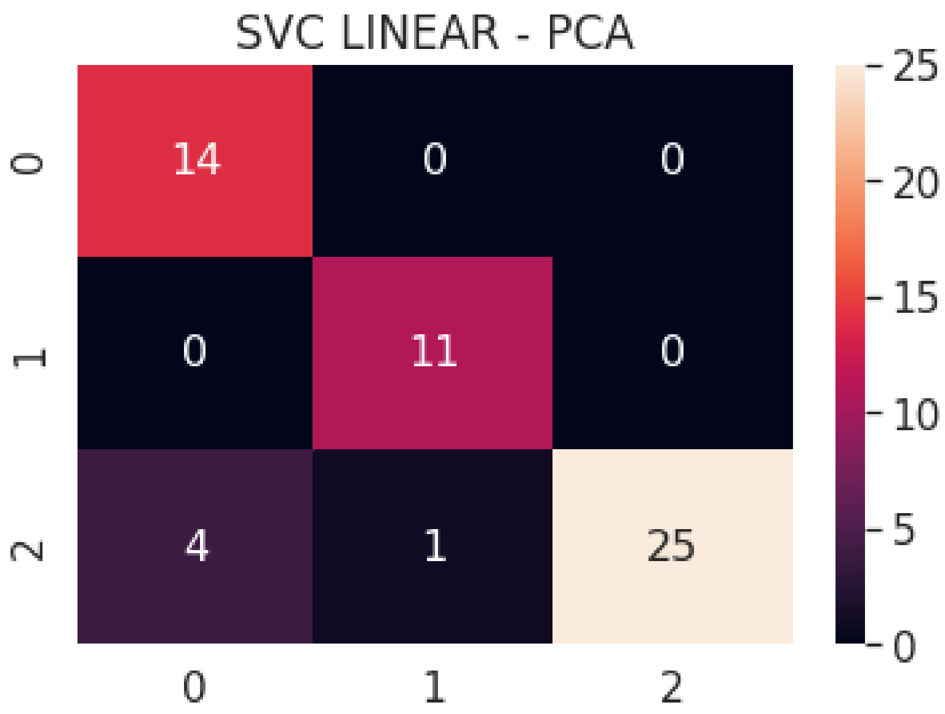
6.A.a SVC Linear - PCA 2D

In [43]:
```
# SVC LINEAR PCA 2D
pca_2d_svc_linear = build_svm(model_type=SVM_MODELS.LINEAR_SVC, x=pca_2d_x_train, y=p
                              max_iter=200000, path='models/pca_2d_', multi_class='ovr')
```

```
print('PCA 2D - SVC LINEAR - Test accuracy', pca_2d_svc_linear.score(pca_2d_x_test, pc
cm = confusion_matrix(pca_2d_svc_linear.predict(pca_2d_x_test), pca_2d_y_test)
df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
plt.title('SVC LINEAR - PCA')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/svm/_base.py:947: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)
```

```
PCA 2D - SVC LINEAR - Test accuracy 0.9090909090909091
```



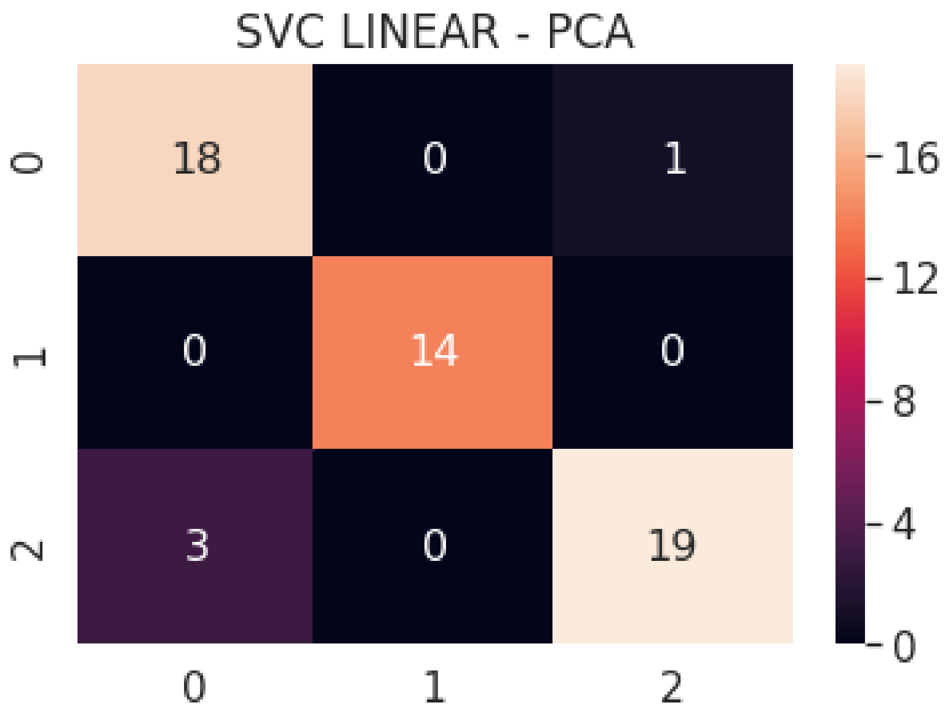
6.A.b SVC Linear - PCA 3D

```
In [44]: # SVC LINEAR PCA 3D
         pca_3d_svc_linear = build_svm(model_type=SVM_MODELS.LINEAR_SVC, x=pca_3d_x_train, y=pc
                                       max_iter=200000, path='models/pca_3d_', multi_class='ovr')
         print('PCA 3D - SVC LINEAR - Test accuracy', pca_3d_svc_linear.score(pca_3d_x_test, pc
         cm = confusion_matrix(pca_3d_svc_linear.predict(pca_3d_x_test), pca_3d_y_test)
         df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
         sns.set(font_scale=1.4)
```

```
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
plt.title('SVC LINEAR - PCA')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/svm/_base.py:947: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)


PCA 3D - SVC LINEAR - Test accuracy 0.9272727272727272
```

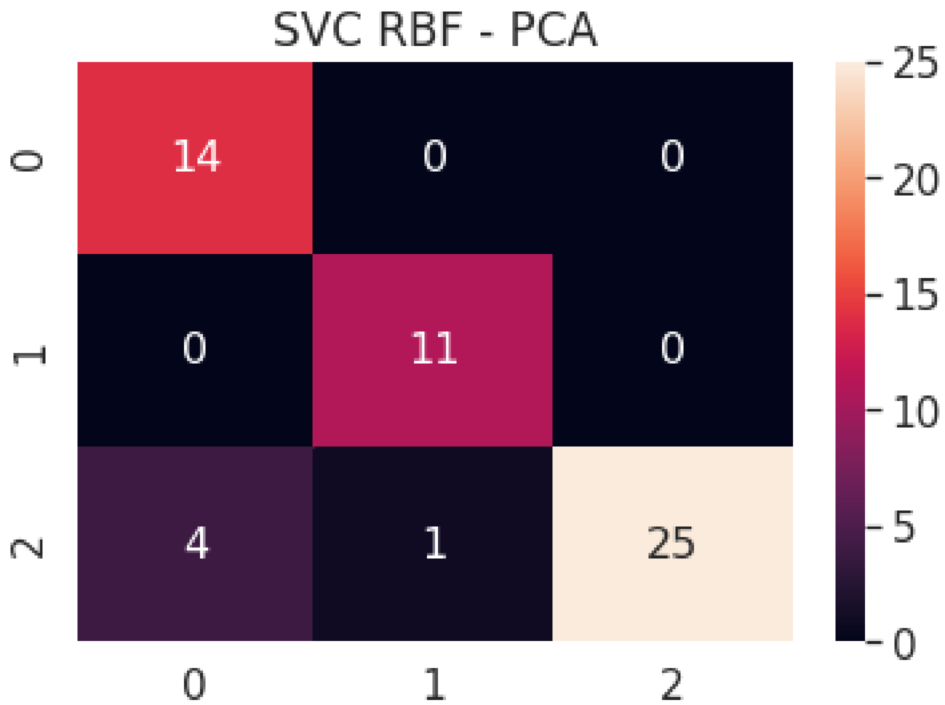


6.A.c SVC RBF - PCA 2D

```
In [45]: # SVC RBF PCA 2D
         pca_2d_svc_rbf = build_svm(model_type=SVM_MODELS.SVC, x=pca_2d_x_train, y=pca_2d_y_tra
                                   path='models/pca_2d_', svc_kernel='rbf')

         print('PCA 2D - SVC RBF - Test accuracy', pca_2d_svc_rbf.score(pca_2d_x_test, pca_2d_
         cm = confusion_matrix(pca_2d_svc_rbf.predict(pca_2d_x_test), pca_2d_y_test)
         df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
         plt.title('SVC RBF - PCA')
         plt.show()
```

PCA 2D - SVC RBF - Test accuracy 0.9090909090909091

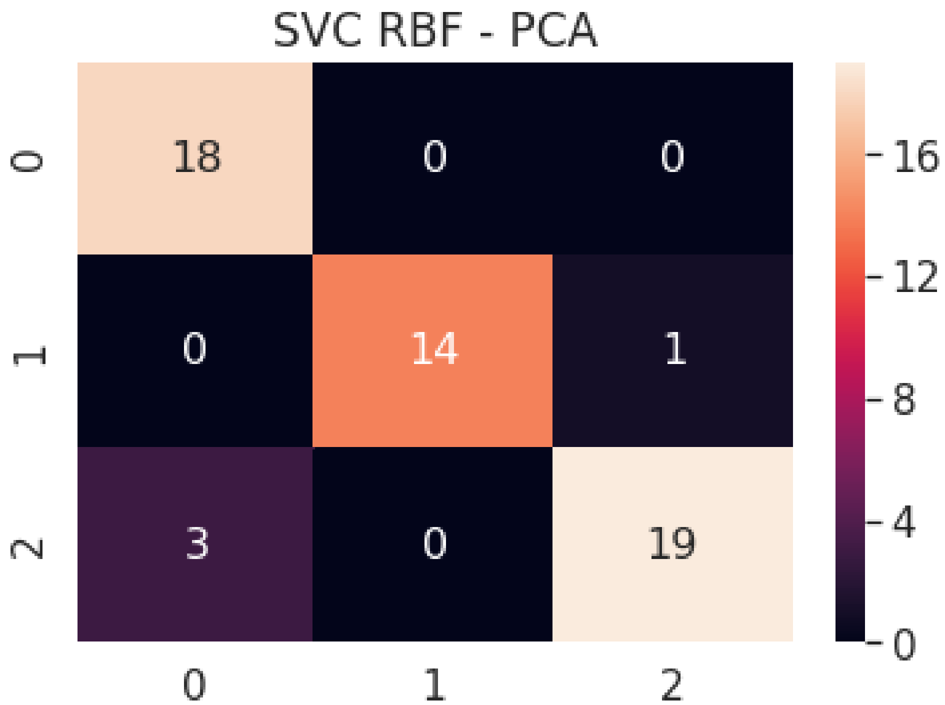


6.A.d SVC RBF - PCA 3D

In [46]:
```
# SVC RBF PCA 3D
pca_3d_svc_rbf = build_svm(model_type=SVM_MODELS.SVC, x=pca_3d_x_train, y=pca_3d_y_tra
                           path='models/pca_3d_', svc_kernel='rbf')

print('PCA 3D - SVC RBF - Test accuracy', pca_3d_svc_rbf.score(pca_3d_x_test, pca_3d_y
cm = confusion_matrix(pca_3d_svc_rbf.predict(pca_3d_x_test), pca_3d_y_test)
df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
plt.title('SVC RBF - PCA')
plt.show()
```

PCA 3D - SVC RBF - Test accuracy 0.9272727272727272



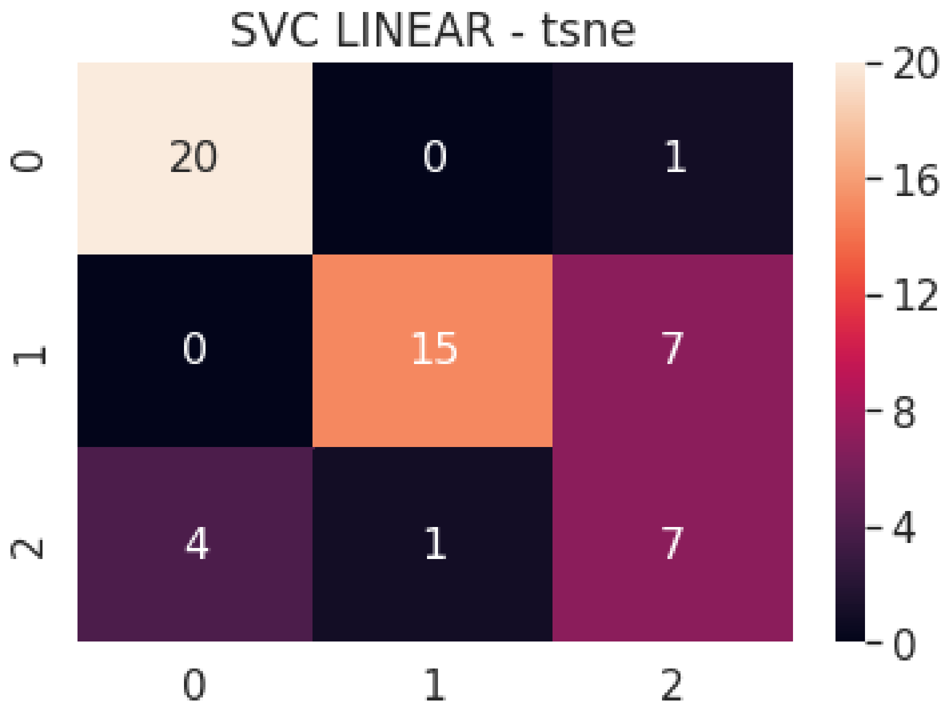
1.6.2 6.B TSN-E

1. SVC Linear - TSN-E 2D
2. SVC Linear - TSN-E 3D
3. SVC RBF - TSN-E 2D
4. SVC RBF - TSN-E 3D

6.B.a SVC Linear - TSN-E 2D

In [47]:
```
# SVC LINEAR TSNE 2D
tsne_2d_svc_linear = build_svm(model_type=SVM_MODELS.LINEAR_SVC, x=tsne_2d_x_train, y=
                               max_iter=200000, path='models/tsne_2d_', multi_class='ovr')
print('tsne 2D - SVC LINEAR - Test accuracy', tsne_2d_svc_linear.score(tsne_2d_x_test
cm = confusion_matrix(tsne_2d_svc_linear.predict(tsne_2d_x_test), tsne_2d_y_test)
df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
plt.title('SVC LINEAR - tsne')
plt.show()
```

```
tsne 2D - SVC LINEAR - Test accuracy 0.7636363636363637
```

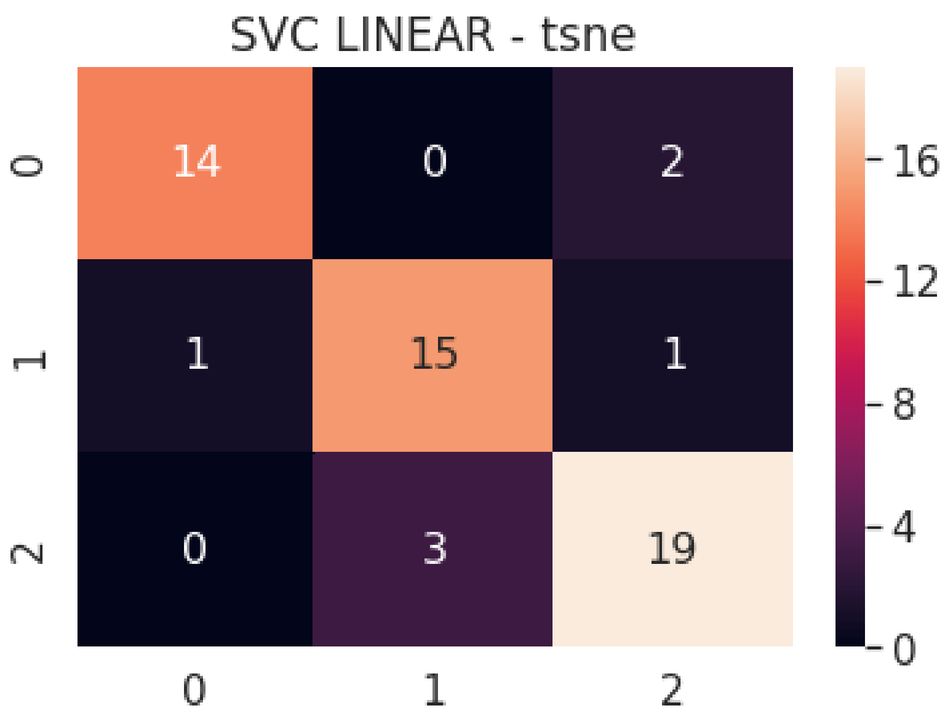


6.B.b SVC Linear - TSN-E 3D

```
In [48]: # SVC LINEAR TSNE 3D
         tsne_3d_svc_linear = build_svm(model_type=SVM_MODELS.LINEAR_SVC, x=tsne_3d_x_train, y
                                        max_iter=200000, path='models/tsne_3d_', multi_class='ovr'
         print('tsne 3D - SVC LINEAR - Test accuracy', tsne_3d_svc_linear.score(tsne_3d_x_test
         cm = confusion_matrix(tsne_3d_svc_linear.predict(tsne_3d_x_test), tsne_3d_y_test)
         df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
         plt.title('SVC LINEAR - tsne')
         plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/svm/_base.py:947: ConvergenceWarning: Liblinear
  "the number of iterations.", ConvergenceWarning)


tsne 3D - SVC LINEAR - Test accuracy 0.8727272727272727
```

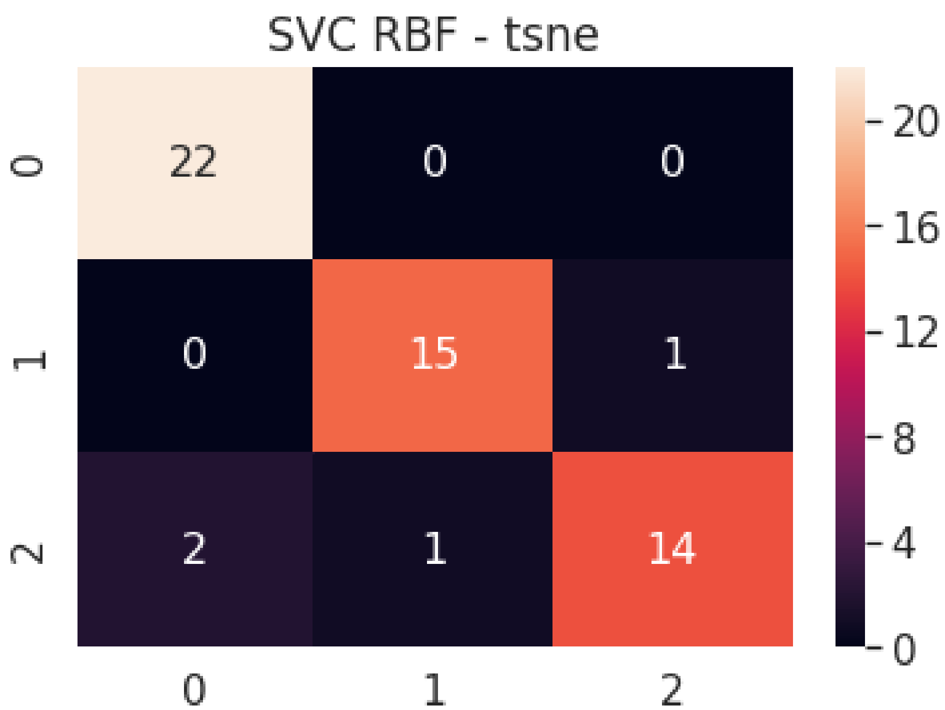


6.B.c SVC RBF - TSN-E 2D

```
In [49]: # SVC RBF tsne 2D
         tsne_2d_svc_rbf = build_svm(model_type=SVM_MODELS.SVC, x=tsne_2d_x_train, y=tsne_2d_y_
                                      path='models/tsne_2d_', svc_kernel='rbf')

         print('tsne 2D - SVC RBF - Test accuracy', tsne_2d_svc_rbf.score(tsne_2d_x_test, tsne_
         cm = confusion_matrix(tsne_2d_svc_rbf.predict(tsne_2d_x_test), tsne_2d_y_test)
         df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
         plt.title('SVC RBF - tsne')
         plt.show()
```

```
tsne 2D - SVC RBF - Test accuracy 0.9272727272727272
```

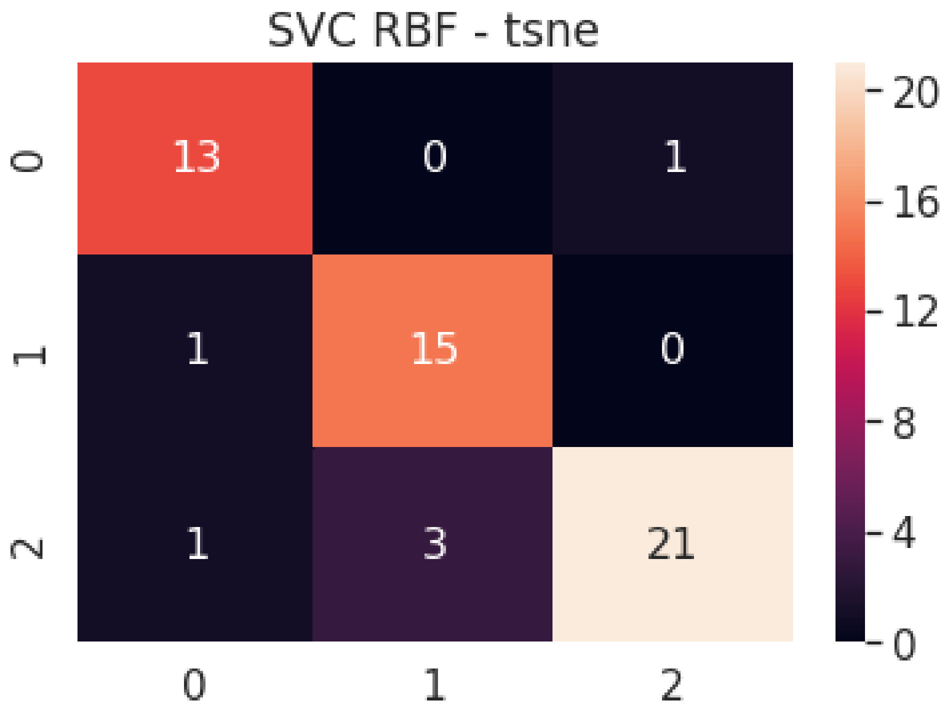


6.B.d SVC RBF - TSN-E 3D

```
In [50]: # SVC RBF tsne 3D
         tsne_3d_svc_rbf = build_svm(model_type=SVM_MODELS.SVC, x=tsne_3d_x_train, y=tsne_3d_y_
                                path='models/tsne_3d_', svc_kernel='rbf')

         print('tsne 3D - SVC RBF - Test accuracy', tsne_3d_svc_rbf.score(tsne_3d_x_test, tsne_
         cm = confusion_matrix(tsne_3d_svc_rbf.predict(tsne_3d_x_test), tsne_3d_y_test)
         df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
         sns.set(font_scale=1.4)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
         plt.title('SVC RBF - tsne')
         plt.show()
```

```
tsne 3D - SVC RBF - Test accuracy 0.8909090909090909
```



1.6.3 6.C Fully Connected

```
In [27]: def fc(input_shape, n_classes, print_summary=True):
             inputs = Input(shape=input_shape)
             x = Flatten(name='flatten')(inputs)
             x = Dense(64, activation='relu', name='fc1')(x)
             x = Dense(64, activation='relu', name='fc2')(x)
             x = Dense(n_classes, activation='softmax', name='predictions')(x)
             model = Model(inputs=inputs, outputs=x)
             if print_summary:
                 model.summary()
             return model

         fc_model = fc(features.shape[1:], n_classes)
         fc_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy

         import os
         def prepare_directory(model_type='vgg19'):
             save_dir = os.path.join(os.getcwd(), 'models')
             model_name = '%s_model.{epoch:03d}.h5' % model_type
             if not os.path.isdir(save_dir):
                 os.makedirs(save_dir)
             filepath = os.path.join(save_dir, model_name)
             return filepath
```

```python
filepath = prepare_directory()
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_acc', verbose=0, save_bes
callbacks = [checkpoint]

fc_model.fit(features, y,
          validation_split=0.1, epochs=50,
          verbose=1, workers=1, callbacks=callbacks)
score = fc_model.evaluate(features, y, batch_size=64)
print(fc_model.metrics_names)
print(score)
```

```
Model: "model_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_8 (InputLayer)         (None, 7, 7, 512)         0         
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0         
_________________________________________________________________
fc1 (Dense)                  (None, 64)                1605696   
_________________________________________________________________
fc2 (Dense)                  (None, 64)                4160      
_________________________________________________________________
predictions (Dense)          (None, 3)                 195       
=================================================================
Total params: 1,610,051
Trainable params: 1,610,051
Non-trainable params: 0
_________________________________________________________________
Train on 486 samples, validate on 55 samples
Epoch 1/50
486/486 [==============================] - 1s 1ms/step - loss: 2.8259 - acc: 0.7469 - val_loss
Epoch 2/50
486/486 [==============================] - 0s 229us/step - loss: 0.5015 - acc: 0.9650 - val_los
Epoch 3/50
486/486 [==============================] - 0s 233us/step - loss: 0.7303 - acc: 0.9403 - val_los
Epoch 4/50
486/486 [==============================] - 0s 223us/step - loss: 0.3563 - acc: 0.9753 - val_los
Epoch 5/50
486/486 [==============================] - 0s 236us/step - loss: 0.3539 - acc: 0.9733 - val_los
Epoch 6/50
486/486 [==============================] - 0s 224us/step - loss: 0.5973 - acc: 0.9609 - val_los
Epoch 7/50
486/486 [==============================] - 0s 238us/step - loss: 0.4245 - acc: 0.9671 - val_los
Epoch 8/50
486/486 [==============================] - 0s 242us/step - loss: 0.3037 - acc: 0.9794 - val_los
Epoch 9/50
```

```
486/486 [==============================] - 0s 243us/step - loss: 0.2898 - acc: 0.9774 - val_los
Epoch 10/50
486/486 [==============================] - 0s 221us/step - loss: 0.2199 - acc: 0.9856 - val_los
Epoch 11/50
486/486 [==============================] - 0s 218us/step - loss: 0.2319 - acc: 0.9835 - val_los
Epoch 12/50
486/486 [==============================] - 0s 236us/step - loss: 0.4203 - acc: 0.9691 - val_los
Epoch 13/50
486/486 [==============================] - 0s 227us/step - loss: 0.2003 - acc: 0.9877 - val_los
Epoch 14/50
486/486 [==============================] - 0s 224us/step - loss: 0.2901 - acc: 0.9774 - val_los
Epoch 15/50
486/486 [==============================] - 0s 238us/step - loss: 0.3266 - acc: 0.9774 - val_los
Epoch 16/50
486/486 [==============================] - 0s 220us/step - loss: 0.1764 - acc: 0.9877 - val_los
Epoch 17/50
486/486 [==============================] - 0s 222us/step - loss: 0.4236 - acc: 0.9712 - val_los
Epoch 18/50
486/486 [==============================] - 0s 233us/step - loss: 0.1862 - acc: 0.9856 - val_los
Epoch 19/50
486/486 [==============================] - 0s 225us/step - loss: 0.1648 - acc: 0.9897 - val_los
Epoch 20/50
486/486 [==============================] - 0s 216us/step - loss: 0.1048 - acc: 0.9918 - val_los
Epoch 21/50
486/486 [==============================] - 0s 224us/step - loss: 0.2432 - acc: 0.9815 - val_los
Epoch 22/50
486/486 [==============================] - 0s 226us/step - loss: 0.1717 - acc: 0.9856 - val_los
Epoch 23/50
486/486 [==============================] - 0s 232us/step - loss: 0.1682 - acc: 0.9877 - val_los
Epoch 24/50
486/486 [==============================] - 0s 233us/step - loss: 0.2213 - acc: 0.9835 - val_los
Epoch 25/50
486/486 [==============================] - 0s 223us/step - loss: 0.4356 - acc: 0.9712 - val_los
Epoch 26/50
486/486 [==============================] - 0s 221us/step - loss: 0.1415 - acc: 0.9897 - val_los
Epoch 27/50
486/486 [==============================] - 0s 248us/step - loss: 0.1024 - acc: 0.9918 - val_los
Epoch 28/50
486/486 [==============================] - 0s 221us/step - loss: 0.1327 - acc: 0.9918 - val_los
Epoch 29/50
486/486 [==============================] - 0s 214us/step - loss: 0.1327 - acc: 0.9918 - val_los
Epoch 30/50
486/486 [==============================] - 0s 228us/step - loss: 0.1327 - acc: 0.9918 - val_los
Epoch 31/50
486/486 [==============================] - 0s 220us/step - loss: 0.1327 - acc: 0.9918 - val_los
Epoch 32/50
486/486 [==============================] - 0s 232us/step - loss: 0.1327 - acc: 0.9918 - val_los
Epoch 33/50
```

```
486/486 [==============================] - 0s 243us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 34/50
486/486 [==============================] - 0s 224us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 35/50
486/486 [==============================] - 0s 221us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 36/50
486/486 [==============================] - 0s 231us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 37/50
486/486 [==============================] - 0s 223us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 38/50
486/486 [==============================] - 0s 224us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 39/50
486/486 [==============================] - 0s 232us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 40/50
486/486 [==============================] - 0s 210us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 41/50
486/486 [==============================] - 0s 213us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 42/50
486/486 [==============================] - 0s 235us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 43/50
486/486 [==============================] - 0s 225us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 44/50
486/486 [==============================] - 0s 225us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 45/50
486/486 [==============================] - 0s 238us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 46/50
486/486 [==============================] - 0s 220us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 47/50
486/486 [==============================] - 0s 210us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 48/50
486/486 [==============================] - 0s 224us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 49/50
486/486 [==============================] - 0s 218us/step - loss: 0.1327 - acc: 0.9918 - val_lo
Epoch 50/50
486/486 [==============================] - 0s 223us/step - loss: 0.1327 - acc: 0.9918 - val_lo
541/541 [==============================] - 0s 74us/step
['loss', 'acc']
[0.20855218491581207, 0.9870609971599966]
```

In [54]:
```python
print('VGG 19 - FC - Test accuracy', fc_model.evaluate(features_test, y_test, batch_s
cm = confusion_matrix(np.argmax(fc_model.predict(features_test), axis=1), np.argmax(y
df_cm = pd.DataFrame(cm, range(n_classes), range(n_classes))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True, annot_kws={"size": 16})
plt.title('FC model on VGG 19 Features')
plt.show()
```

```
31/31 [==============================] - 0s 252us/step
```

```
VGG 19 - FC - Test accuracy 1.0
```