Image Classification and Sentiment Analysis with Adaboost and SVM

Abstract

This analysis explores the performance of Support Vector Machines (SVM) and Adaboost with decision trees. The goal of the models is to train accurate classifiers for two datasets. The first task is to identify images as containing either bikes, a car, or people. The second task is to classify a text document of movie reviews as either positive or negative in its sentiment. In addition, the necessary preprocessing of the data was conducted including feature extraction, data augmentation, and dimensionality reduction. To evaluate the performance, five-fold cross validation of the resulting models was performed as well as an analysis of the resulting model confusion matrix. Lastly, custom kernels were developed and tested for the SVM model on both image classification and sentiment analysis as a method for improving accuracy.

1. Boosting for Image Classification

The first task involves implementing a boosting algorithm while utilizing a decision tree or decision stump for image classification.

1.1 Image Dataset & Feature Extraction

The goal is to develop a model to accurately identify images as containing either: bikes, cars, or people. The dataset has 154 images split approximately evenly between the three classes. An example image of each class is shown below in Figure 1.

Figure 1. Three example images of each possible class: Person (left), Bike (middle), and Car (right). These examples also illustrate the possible similarity for images between different classes.

To develop an image classification model its first necessary to extract features, so to develop an input to the model. The features can then be mapped to the respective target class by training on a portion of the image dataset. The performance can then be assessed on another portion of unseen data known as the test set. Histogram of Oriented Gradients (HOG) was extracted using the OpenCV python library. HOG is a feature descriptor that converts the image to several vectors that more concisely describe the contents, or shapes, within the image (Tomasi, 2016). In addition, image augmentation was performed to increase the exemplars of each class. This was used as a method to increase the accuracy of the classifier by providing more variation in example images for the model to learn from. The augmentation was conducted using the Keras library and included variations in image brightness, zoom, shear, rotation, and image mirroring. Lastly, due to the large number of HOG features extracted the curse of dimensionality may cause a drastic decrease in accuracy from the classifier. A feature reduction technique, Principal Component Analysis (PCA), was conducted to reduce 34020 features to 125.

1.2 Adaboost Algorithm Overview

The Adaboost algorithm is meant to be combined with other 'weak learning' algorithms as a method of improving performance. In this case, it is an ensemble method that is combined with short decision trees.

1.2.1 Decision Trees

The construction of a decision tree is an iterative process that builds a 'tree' of decisions. The tree ultimately ends with a leaf node when the 'impurity' from a new split is zero, or the maximum tree depth has been reached. The impurity is a measure of the predictive ability of each feature on predicting the target class.

1.2.2 Boosting Method

Boosting, analogous to bagging, is a machine learning technique that converts a weak learner into a strong learner. This can be done by initializing weights to the exemplars in the data. The weights are then adjusted iteratively by further adjusting the weights of observations with higher prediction error (Analytics Vidhya, 2020).

1.3 Model Results & Evaluation

After preprocessing the image dataset with HOG feature extraction, augmentation, and dimensionality reduction the mean score resulting from five-fold cross validation was 0.54. This accuracy is relatively low to be considered reliable by real-world application or industry standards.

However, since the problem is triple classification, a theoretically random classifier should achieve an accuracy of about 0.33. This model demonstrates a proof of concept by significantly outperforming a random classifier. A confusion matrix is shown below in Figure 2, further detailing the accuracy of the model on each class.

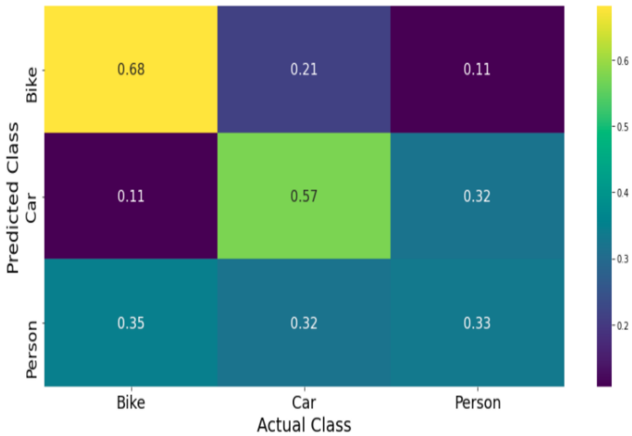


Figure 2. Confusion matrix of the Adaboost model on the three image classes: Bikes, Cars, and People.

The confusion matrix above shows that the Adaboost model can perform best when identifying bikes and cars, with 68% and 57% accuracy, respectively. However, the model performs poorly when classifying people at only 33%. This becomes more noticeable when analyzing the false positive rate for the model on identifying people, where it's more likely to identify a person as a bike than as a person. This can be seen in more detail by plotting the true positive rate for each class in a triple class Receiver Operating Characteristic (ROC) curve, shown below in Figure 3.

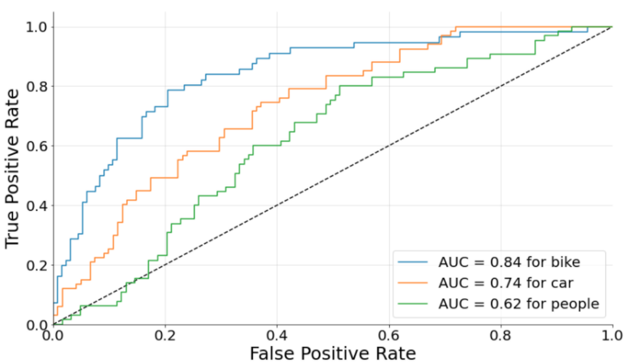


Figure 3. ROC curve for the performance of the Adaboost model on each class.

2. SVM for Image Classification

The next task involves implementing a Support Vector Machine (SVM) classifier using the Sci-Kit Learn python library. In addition, custom kernels are used as input to the SVM to map the data to a new space as an attempt to improve the model performance. The goal remains the same, to train the model to accurately identify bikes, cars, or people in an image.

2.1 Support Vector Machine Algorithm Overview

The basic premise when implementing an SVM is to create a model to find a hyperplane in the optimization space that maximizes the distance between classes (Ying & Fuyong, 2006). Many variations to the algorithm exist including soft or hard margin hyperplane, as well as the utilization of custom kernels (Namboodiri, Lecture, 2021). SVM's can utilize a provided kernel to map the data to a different (usually non-linear) dimension. This allows a linear SVM to fit a hyperplane to non-linearly separable data.

2.1.1 Default Kernels

The following kernels have a default option within the Sci-Kit Learn framework. The first and most simple is the linear kernel shown below:

$$k(x, y) = x^T y + c$$

Another non-linear kernel is a polynomial kernel with a coefficient and exponent parameter show as follows:

$$k(x, y) = (\alpha x^T y + c)^d$$

A variant of one of the most used kernels is the Gaussian (or Radial Basis Function) kernel, which can be seen below:

$$k(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right)$$

2.1.2 Custom Kernels

The first custom kernel is another variant of a radial basis function known as the exponential kernel:

$$k(x, y) = \exp\left(-\frac{\|x - y\|}{2\sigma^2}\right)$$

Another kernel used was the hyperbolic tangent, it is sometimes referred to as the Multilayer Perceptron kernel because of its use as an activation function in some neural networks (Souza, 2010).

$$k(x, y) = tanh(\alpha x^T y + c)$$

Next, the rational quadratic kernel is similar to a gaussian kernel, but it generally requires less computational power (Souza, 2010).

$$k(x,y) = 1 - \frac{\|x-y\|^2}{\|x-y\|^2 + c}$$

The log kernel, shown below, is the last custom kernel tested in the SVM.

$$k(x,y) = -\log\left(\|x-y\|^d + 1\right)$$

2.2 Model Results & Evaluation

This task is conducted on the same image dataset; thus, the same preprocessing (HOG extraction, augmentation, & PCA) was conducted to maximize model accuracy. Five-fold cross validation was then performed on the model to produce a mean accuracy of 0.64. The resulting confusion matrix from the SVM model is shown in Figure 4, depicting the performance on each class.

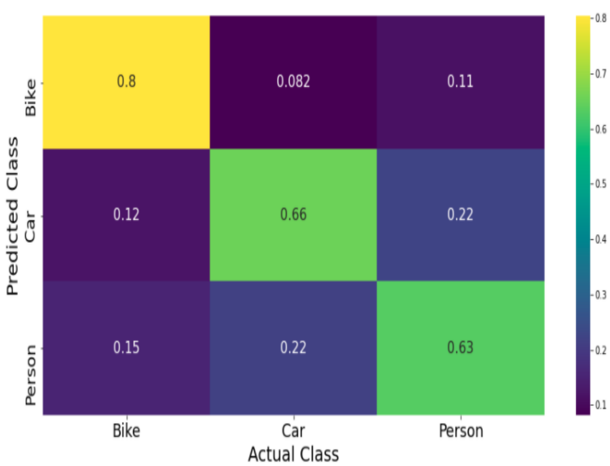


Figure 4. Confusion matrix of the SVM model on the three classes: Bikes, Cars, or People.

The SVM was able to significantly outperform the Adaboost model when identifying the classes of each image. However, a similar pattern emerges when analyzing the performance of the model on each of the three classes. Its apparent the models can more accurately identify the images containing bikes and cars, when compared to the performance of classifying people. Though, this affect appears to less significant in the results of the SVM it is still significant. This is apparent from the resulting false positive rates for images with cars and people, where the classifier is mistaking people for cars and vise versa about 22% of the time. This can be further investigated in the ROC curve in Figure 5.

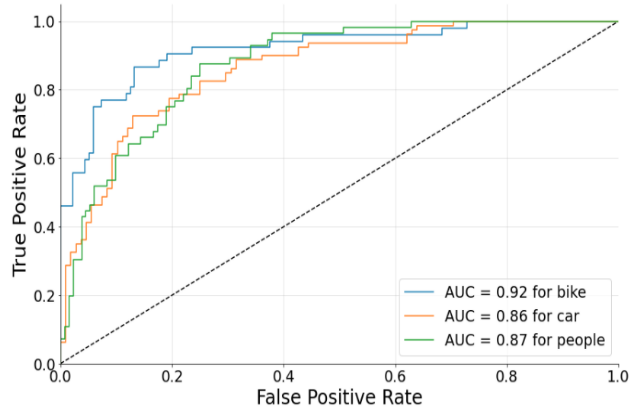


Figure 5. ROC curve for the performance of the SVM on each class.

Lastly, several custom kernels were tested in conjunction with the default Sci-Kit Learn kernels to maximize the performance of the SVM classifier. A simple bar chart is shown in Figure 6 depicting the average accuracy of each kernel on the image classification task.

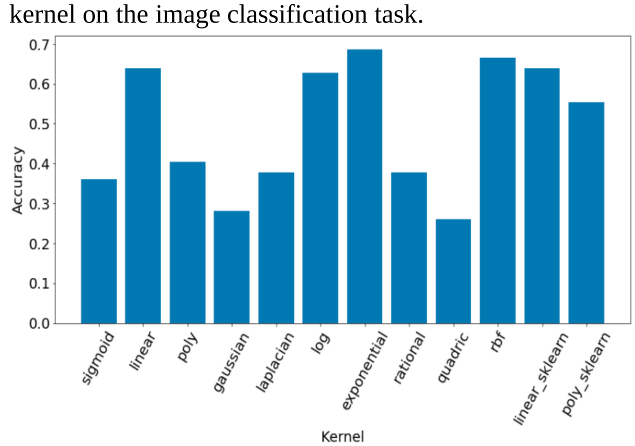


Figure 6. Model accuracy for each custom kernel tested in the SVM classifier.

The above chart shows the previously discussed exponential kernel to have the highest average accuracy. The linear, log, and RBF kernels have the next highest accuracies.

3. Boosting for Sentiment Analysis

This task consists of utilizing the previously implemented boosting algorithm (Adaboost) to train a model to accurately classify movie reviews as either positive or negative in its sentiment. Bag of words feature extraction as well as the necessary preprocessing of the data and the final model performance will be discussed.

3.1 Text Dataset & Feature Extraction

The goal of the model is to accurately classify a movie review as either positive or negative. The dataset contains

5000 movie reviews each containing the text of the review along with a label of its sentiment. An example of a positive and negative review is shown in Table 1.

Table 1. Portion of a positive and negative movie review.

Partial Review	*Sentiment (Class)*
"I cannot believe I enjoyed this as much as I did. The anthology stories were better than par, but the linking story and its surprise ending hooked me. …"	Positive
"Of all the films I have seen, this one, The Rage, has got to be one of the worst yet. The direction, LOGIC, continuity, changes in plot-script and dialog made me cry out in pain. …"	Negative

The text of each review is then vectorized and the words are counted with Sci-Kit Learns 'CountVectorizer' function. This function also ignores English stop words that may be irrelevant to the sentiment. In addition, a minimum 5% document frequency is set in the vectorizer to ignore terms that are used very rarely in the reviews. This vector is then transformed using Sci-Kit Learns 'TfidfTransformer' function. This creates a ratio of the term frequency to document frequency which can then be used as input to a classification model (Sklearn n.d.). Once the necessary features are extracted for the 5000 exemplars, PCA is conducted to reduce 4600 features into 50. This will minimize the influence from the curse of dimensionality on the model performance.

3.2 Model Results & Evaluation

After feature extraction and preprocessing the average accuracy from five-fold cross validation with Adaboost is 0.78. A confusion matrix for the results of the model is shown in Figure 7.

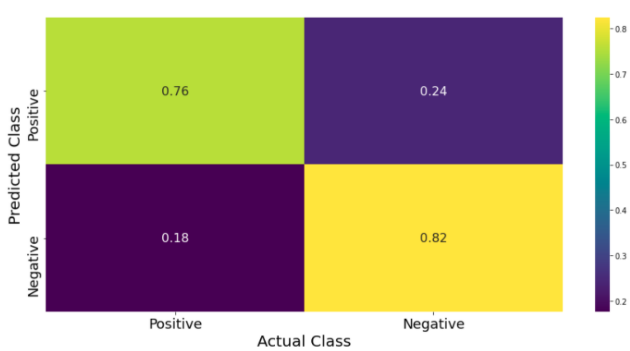


Figure 7. Confusion matrix of the Adaboost model on the sentiment of movie reviews.

This shows the model is fairly accurate at identifying negative reviews and positive reviews alike. However, there are more false positives than there are false negatives. The model is therefore more likely to mistakenly predict a review is positive when it is in fact negative. To explore this further the Receiver Operating Characteristic (ROC) curve was plotted for the results. This True vs False positive rate relationship is shown in Figure 8.

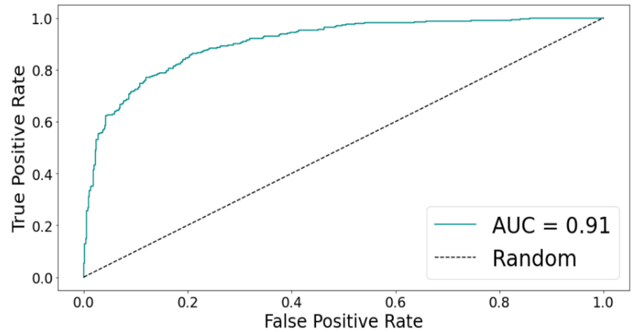


Figure 8. Receiver Operating Characteristic curve for true positive rate of the Adaboost results on movie review sentiment.

The area under the ROC curve is 0.91 indicating that the model has approximately a 91% chance of correctly distinguishing between positive and negative sentiment movie reviews.

4. SVM for Sentiment Analysis

The final task involves using the previously implemented SVM classifier to identify the movie reviews as either positive or negative. The custom kernels previously mentioned, as well as NLP specific kernels will be explored. In addition, the model results will be discussed along with an evaluation of its performance.

4.1 NLP Kernel

The intersection kernel, shown below, was designed specifically for use in NLP tasks (Namboodiri, Lecture, 2021). In one experiment in 2017, this kernel performed the best when classifying texts in English, Chinese, and Arabic (Popescu et al, 2017).

$$k(x, y) = \sum_{i=1}^{d} min\{c_i(x), c_i(y)\}$$

4.2 Model Results & Evaluation

The average accuracy of the resulting SVM model from five-fold cross validation was 0.84. To compare the performance across positive and negative reviews a confusion matrix was constructed, this is shown below in Figure 9.

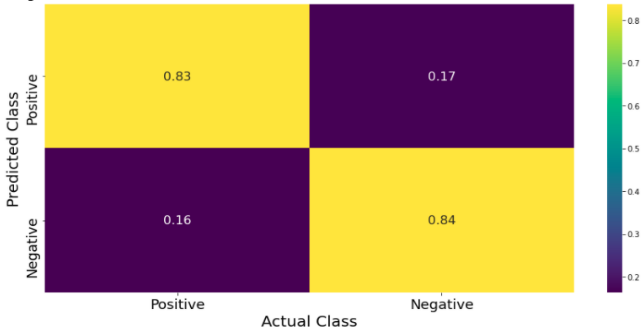


Figure 9. Confusion matrix of the SVM model on the sentiment of movie reviews.

One can see the SVM classifier attains similar accuracy on both negative and positive reviews. The relatively strong performance of the SVM can be seen in the ROC curve in Figure 9.

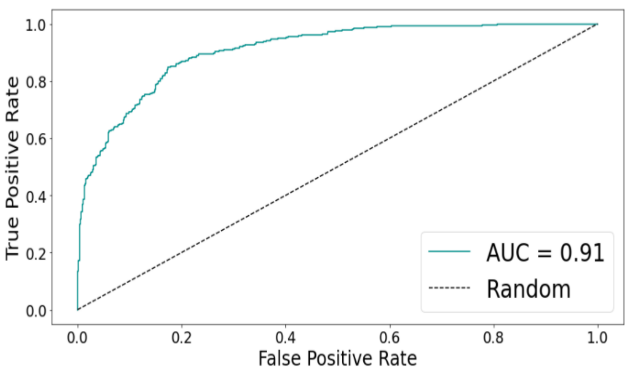


Figure 9. ROC curve depicting the true positive rate and the AUC of the classifier.

Lastly, the performance of each kernel was tested and plotted in Figure 10. The exponential and RBF kernel had marginally higher performance than several close seconds. Surprisingly for this task, the NLP specific intersection kernel did not show improvement in classifying the movie reviews.

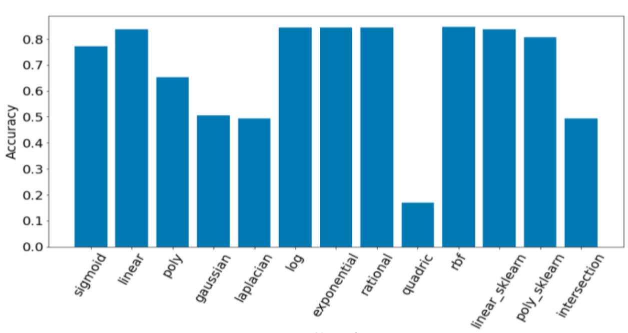


Figure 10. Bar chart comparison of the custom kernels used in the SVM for sentiment analysis.

References

Analytics Vidhya. (2020, June 26). Boosting algorithm: Boosting algorithms in machine learning. Retrieved March 21, 2021, from https://www.analyticsvidhya.com/blog/2015/11/quick-introduction-boosting-algorithms-machine-learning/

Popescu, M., Grozea, C., & Tudor Ionescu, R. (2017). HASKER: An efficient algorithm for String kernels. application to POLARITY classification in various languages. *Procedia Computer Science, 112*, 1755-1763. doi:10.1016/j.procs.2017.08.207

Sklearn.feature_extraction.text.TfidfTransformer¶. (n.d.). Retrieved March 21, 2021, from https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfTransformer.html

Souza , Cesar. (2010, March 17). César Souza. Retrieved March 21, 2021, from http://crsouza.com/2010/03/17/kernel-functions-for-machine-learning-applications/

Tomasi, C. (2016). Histogram of Oriented Gradients. https://www2.cs.duke.edu/courses/fall15/compsci527/notes/hog.pdf

Ying, Z., & Fuyong, W. (2006). A algorithm to incremental learning with support vector machine and its application IN Multi-class classification. *2006 Chinese Control Conference*. doi:10.1109/chicc.2006.280868

Coursework 1

In this coursework you will be aiming to complete two classification tasks. One of the classification tasks is related to image classification and the other relates to text classification.

The specific tasks and the marking for the various tasks are provided in the notebook. Each task is expected to be accompanied by a lab-report. Each task can have a concise lab report that is maximum of one page in an A4 size. You will be expected to submit your Jupyter Notebook and all lab reports as a single PDF file. You could have additional functions implemented that you require for carrying out each task.

Task 1

In this task, you are provided with three classes of images, cars, bikes and people in real world settings. You are provided with code for obtaining features for these images (specifically histogram of gradients (HoG) features). You need to implement a boosting based classifier that can be used to classify the images.

This task is worth 30 points out of 100 points. Implementing a working boosting based classifier and validating it by cross-validation on the training set will be evaluated for 15 out of 30 points. 10 points are based on the evaluation carried out on a separate test dataset that will be done at the time of evaluation. Finally 5 points are reserved for analysis of this part of the task and presenting it well in a lab report.

Note that the boosting classifier you implement can include decision trees from your previous ML1 coursework or can be a decision stump. Use the image_dataset directory provided with the assignment and save it in the same directory as the Python notebook

Write your Image feature extraction code

In [1]:
```
import numpy as np
import cv2 as cv
import glob
import pandas as pd
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import os
from tqdm import tqdm
import time
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
plt.rcParams['figure.figsize'] = [10, 6]
from IPython.display import clear_output
```

In [2]:
```
def obtain_dataset(folder_name,
                   include_augmented = True,
                   Hog_features = True):
    feature_len = 34020
    hog = cv.HOGDescriptor()

    y = []
    X = []

    c = 0

    # store images to visualize if necessary
    image_dict = {}

    class_dict = {'bike'    : 1,
                  'car'     : 2,
                  'people'  : 3}

    for subdir, dirs, files in os.walk(folder_name):
        for file in files:

            if not include_augmented:
                if 'aug' in file:
                    file = ''

            # get file location from directory
            file_location = subdir + "\\" + file

            try:
                img = cv.imread(file_location)
                image_dict.update({file:img})
                h = hog.compute(img)

                if Hog_features:
                    X.append(h)
                else:
                    X.append([img])

                if 'bike' in file:
                    y.append(class_dict['bike'])
                elif 'car' in file:
                    y.append(class_dict['car'])
                elif 'person' in file:
                    y.append(class_dict['people'])
                else:
                    y.append(np.nan)

            except:
                print('Error when loading file : ', file)
    if Hog_features:
        X = np.concatenate(X, axis = 1).T
    print('Data Loaded.')
    return X, y
```

Decision Tree Class

In [3]:
```
class Decision_Tree:

    def __init__(self, x, y,
                 start_feature,
                 num_features,
                 min_leaf,
                 max_depth):

        self.features = np.arange(start_feature, start_feature + num_features)

        # init data
        self.x = x #x.iloc[:,self.features].values
        self.y = y #y.values
        self.num_rows = x.shape[0]

        # init hyperparameters
        self.min_leaf = min_leaf
        self.max_depth = max_depth

        # data charactersitics
        self.num_features = num_features
        self.val = np.mean(y)

        self.score = np.inf

        self.tree = self.build_tree(self.x, self.y, max_depth)

    def calculate_entropy(self,y):

        prob = pd.Series(y).value_counts(normalize = True)
        return - np.sum(prob * np.log(prob)) / np.log(2)

    def find_split(self, x, y):
        """Given a dataset and its target values, this finds the optimal combination
        of feature and split point that gives the maximum information gain."""

        # Need the starting entropy so we can measure improvement...
        start_entropy = self.calculate_entropy(y)

        # all possible indices
        indices = np.arange( len(x) )

        # Best thus far, initialised to a dud that will be replaced immediately...
        best = {'infogain' : -np.inf}

        # Loop every possible split of every dimension...
        for i in range(x.shape[1]):
            for split in np.unique(x[:,i]):


                # indices that are greater than or less than split value
                left_indices  = indices[x[:,i] <= split]
                right_indices = indices[x[:,i] >  split]

                left_ratio = ( len(left_indices) / len(x) )
                right_ratio = ( len(right_indices) / len(x) )

                infogain = start_entropy - left_ratio \
                                         * self.calculate_entropy( y[left_indices] ) - \
                                         right_ratio * self.calculate_entropy( y[right_indices] )

                # update dictionary with optimal values
                if infogain > best['infogain']:
                    best = {'feature' : i,
                            'split' : split,
                            'infogain' : infogain,
                            'left_indices' : left_indices,
                            'right_indices' : right_indices}

        return best

    def build_tree(self, x, y, max_depth = np.inf):

        # Check if either of the stopping conditions have been reached. If so generate a leaf node...
        if max_depth == 1 or (y == y[0]).all():
            # Generate a leaf node...
            classes, counts = np.unique(y, return_counts=True)
            return {'leaf' : True, 'class' : classes[np.argmax(counts)]}

        else:
            move = self.find_split(x, y)

            left = self.build_tree(x[move['left_indices'],:], y[move['left_indices']], max_depth - 1)
            right = self.build_tree(x[move['right_indices'],:], y[move['right_indices']], max_depth - 1
)

            return {'leaf' : False,
                    'feature' : move['feature'],
                    'split' : move['split'],
                    'infogain' : move['infogain'],
                    'left' : left,
                    'right' : right}

    def predict_one(self, tree, sample):
        """Does the prediction for a single data point"""
        if tree['leaf']:
            return tree['class']

        else:
            if sample[tree['feature']] <= tree['split']:
                return self.predict_one(tree['left'], sample)
            else:
                return self.predict_one(tree['right'], sample)

    def predict(self, x_test):
        """Predicts class for every entry of a data matrix."""

        samples = x_test #.iloc[:,self.features].values

        ret = np.empty(samples.shape[0], dtype=int)
        ret.fill(-1)
        indices = np.arange(samples.shape[0])

        def tranverse(node, indices):
            nonlocal samples
            nonlocal ret

            if node['leaf']:
                ret[indices] = node['class']

            else:
                going_left = samples[indices, node['feature']] <= node['split']
                left_indices = indices[going_left]
                right_indices = indices[np.logical_not(going_left)]

                if left_indices.shape[0] > 0:
                    tranverse(node['left'], left_indices)

                if right_indices.shape[0] > 0:
                    tranverse(node['right'], right_indices)

        tranverse(self.tree, indices)
        return ret
```

Boosting classifier class

In [4]:
```
class BoostingClassifier:

    def __init__(self,n_estimators = 10,
                 max_depth = 5,
                 num_features = 1000,
                 start_feature = 200,
                 sklearn = True):

        self.sklearn = sklearn

        self.n_est = n_estimators
        self.depth = max_depth

        self.trees = []
        self.tree_weights = []

        self.num_features = num_features
        self.start = start_feature

    def update_weights(self, weights, y, y_dt, tree_weights):

        for i in range(weights.shape[0]):
            if y[i] != y_dt[i]:
                weights[i] = weights[i]*np.exp(tree_weights)

        weights /= np.sum(weights)
        return weights

    def fit(self, X, y):

        n_class = np.unique(y).shape[0]

        # init weights, value is aribitrary
        weights = np.array([1/X.shape[0] for i in range(X.shape[0])])
        weights = weights.reshape([-1,1])

        start = self.start
        features = np.arange(start , start + self.num_features)

        for i in tqdm(range(self.n_est)):
            if self.sklearn == False:
                # instantiate DT & fit to data
                DT = Decision_Tree(X, y,
                      num_features = self.num_features,
                      max_depth = self.depth,
                      start_feature = self.start)
            elif self.sklearn == True:
                DT = DecisionTreeClassifier(max_depth = self.depth)
                DT.fit(X,y)

            # predict with trees
            dt_pred = DT.predict(X)

            # update tree weights
            error = np.sum(weights[np.where(y != dt_pred)])
            self.tree_weights.append(np.log((1 - error) / error) \
                                     + np.log(n_class - 1))

            # update data weights
            weights = self.update_weights(weights,
                                          y,
                                          dt_pred,
                                          self.tree_weights[-1])
            # store each tree
            self.trees.append(DT)


    def predict(self, X):

        n = X.shape[0]

        pred = np.array([tree.predict(X) for tree in self.trees]).T

        y_pred = []
        for i in range(n):

            current = pred[i,:]
            class_weights = {prediction : 0 for prediction in np.unique(current)}
            for j, prediction in enumerate(current):
                class_weights[prediction] += self.tree_weights[j]

            optimal_weight = max(class_weights, key = class_weights.get)
            y_pred.append(optimal_weight)

        return np.array(y_pred)
```

define train test split function & normilization functions

In [5]:
```
def train_test_valid(df, train_ratio = 0.6, valid_ratio = 0.2 ):

    train, validation, test = np.split(df.sample(frac = 1,
                                                 random_state = np.random.randint(1,1e3)),
                                       [int(train_ratio * len(df)),
                                        int((train_ratio + valid_ratio) * len(df))])

    return train, test, validation

# function for normalizing data
def normalize(df, mean_method = True ):
    if mean_method:
        # mean normalization
        normalized_df = (df - df.mean()) / df.std()
        a, b = df.std(), df.mean()
    else:
        # min max normalization
        normalized_df = (df - df.min()) / (df.max() - df.min())
        a, b = df.min(), df.max()
    return normalized_df, a, b

def unnormalize(df, a, b, mean_method = True):
    if mean_method:
        # mean normalization
        unnormalized_df = df * a + b
    else:
        # min max normalization
        unnormalized_df = (df * (b - a)) + a
    return unnormalized_df
```

Option to download augmented images to image folder

In [6]:
```
from keras.preprocessing.image import ImageDataGenerator,array_to_img, img_to_array, load_img

datagen = ImageDataGenerator(
        rotation_range = 40,
        shear_range = 0.2,
        zoom_range = 0.2,
        horizontal_flip = True,
        brightness_range = (0.5, 1.5))

def augment_images(image_name, fname, directory):
    img = load_img(image_name)
    x = img_to_array(img)
    x = x.reshape((1,) + x.shape)

    i = 0
    for batch in datagen.flow(x, batch_size = 1,
                     save_to_dir = directory,
                     save_prefix = fname,
                     save_format = 'png'):
        i += 1
        if i >= 5:
            break


perform_augmentation = False
if perform_augmentation:
    folder_name = 'image_dataset'
    for subdir, dirs, files in os.walk(folder_name):
            for file in files:

                # get file location from directory
                file_location = subdir + "\\" + file

                if 'bike' in file:
                    fname = 'bike_aug'
                elif 'car' in file:
                    fname = 'car_aug'
                elif 'person' in file:
                    fname = 'person_aug'
                else:
                    y.append(np.nan)

                if 'img' in file: # only augment OG images
                    augment_images(file_location, fname, subdir)
```

Image augmentation and HOG feature extraction function

In [7]:
```
from keras.preprocessing.image import ImageDataGenerator, img_to_array, array_to_img
def HOG_augment(df, augment = True, n = 2):

    datagen = ImageDataGenerator(
            rotation_range = 40,
            shear_range = 0.2,
            zoom_range = 0.2,
            horizontal_flip = True,
            brightness_range = (0.5, 1.5))

    hog = cv.HOGDescriptor()

    x = []
    y = []



    for image, target in tqdm(df.values):

        # get hog features for OG images
        x.append(hog.compute(image))
        y.append(target)

        x_array = img_to_array(image)
        x_array = x_array.reshape((1,) + x_array.shape)

        if augment:
            i = 0
            for batch in datagen.flow(x_array):

                b = np.asarray(array_to_img(np.squeeze(batch)))
                h = hog.compute(b)

                # save hog features and class for augmented images
                x.append(h)
                y.append(target)

                i+=1
                if i >= n:
                    break


    X = np.hstack(x).T

    df_augmented = pd.DataFrame(X)
    df_augmented['y'] = y

    return df_augmented
```

principal component analysis for dimensionality reduction

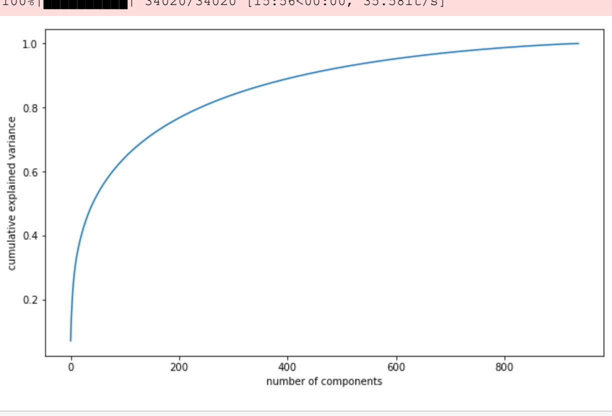
In [8]:
```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.decomposition import PCA

def reduce_features(df, num_features = 20, solver = 'full'):

    encoder = LabelEncoder()

    # split input and target
    x, y = df.iloc[:,:-1], df.iloc[:,-1]

    for col in tqdm(x.columns[:]):
        x[col] = encoder.fit_transform(x[col])

    # apply scaler to input features
    scaler = StandardScaler()
    x = scaler.fit_transform(x)

    # transform features
    pca = PCA(svd_solver = solver)
    pca.fit_transform(x)
    pca_variance = pca.explained_variance_

    plt.plot(np.cumsum(pca.explained_variance_ratio_))
    plt.xlabel('number of components')
    plt.ylabel('cumulative explained variance');

    # fit
    pca2 = PCA(n_components = num_features, whiten = True)
    pca2.fit(x)
    pca_x = pca2.transform(x)

    # recreate dataframe after PCA
    df_pca = pd.DataFrame(pca_x)
    df_pca['y'] = y.values

    return df_pca
```

In [9]:
```
folder_name = 'image_dataset'
x, y = obtain_dataset(folder_name,
                      include_augmented = True,
                      Hog_features = False)

df = pd.DataFrame(x)
df['y'] = y
```

```
Error when loading file :  .DS_Store
Error when loading file :  reports.docx
Data Loaded.
```

In [10]:
```
df_hog = HOG_augment(df, augment = False)
df_pca = reduce_features(df_hog, num_features = 125)
```

```
100%|██████████| 937/937 [00:00<00:00, 2169.75it/s]
100%|██████████| 34020/34020 [15:56<00:00, 35.58it/s]
```



In [11]:
```
# random split for test and training set
train1, test1, val1 = train_test_valid(df_pca,
                                       train_ratio = 0.8,
                                       valid_ratio = 0.0)
```

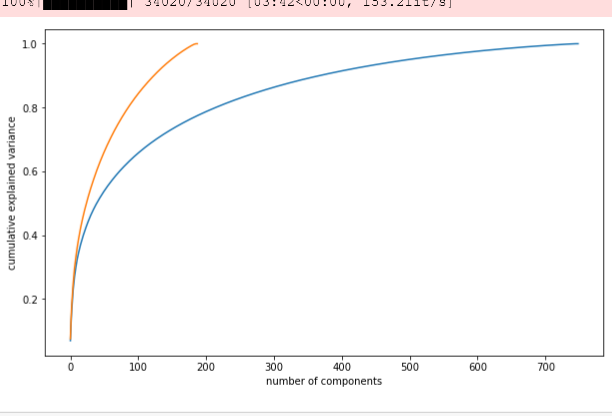
In [12]:
```
# random split for test and training set
train, test, val = train_test_valid(df,
                                    train_ratio = 0.8,
                                    valid_ratio = 0.0)
```

In [13]:
```
train = HOG_augment(train, augment = False, n = 0)
test = HOG_augment(test, augment = False)
```

```
100%|██████████| 749/749 [00:00<00:00, 2127.48it/s]
100%|██████████| 188/188 [00:00<00:00, 2298.58it/s]
```

In [14]:
```
train = reduce_features(train, num_features = 30, solver = 'auto')
test = reduce_features(test, num_features = 30, solver = 'auto')
```

```
100%|██████████| 34020/34020 [13:01<00:00, 43.54it/s]
100%|██████████| 34020/34020 [03:42<00:00, 153.21it/s]
```



In [15]:
```
# seperate input X from target variable y
x_train, y_train = train1.iloc[:,:-1], train1.iloc[:,-1]
x_test, y_test = test1.iloc[:,:-1], test1.iloc[:,-1]

# normalize test and train data
x_train, x_test = normalize(x_train)[0], normalize(x_test)[0]
```

In [16]:
```
DT = DecisionTreeClassifier(max_depth = 1000)
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.526595744680851
```

Train the boosting classifer and evaluate it on the train-test split

In [17]:
```
bc = BoostingClassifier(n_estimators = 100,
                        max_depth = 10,
                        sklearn = True)

bc.fit(x_train.values, y_train.values)

y_pred = bc.predict(x_test.values)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
100%|██████████| 100/100 [00:05<00:00, 19.75it/s]
accuracy:  0.5
```

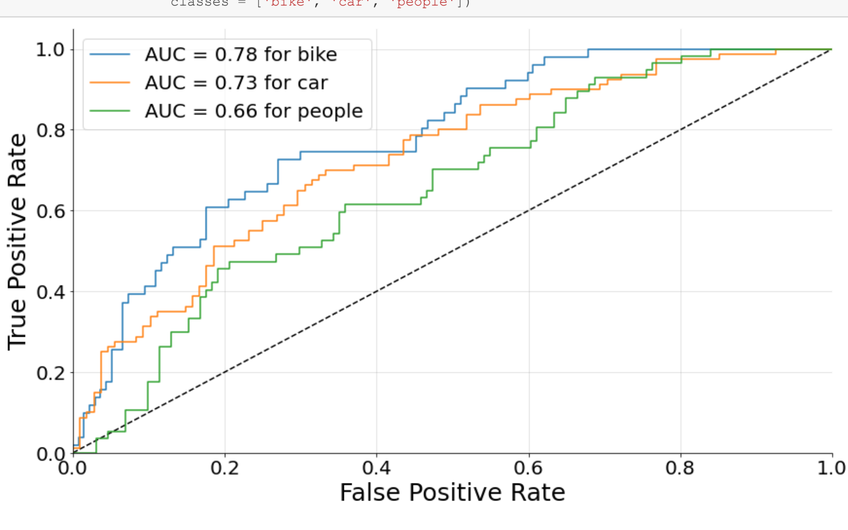
In [18]:
```
from sklearn.ensemble import AdaBoostClassifier as boost

bc = boost(n_estimators = 50)

bc.fit(x_train,y_train)

y_pred = bc.predict(x_test.values)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.5531914893617021
```

Define multiclass ROC curve function

In [19]:
```
from sklearn import metrics
def plot_multiclass_roc(clf, X_test, y_test, classes = [], figsize=(14, 8)):
    y_score = clf.decision_function(X_test)

    # structures
    fpr = dict()
    tpr = dict()
    roc_auc = dict()
    n_classes = len(classes)

    # calculate dummies once
    y_test_dummies = pd.get_dummies(y_test, drop_first=False).values
    for i in range(n_classes):
        fpr[i], tpr[i], _ = metrics.roc_curve(y_test_dummies[:, i], y_score[:, i])
        roc_auc[i] = metrics.auc(fpr[i], tpr[i])

    # roc for each class
    fig, ax = plt.subplots(figsize=figsize)
    ax.plot([0, 1], [0, 1], 'k--')
    ax.set_xlim([0.0, 1.0])
    ax.set_ylim([0.0, 1.05])
    ax.set_xlabel('False Positive Rate', size = 25)
    ax.set_ylabel('True Positive Rate', size = 25)
    plt.tick_params(axis='x', which='major', labelsize=20)
    plt.tick_params(axis='y', which='major', labelsize=20)
    for i in range(n_classes):
        ax.plot(fpr[i], tpr[i], label='AUC = {:0.2f} for {}'.format(roc_auc[i], classes[i]))
    ax.legend(loc="best", fontsize = 20)
    ax.grid(alpha=.4)
    sns.despine()
    plt.show()
```

In [20]:
```
plot_multiclass_roc(bc, x_test, y_test,
                    classes = ['bike', 'car', 'people'])
```



Define Cross validation function

In [21]:
```
def kfoldCV(df, kfolds = 5, norm = True, model_type = 'boosting',
            sklearn = True,
            n_est = 100,
            depth = 5,
            k = 'exponential',
            reg = 1,
            deg = 3):


    # get K folds
    folds = np.array_split(df.sample(frac = 1, random_state = np.random.randint(0,1000)), kfolds)

    scores = []
    for i in range(kfolds):
        clear_output(wait=True)
        print('Fold: ', i)
        # set test set to current fold
        test = folds[i]

        # train on remaining folds combined
        train = folds.copy()
        del train[i] #remove current fold
        df_train = pd.DataFrame(np.vstack(train))

        # seperate input and target variable
        x_train, y_train = df_train.iloc[:,:-1], df_train.iloc[:,-1]
        x_test, y_test = test.iloc[:,:-1], test.iloc[:,-1]

        if norm:
            # normalize test and train data
            x_train, x_test = normalize(x_train)[0], normalize(x_test)[0]

        if model_type == 'boosting':
            model = BoostingClassifier(n_estimators = n_est,
                                       max_depth = depth,
                                       sklearn = sklearn)
        elif model_type == 'svm':
            model = SVMClassifier(kernel = k,
                                  reg_param = reg,
                                  degree = deg)

        # fit model to training data and predict on test data
        model.fit(x_train.values, y_train.values)
        y_pred = model.predict(x_test.values)

        # store accuracy data
        scores.append(accuracy_score(y_test, y_pred))

    return scores
```

Average Score from Cross Validation

In [22]:
```
scores = kfoldCV(df_pca, kfolds = 5,
                 model_type = 'boosting',
                 n_est = 100,
                 depth = 5)

print('Average score from Cross Validation: {:.2f}'.format(np.mean(scores)))
```

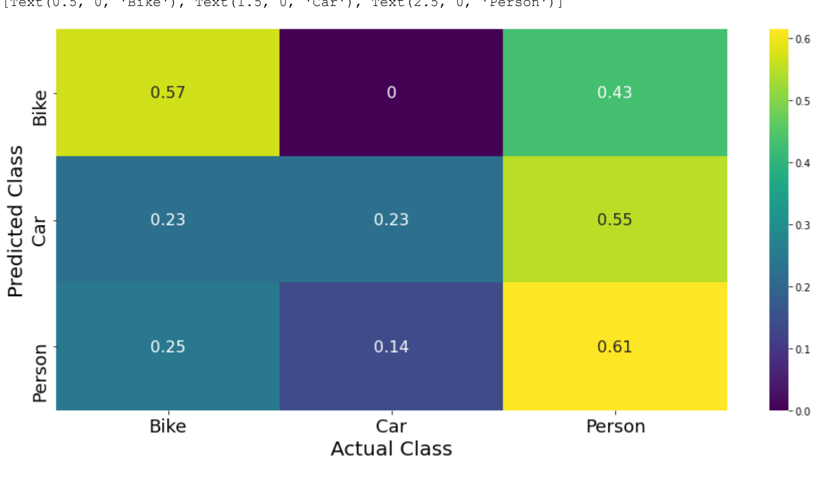
```
  0%|          | 0/100 [00:00<?, ?it/s]
Fold:  4
100%|██████████| 100/100 [00:03<00:00, 30.50it/s]
Average score from Cross Validation: 0.47
```

In [23]:
```
bc = BoostingClassifier(n_estimators = 100,
                        max_depth = 5,
                        sklearn = True)

bc.fit(x_train.values, y_train.values)

y_pred = bc.predict(x_test.values)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
100%|██████████| 100/100 [00:03<00:00, 31.09it/s]
accuracy:  0.43617021276595747
```

In [24]:
```
plt.rcParams['figure.figsize'] = [15, 7]
res = sns.heatmap(confusion_matrix(y_test,y_pred, normalize = 'true'),
            annot = True,
            xticklabels = ['Bike', 'Car', 'Person'],
            yticklabels = ['Bike', 'Car', 'Person'],
            cmap = 'viridis', annot_kws={"size": 16})

plt.xlabel('Actual Class', size = 20)
plt.ylabel('Predicted Class', size = 20)
res.set_yticklabels(res.get_ymajorticklabels(), fontsize = 18)
res.set_xticklabels(res.get_xmajorticklabels(), fontsize = 18)
```

Out[24]:
```
[Text(0.5, 0, 'Bike'), Text(1.5, 0, 'Car'), Text(2.5, 0, 'Person')]
```



Task 2

In this task, you need to classify the above dataset using a Support Vector Machine (SVM).

This task is worth 25 points out of 100 points. You are allowed to use existing library functions such as scikit-learn for obtaining the SVM. The main idea is to analyse the dataset using different kind of kernels. You are also supposed to write your own custom kernels. The marking will be 15 marks for analysing the dataset using various kernels including your own kernels, 5 points for the performance on the test dataset and 5 points for a lab-report that provides the analysis and comparisons.

SVM class w/ custom kernels

In [25]:
```python
from sklearn import svm
class SVMClassifier:

    def __init__(self, kernel = 'exponential',
                       reg_param = 1.0,
                       degree = 3,
                       max_iter = 1e5,
                       tol = 1e-3):


        if kernel == 'sigmoid':
            k = self.sigmoid
        elif kernel == 'linear':
            k = self.linear
        elif kernel == 'poly':
            k = self.polynomial
        elif kernel == 'gaussian':
            k = self.gaussian
        elif kernel == 'laplacian':
            k = self.laplacian
        elif kernel == 'log':
            k = self.log
        elif kernel == 'exponential':
            k = self.exponential
        elif kernel == 'rational':
            k = self.rational
        elif kernel == 'quadric':
            k = self.quadric
        elif kernel == 'rbf':
            k = kernel
        elif kernel == 'linear_sklearn':
            k = 'linear'
        elif kernel == 'poly_sklearn':
            k = 'poly'
        elif kernel == 'intersection':
            k = self.intersect
        else:
            print('Using externel kernel.')
            k = kernel
            #return

        # instantial svm classifier
        self.clf = svm.SVC(C = reg_param,
              kernel = k,
              degree = degree,
              gamma = 'scale')

    def kernels_list(self):
        return ['sigmoid', 'linear', 'poly', 'gaussian', 'laplacian',
                'log', 'exponential', 'rational', 'quadric', 'rbf',
                'linear_sklearn', 'poly_sklearn']

    def linear(self, x,y):
        return np.inner(x,y)

    def sigmoid(self, x,y, alpha = 1):
        return np.tanh(alpha*np.inner(x,y))

    def polynomial(self, x,y, coef = 1, p = 6):
        return (np.inner(x,y) + coef) ** p

    def gaussian(self, U,V,sigma = 0.1):
        def gaussianKernel(U,V,sigma = 0.1):
            return np.exp(np.linalg.norm(U-V) ** 2 / (2*sigma**2))

        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = gaussianKernel(U[i],V[j],sigma)
        return G

    def laplacian(self, U,V,sigma = 0.1):
        def LaplacianKernel(U,V,sigma = 0.1):
            return np.exp(-np.linalg.norm(U-V) / sigma)

        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = LaplacianKernel(U[i],V[j],sigma)
        return G

    def log(self, U,V):
        def logKernel(U,V):
            return -np.log(np.linalg.norm(U-V) + 1)

        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = logKernel(U[i],V[j])
        return G

    def exponential(self, U,V,sigma = 0.1):
        def expKernel(U,V,sigma = 0.1):
            return - np.linalg.norm(U-V) /  (2*sigma**2)
        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = expKernel(U[i],V[j],sigma)
        return G

    def rational(self, U,V,c = 100):
        def RationalKernel(U,V,c = 100):
            return 1 - (np.linalg.norm(U-V)**2 / (np.linalg.norm(U-V)**2 + c))

        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = RationalKernel(U[i],V[j],c)
        return G

    def quadric(self, U,V,c = 100):
        def quadricKernel(U,V,c = 100):
            return np.sqrt(np.sum(np.power((U-V),2)) + c**2)

        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = quadricKernel(U[i],V[j],c)
        return G

    def intersect(self, U,V,sigma = 0.1):
        def Kernel(U,V,sigma = 0.1):
            return  np.sum((min(U),  min(V)), axis = 0)
        G = np.zeros((U.shape[0], V.shape[0]))
        for i in range(0,U.shape[0]):
            for j in range(0,V.shape[0]):
                G[i][j] = Kernel(U[i],V[j],sigma)
        return G

    def fit(self, X,y):
        self.clf.fit(X,y)

    def fit_image(self, X,y):
        self.clf.fit(X,y)

    def fit_text(self, X,y):

        self.clf.fit(X,y)

    def predict(self, X):
        y_pred = self.clf.predict(X)
        return y_pred

    def predict_image(self, X):
        y_pred = self.clf.predict(X)
        return y_pred

    def predict_text(self, X):
        y_pred = self.clf.predict(X)
        return y_pred
```

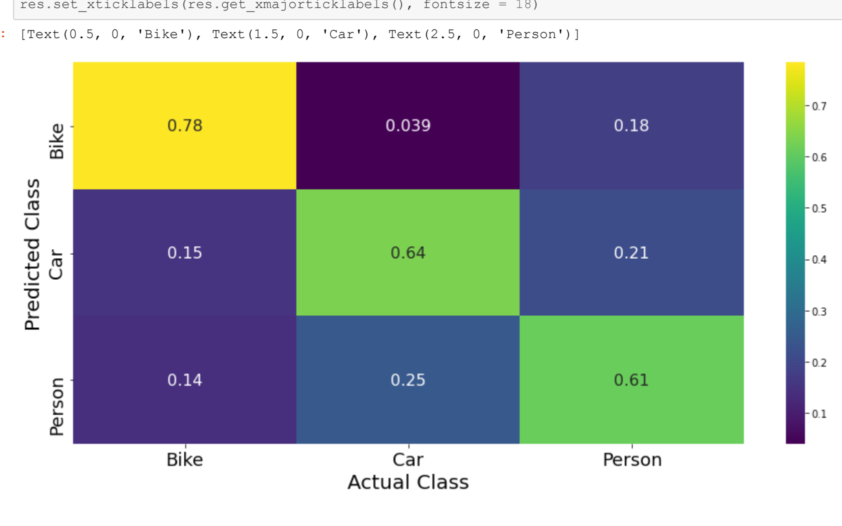
Train the SVM classifer and evaluate it on the train-test split

In [26]:
```python
sc = SVMClassifier(kernel = 'rbf',
                   reg_param = 1,
                   degree = 3)

sc.fit_image(x_train.values, y_train.values)
y_pred = sc.predict_image(x_test.values)
print('accuracy', accuracy_score(y_test, y_pred))
```

```
accuracy 0.6702127659574468
```

In [27]:
```python
plt.rcParams['figure.figsize'] = [15, 7]
res = sns.heatmap(confusion_matrix(y_test,y_pred, normalize = 'true'),
            annot = True,
            xticklabels = ['Bike', 'Car', 'Person'],
            yticklabels = ['Bike', 'Car', 'Person'],
            cmap = 'viridis', annot_kws={"size": 16})

plt.xlabel('Actual Class', size = 20)
plt.ylabel('Predicted Class', size = 20)
res.set_yticklabels(res.get_ymajorticklabels(), fontsize = 18)
res.set_xticklabels(res.get_xmajorticklabels(), fontsize = 18)
```

Out[27]: `[Text(0.5, 0, 'Bike'), Text(1.5, 0, 'Car'), Text(2.5, 0, 'Person')]`



Score with 5-fold Cross Validation

In [28]:
```python
scores = kfoldCV(df_pca, kfolds = 5, model_type = 'svm',
                 k = 'exponential',
                 reg = 1,
                 deg = 3)

print('Average score from Cross Validation: {:.2f}'.format(np.mean(scores)))
```

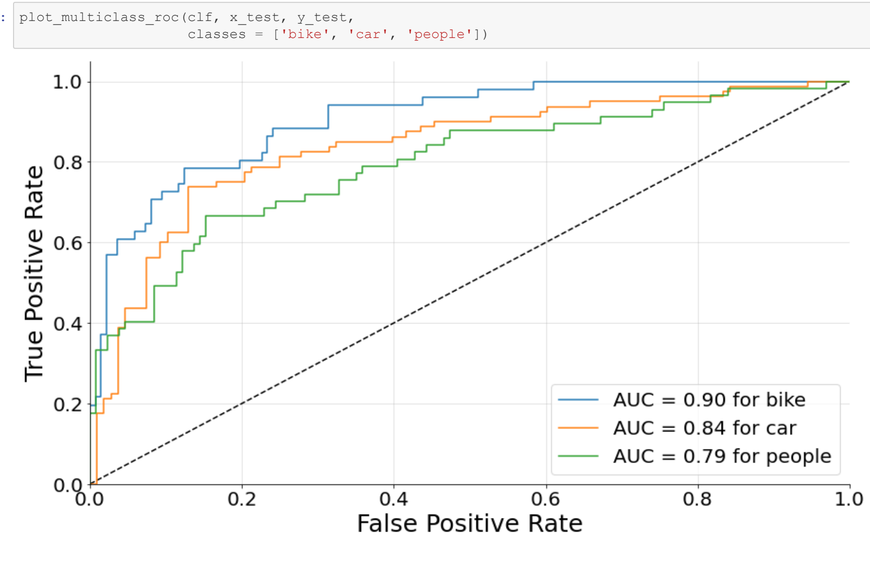
```
Fold:  4
Average score from Cross Validation: 0.65
```

In [29]:
```python
clf = svm.SVC(C = 2,
              kernel = 'rbf',
              degree = 3,
              gamma = 'scale')
clf.fit(x_train, y_train)

y_pred = clf.predict(x_test)

print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.7180851063829787
```

In [30]:
```python
from sklearn import metrics
```

In [31]:
```python
plot_multiclass_roc(clf, x_test, y_test,
                    classes = ['bike', 'car', 'people'])
```



Evaluate each custom kernel

In [33]:
```python
accuracy = []

for k in sc.kernels_list():
    print(k)
    sc = SVMClassifier(kernel = k,
                       reg_param = 1,
                       degree = 3)

    sc.fit_image(x_train.values, y_train.values)
    y_pred = sc.predict_image(x_test.values)
    accuracy.append(accuracy_score(y_test, y_pred))
    clear_output(wait=True)
```

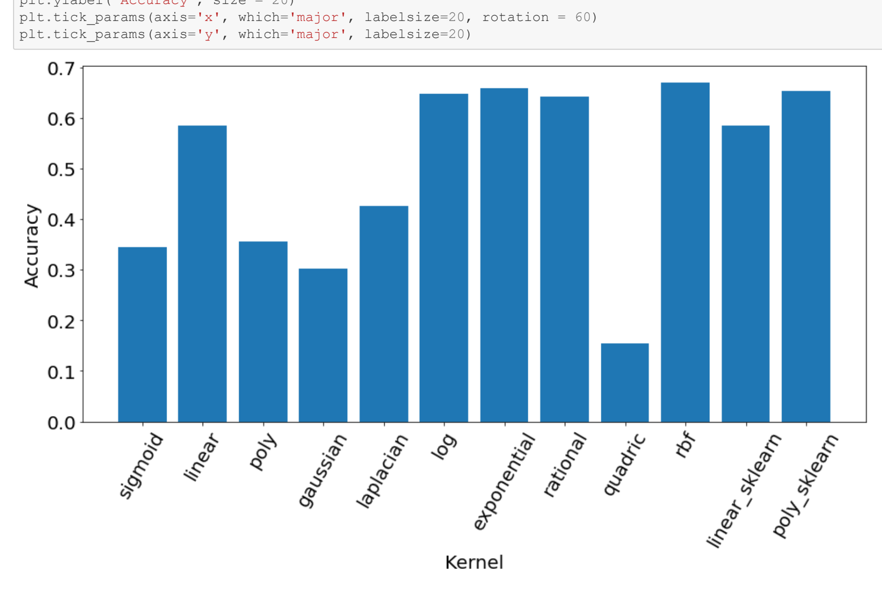
```
sigmoid
linear
poly
gaussian
```

```
<ipython-input-25-80667e6d14ad>:64: RuntimeWarning: overflow encountered in exp
  return np.exp(np.linalg.norm(U-V) ** 2 / (2*sigma**2))
```

```
laplacian
log
exponential
rational
quadric
rbf
linear_sklearn
poly_sklearn
```

Comparing Custom SVM Kernels

In [34]:
```python
res = plt.bar(sc.kernels_list(), accuracy)
plt.xlabel('Kernel', size = 20)
plt.ylabel('Accuracy', size = 20)
plt.tick_params(axis='x', which='major', labelsize=20, rotation = 60)
plt.tick_params(axis='y', which='major', labelsize=20)
```



Task 3

In this task, you need to obtain sentiment analysis for the provided dataset. The dataset consists of movie reviews with the sentiments being provided. The sentiments are either positive or negative. You need to train a boosting based classifier to obtain train and cross-validate on the dataset provided. The method will be evaluated against an external test set.

This task is worth 25 points out of 100 points. 15 points will be for implementing the pre-processing and Bag of Words based feature extractor correctly and evaluating the boosting based classifier for the text features and validating it by cross-validation on the training set. 5 points are based on the evaluation carried out on a separate test dataset that will be done at the time of evaluation. Finally 5 points are reserved for analysis of this part of the task and presenting it well in a lab report.

Use the movie_review_train.csv file provided with the assignment, and save it in the same directory as the Python notebook

Process the text and obtain a bag of words-based features

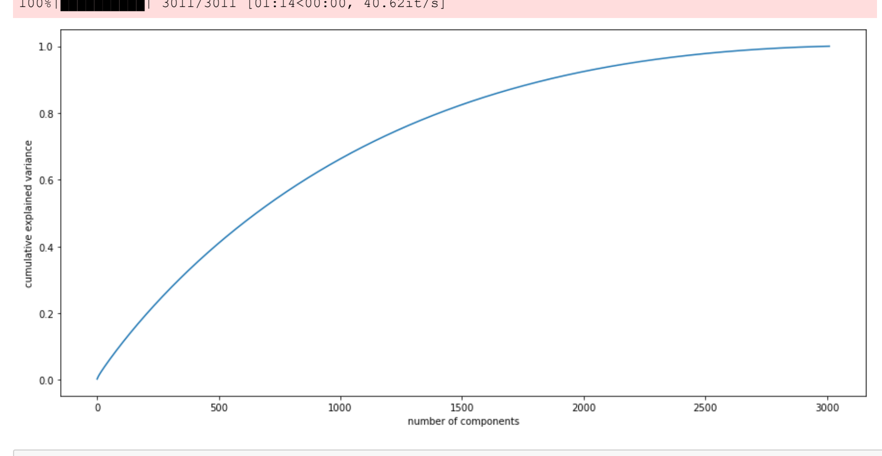
In [35]:
```python
# load csv file
df_movies = pd.read_csv('movie_review_train.csv')

import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
import re
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
```

In [36]:
```python
def extract_bag_of_words(df,
                         max_features = 1000,
                         min_df = 0.05):

    vectorizer = CountVectorizer(stop_words = 'english',
                                 min_df = min_df,
                                 max_features = int(max_features))
    x = vectorizer.fit_transform(df.iloc[:,-2])

    transformer = TfidfTransformer()
    tf = transformer.fit_transform(x)

    df_tf = pd.DataFrame(tf.toarray())
    df_tf['y'] = df.iloc[:,-1]
    df_tf['y'].replace('positive', 1, inplace = True)
    df_tf['y'].replace('negative', 0, inplace = True)

    return df_tf
```

In [37]:
```python
# extract features from documents / reviews in dataset
df_tf = extract_bag_of_words(df_movies,
                             max_features = 1e4,
                             min_df = .005) # minimum allowable document frequency
```

In [38]:
```python
# dimensionality reduction with pca
df_pca = reduce_features(df_tf, num_features = 100)
```

```
  0%|          | 0/3011 [00:00<?, ?it/s]<ipython-input-8-e4e3b2f1243c>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy
  x[col] = encoder.fit_transform(x[col])
100%|██████████| 3011/3011 [01:14<00:00, 40.62it/s]
```



In [39]:
```python
# random split for test and training set
train, test, val = train_test_valid(df_pca,
                                    train_ratio = 0.8,
                                    valid_ratio = 0.0)

# seperate input X from target variable y
x_train, y_train = train.iloc[:,:-1], train.iloc[:,-1]
x_test, y_test = test.iloc[:,:-1], test.iloc[:,-1]
```

In [40]:
```python
# instantiate, fit, and predict with boosting classifier
bc = BoostingClassifier(n_estimators = 100,
                        max_depth = 5,
                        sklearn = True)
bc.fit(x_train.values, y_train.values)

y_pred = bc.predict(x_test.values)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
100%|██████████| 100/100 [00:15<00:00,  6.47it/s]
```

```
accuracy:  0.784
```

Cross Validation

In [41]:
```python
# 5 fold cross validation on boosting estimator
scores = kfoldCV(df_pca, kfolds = 5, model_type = 'boosting',
                 n_est = 100,
                 depth = 5)

print('Average score from Cross Validation: {:.2f}'.format(np.mean(scores)))
```

```
  0%|          | 0/100 [00:00<?, ?it/s]
```

```
Fold:  4
```

```
100%|██████████| 100/100 [00:15<00:00,  6.54it/s]
```

```
Average score from Cross Validation: 0.77
```

In [42]:
```python
plt.rcParams['figure.figsize'] = [15, 7]
res = sns.heatmap(confusion_matrix(y_test,y_pred, normalize = 'true'),
            annot = True,
            xticklabels = ['Positive', 'Negative'],
            yticklabels = ['Positive', 'Negative'],
            cmap = 'viridis', annot_kws={"size": 16})

plt.xlabel('Actual Class', size = 20)
plt.ylabel('Predicted Class', size = 20)
res.set_yticklabels(res.get_ymajorticklabels(), fontsize = 18)
res.set_xticklabels(res.get_xmajorticklabels(), fontsize = 18)
```

Out[42]: `[Text(0.5, 0, 'Positive'), Text(1.5, 0, 'Negative')]`

In [43]:
```python
DT = DecisionTreeClassifier(max_depth = 1000)
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.712
```

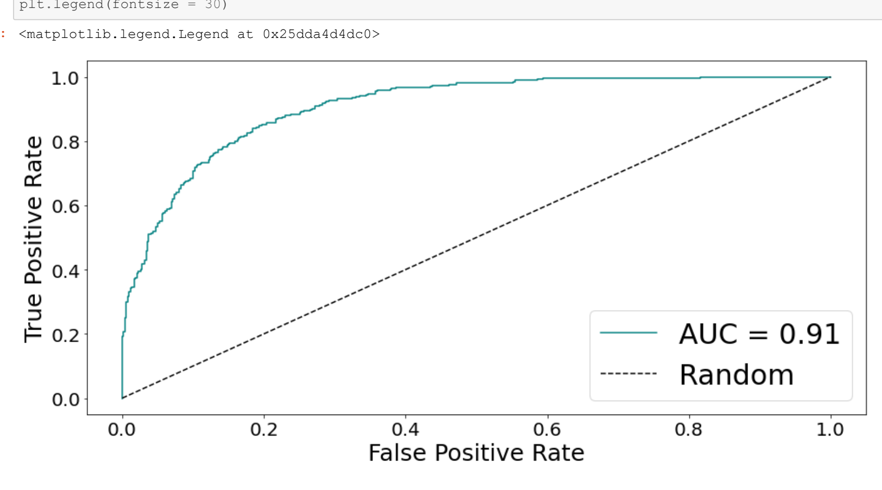
In [44]:
```python
from sklearn.ensemble import AdaBoostClassifier as boost

bc = boost(n_estimators = 50)

bc.fit(x_train,y_train)

y_pred = bc.predict(x_test.values)
print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.822
```

In [45]:
```python
probs = bc.predict_proba(x_test)

preds = probs[:,1]

fp, tp, thresh = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fp, tp)
```

In [46]:
```python
plt.plot(fp, tp, 'teal', label = 'AUC = %0.2f' % roc_auc)
plt.plot([0,1],[0,1], 'black', linestyle = '--', label = 'Random')
plt.xlabel('False Positive Rate', size = 25)
plt.ylabel('True Positive Rate', size = 25)
plt.tick_params(axis='x', which='major', labelsize=20)
plt.tick_params(axis='y', which='major', labelsize=20)
plt.legend(fontsize = 30)
```

Out[46]: `<matplotlib.legend.Legend at 0x25dda4d4dc0>`



Task 4

In this task, you need to classify the above movie review dataset using a Support Vector Machine (SVM).

This task is worth 20 points out of 100 points. You are allowed to use existing library functions such as scikit-learn for obtaining the SVM. The main idea is to analyse the dataset using different kind of kernels. You are also supposed to write your own custom text kernels. The marking will be 10 marks for analysing the dataset using various kernels including your own kernels, 5 points for the performance on the test dataset and 5 points for a lab-report that provides the analysis and comparisons.

In [47]:
```python
t1 = time.time()
# your code for svm based training of the dataset
sc = SVMClassifier(kernel = 'exponential',
                   reg_param = 1.0,
                   degree = 3,
                   max_iter = 1e3,
                   tol = 1e-3)

sc.fit_text(x_train.values, y_train)
y_pred = sc.predict_text(x_test.values)
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Time: {} seconds'.format(time.time() - t1))
```

```
Accuracy: 0.845
Time: 148.17798256874084 seconds
```

In [48]:
```python
plt.rcParams['figure.figsize'] = [15, 7]
res = sns.heatmap(confusion_matrix(y_test,y_pred, normalize = 'true'),
            annot = True,
            xticklabels = ['Positive', 'Negative'],
            yticklabels = ['Positive', 'Negative'],
            cmap = 'viridis', annot_kws={"size": 16})

plt.xlabel('Actual Class', size = 20)
plt.ylabel('Predicted Class', size = 20)
res.set_yticklabels(res.get_ymajorticklabels(), fontsize = 18)
res.set_xticklabels(res.get_xmajorticklabels(), fontsize = 18)
```

Out[48]: `[Text(0.5, 0, 'Positive'), Text(1.5, 0, 'Negative')]`

Cross Validation

In [56]:
```python
scores = kfoldCV(df_pca, kfolds = 5, model_type = 'svm',
                 k = 'exponential',
                 reg = 1,
                 deg = 3)

print('Average score from Cross Validation: {:.2f}'.format(np.mean(scores)))
```

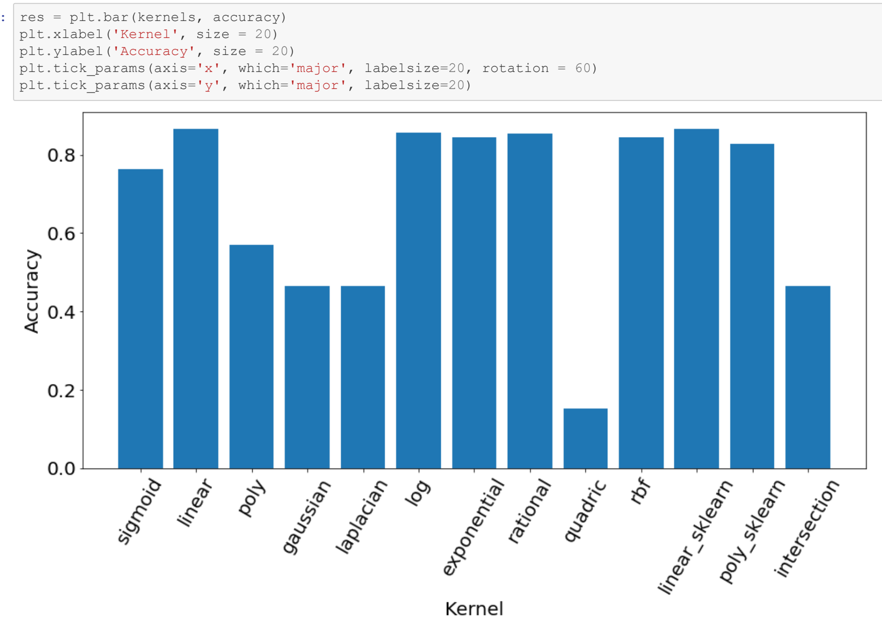
```
Fold:  4
Average score from Cross Validation: 0.85
```

Comparing various kernel performance on sentiment classification

In [50]:
```python
# test each kernel with CV and plot performance


kernels = sc.kernels_list() + ['intersection']
accuracy = []
for k in tqdm(kernels):

    # run CV on model
    sc = SVMClassifier(kernel = k,
                       reg_param = 1.0,
                       degree = 3,
                       max_iter = 1e3,
                       tol = 1e-3)

    sc.fit_text(x_train.values, y_train)
    y_pred = sc.predict_text(x_test.values)
    accuracy.append(accuracy_score(y_test, y_pred))
```

```
 23%|██        | 3/13 [00:04<00:11,  1.17s/it]<ipython-input-25-80667e6d14ad>:64: RuntimeWarning: ov
erflow encountered in exp
  return np.exp(np.linalg.norm(U-V) ** 2 / (2*sigma**2))
100%|██████████| 13/13 [1:03:43<00:00, 294.10s/it]
```

In [51]:
```python
res = plt.bar(kernels, accuracy)
plt.xlabel('Kernel', size = 20)
plt.ylabel('Accuracy', size = 20)
plt.tick_params(axis='x', which='major', labelsize=20, rotation = 60)
plt.tick_params(axis='y', which='major', labelsize=20)
```



In [52]:
```python
clf = svm.SVC(C = 2,
              kernel = 'rbf',
              degree = 3,
              gamma = 'scale')
clf.fit(x_train, y_train)

y_pred = clf.predict(x_test)

print('accuracy: ', accuracy_score(y_test, y_pred))
```

```
accuracy:  0.841
```

In [53]:
```python
probs = bc.predict_proba(x_test)

preds = probs[:,1]

fp, tp, thresh = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fp, tp)

plt.plot(fp, tp, 'teal', label = 'AUC = %0.2f' % roc_auc)
plt.plot([0,1],[0,1], 'black', linestyle = '--', label = 'Random')
plt.xlabel('False Positive Rate', size = 25)
plt.ylabel('True Positive Rate', size = 25)
plt.tick_params(axis='x', which='major', labelsize=20)
plt.tick_params(axis='y', which='major', labelsize=20)
plt.legend(fontsize = 30)
```

Out[53]: `<matplotlib.legend.Legend at 0x25ddc658ac0>`