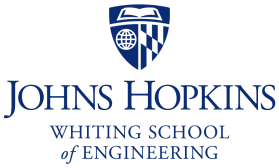
Application of Machine Learning in Computer Vision



Introduction

Machine Learning (ML) is the art of solving a computation problem using a computer without an explicit program. ML is so pervasive today that various ML applications such as image recognition, stock trading, email spam detection, product recommendation, medical diagnosis, predictive maintenance, cybersecurity, etc. are constantly used by organizations around us and probably sometimes without our awareness.

Digit Recognizer ML Model

Adapted from scikit-learn.org examples

Prediction Problem:

Recognizing hand-written digit images so that they can be converted to natural numbers (in the format a computing system could use) and be easily processed by automated systems, e.g. hand-written zip codes on letters (snail mail) for sorting letters according to zip codes for faster and cheaper processing.

Problem Notes:

There is a camera capturing images of mail envelope faces one by one, and a computer program to extract sections of digit images from these camera images to be used in the computing pipeline.
Our job, as the machine learning model developer is to *pre-process* the captured dataset (i.e. segmented pictures of hand-written digit images), apply ML learning algorithms, and evaluate and verify the performance of the developed model meets the performance goals.

Proposed Solution:

Supervised-learning zip code digit images from a proper dataset.

1. Take digital snapshots of letter faces
2. Locate zip codes in images
3. Segment images to find each digit
4. Convert (i.e. scale, stretch, etc.) each digit image to 8x8 images as **feature vectors**

5. Label the **training** image. Labels are set by human SME as the **ground truth**
6. Pass the labeled training image dataset to a **classifier** to **train** a model
   ⟵ ML methodology starts

Steps (1.) to (5.) above are data preparation stage, and it is expected to be the most costly. Once the model is generated (i.e. trained), feature vectors extracted from **never-seen-before** data can be **tested** to **predict** these new digit images. This new data is called **testing** dataset.

The labels used by human experts to mark the training dataset would be the **category**, or class, or group that a digit image would belong to. The category is also similar to a **feature** given by the dataset for classification (in this example it is not obvious). To make a distinction between the data set feature (a column in the training dataset matrix) and the group feature we want to find out for a new data point, we call it a **category** or a class. Here the prediction is finding out (with or without a score or a probability) which category the new data point would most likely belong to.

Import Open-source Libraries

Open source libraries such as NumpPy, SciPy, matplotlib, scikit-learn are developed and maintained by tens of thousands of developers, researchers, engineers from various organizations like universities and industry.

APIs

`scikit-learn` - https://scikit-learn.org/stable/modules/classes.html
`numpy` - https://docs.scipy.org/doc/numpy/reference/

Why do we use Python in Machine Learning and in this Course?

Because Python is taking over as the number 1 data science programming language (reference)

In [1]:
```
# Standard scientific Python imports
%matplotlib inline
import matplotlib.pyplot as plt
plt.rcParams["figure.dpi"] = 72
import numpy as np

# Import datasets, classifiers and performance metrics
from sklearn import datasets
```

Real-world Dataset

The library `sklearn` (short proxy for `scikit-learn`) includes several datasets to give the opportunity to users for a data science quick-start. In the following notebook cells,the digit data set is used to train a classifier model. These digit images are from **MNIST dataset** collected 20 years ago from actual hand-written letters to automate USPS zip code sorting.

In [2]:
```
# The digits dataset for training
digits = datasets.load_digits()

# The data is made of 8x8 images of digits
# zip the image and label (dependent variable) together
images_and_labels = list(zip(digits.images, digits.target))
```

Let's examine the problem dataset to gain insight. This step is crucial as the model developer (i.e. data scientist) will have better understanding of the dataset to solve the problem. Many questions will be answered towards using the right features, doing the right **feature engineering**, picking the right learning model, and avoiding bugs, etc. The representation of the dataset might not conform to what the developer might expect. Example,

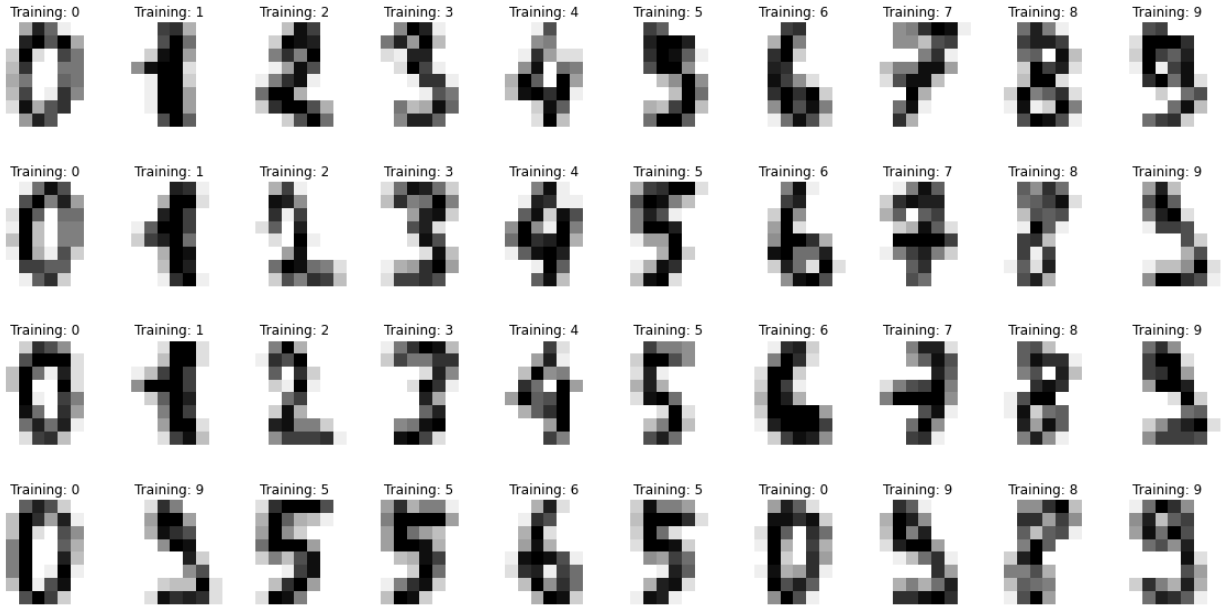
- What is the computer representation of the data set?
- A matrix? Which data structure?
- A row of a matrix is a data point?
- Are ground truth labels in this matrix?
- Do we have missing data?
- What about outliers?
- Which features are **numerical** and which are **nominal** and which are neither?

Question: What is the number format/type of the data? Integer? Floating point? Long? Double?

In [3]:
```
print(f'Number of images in the training set, N= {len(images_and_labels)}')
```

```
Number of images in the training set, N= 1797
```

In [4]:
```
# Draw the first 40 data points - in this case a single data point is an image
plt.figure(1, figsize=(20, 10), dpi=72)
for index, (image, label) in enumerate(images_and_labels[:40]):
    plt.subplot(4, 10, index+1)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title(f'Training: {label}')
```



In [5]:
```
# Check how the data looks like, examine the label as the last element, 1st dat
print(images_and_labels[0])
print(images_and_labels[1])
```

```
(array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]]), 0)
(array([[ 0.,  0.,  0., 12., 13.,  5.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16.,  9.,  0.,  0.],
       [ 0.,  0.,  3., 15., 16.,  6.,  0.,  0.],
       [ 0.,  7., 15., 16., 16.,  2.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  3.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16., 10.,  0.,  0.]]), 1)
```

In [6]:
```
# Check the size of the data structures, data vectors, examine the indices
print(len(images_and_labels))
print(len(images_and_labels[0]))
print(len(images_and_labels[0][0]))
print(len(images_and_labels[0][0][0]))
```

```
1797
2
8
8
```

Question: Do above numbers make sense? Explain to yourself the details of this data structure.

Pre-processing the Dataset

Usually the data pre-processing stage takes bulk of the data science task.

Pre-processing includes correcting number formats, setting ranges, converting feature types, checking for erroneous input (e.g. February 31, 2119), erroneous data entry (e.g. 5-year-old child with a Ph.D. degree), cleaning outliers that can throw off the model, **imputing** missing values for robust model generation, etc.

Once a reasonable, good, sufficient (all of these properties are clearly subjective) data set is achieved, then the learning stage is a short script or pressing a few buttons in a program in the data science platform we use, such as Weka (source: https://www.cs.waikato.ac.nz/~ml/weka/index.html) or a Python pipeline using `sklearn`.

Data reduction, feature engineering or feature selection process is within or overlapping with the pre-processing stage. Reducing the data (in terms of data points N or features M) helps generation of robust models with high **generalization** ability.

The Pitfall

Any error made in the input training dataset will be reflected on the generated model and test set outputs (i.e. predictions). In data science, it is very easy to trick ourselves about a model performance by committing data errors during the preparation of the data.

In [7]:
```
# To apply a classifier on this data, we need to flatten the image
# Turn the data in a (samples, feature) matrix
n_samples = len(digits.images)
X = digits.images.reshape((n_samples, -1))

print(f'N={len(X)}, M={len(X[0])}')
```

```
N=1797, M=64
```

Classification with Support Vector Machine Classifier

Support Vector Machines (SVM) were very popular machine learning methods (algorithms) which gained popularity a lot over Artificial Neural Networks (ANN) before the deep learning time has begun. There are a few advantages and disadvantages between them:

- Early ANN methods were mostly heuristic, trial-and-error approaches, where SVM has a sound theory
- ANN minimizes empirical risk (or cost), SVM minimizes structural risk (maximizes the margin between the data points and the separating hyperplane)
- If done right, both ANN and SVM could generate identical **decision surfaces** after successful training stages
- SVM solves the problem by finding the optimum solution (solving a real convex optimization problem – because the algorithm sets up the problem accordingly) while ANN looks for a solution with gradient descent optimization algorithm. Literally, ANN fits

a hypersurface (decision surface) to the data and that is why ANN are also called *function approximators*.
- Local minima is problem for ANN classifiers, since the optimization method is greedy
- Setting the network structure is a problem of ANN model development
- Selection of a suitable kernel and its parameters is a problem of SVM model development
- SVM has very high generalization ability and automatically sets the model size (with support vectors)
- ANN is best with high number of data points, SVM *can* work with very low number of data points

In the following cell SVM is picked as the classifier for the digit recognition problem. Using the trained model, the prediction stage will generate the class labels for the new (never-seen-before) test data input.

In [8]:
```
from sklearn import svm, metrics

# Create a classifier: a support vector classifier
# gamma is normally determined using a hyperparameter search which would need a
classifier = svm.SVC(gamma=0.001)

# Learn the digits on the first half of the digits - 50% data is used as the tr
classifier.fit(X[:n_samples//2], digits.target[:n_samples//2])

# Predict the value of the digit on the second half
expected = digits.target[n_samples//2:]
predicted = classifier.predict(X[n_samples//2:])
```

Note that the above model is stored in the `classifier` object.

Evaluate the Classifier Model

Once the classification model (i.e. trained model generated by the learning SVM program) is acquired, an evaluation has to be conducted to measure the model performance.

A natural metric: The ratio of the number of data points the model predicts correct over the total number of data points.

$$\texttt{Accuracy} = \frac{\texttt{number of correct predictions}}{\texttt{number of total predictions}}$$

When many categories are involved as in the above example (there are 10 classes - digits from zero to nine), a **confusion matrix** is used to present the accuracy. Each column shows the predicted class and each row shows the actual. An ideal confusion matrix is all 100% in all diagonal elements, and zeros everywhere except for the diagonal.

An **unbalanced** machine learning problem has one class much larger than the other(s).

Consider an unbalanced problem (such as patient cancer prediction in health care), then Accuracy is not the best metric but rather, F1-score and similar metrics must be used.

Reclassification is defined as using the entire training dataset as the testing dataset after the model is trained. Reclassification helps to monitor how well the learning pipeline works, which would indicate bugs, data problems, algorithm problems, or **overfitting.**

Also, we should not just train the model on the entire dataset, test on the entire dataset and report how many predicted correctly over the total number data points, i.e. reclassification accuracy.

Example, an overfitting learning model would have 100% reclassification.

Question: Can we report the reclassification performance as our model performance?

A right way of training, testing and evaluating an ML model requires the following generic stages:

- Divide the dataset in a non-overlapping fashion for training set, testing set, and validation set
- Use training dataset to develop, and then generate the model
- Use validation dataset to tune model hyperparameters (e.g. Radial Basis Function gamma parameter of an SVM)
- Use testing dataset to measure the probable real-world performance of the model

Question: How would one deploy the generated ML model? For example the trained model as in the above? (i.e. not adding the testing/validation dataset to the model learning?)

In [9]:
```
%%time

acc = metrics.accuracy_score(expected, predicted)

print(f'Classification report for classifier {classifier}:\nAccuracy={acc:.3f}\
```

```
Classification report for classifier SVC(gamma=0.001):
Accuracy=0.969

CPU times: total: 0 ns
Wall time: 12 ms
```

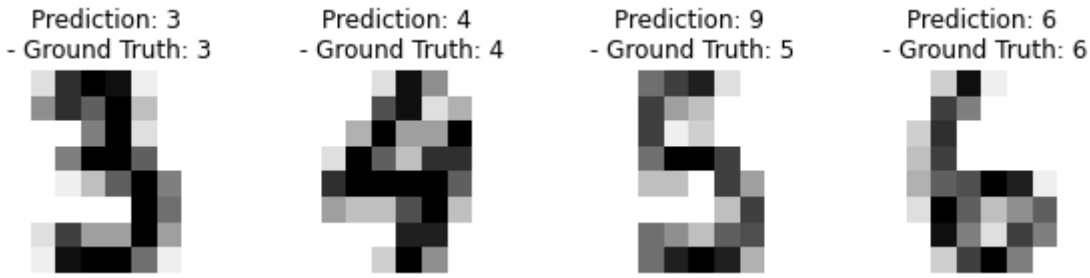
The confusion matrix below shows the prediction versus actual (dataset labels) on the matrix where the rows are the actual and columns are the predicted classes. Since we have 10 classes in the MNIST digit dataset (for each digit), the matrix is 10×10. As can be seen, very few testing data points are confused with other classes.

In [10]:
```
print(f'Confusion matrix:\n{metrics.confusion_matrix(expected, predicted)}')
```

```
Confusion matrix:
[[87  0  0  0  1  0  0  0  0  0]
 [ 0 88  1  0  0  0  0  0  1  1]
 [ 0  0 85  1  0  0  0  0  0  0]
 [ 0  0  0 79  0  3  0  4  5  0]
 [ 0  0  0  0 88  0  0  0  0  4]
 [ 0  0  0  0  0 88  1  0  0  2]
 [ 0  1  0  0  0  0 90  0  0  0]
 [ 0  0  0  0  0  1  0 88  0  0]
 [ 0  0  0  0  0  0  0  0 88  0]
 [ 0  0  0  1  0  1  0  0  0 90]]
```

Let's see some example predictions:

In [11]:
```
# Change the indices in images_and_predictions below to see more predictions
images_and_predictions = list(zip(digits.images[n_samples//2:], predicted))

plt.figure(1, figsize=(10, 4), dpi=72)
for index, (image, prediction) in enumerate(images_and_predictions[30:34]):
    plt.subplot(2, 4, index + 5)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title(f'Prediction: {prediction}\n - Ground Truth: {expected[index+30]}

plt.show()
```



At this point, model development pipeline and performance evaluation is completed.

Multiple Models

Let's run three more SVM models with different model parameters and observe the accuracy changes.

In [12]:
```
# Hyperparameter search
gamma_param = [1e-1, 1e-2, 1e-4, 1e-5]

Classifiers = [svm.SVC(gamma=param) for param in gamma_param]

training, training_labels = X[:n_samples//2], digits.target[:n_samples//2]
testing, testing_labels = X[n_samples//2:], digits.target[n_samples//2:]

for clf in Classifiers:
    clf.fit(training, training_labels)

predicteds = [clf.predict(testing) for clf in Classifiers]

for i, clf in enumerate(Classifiers):
```

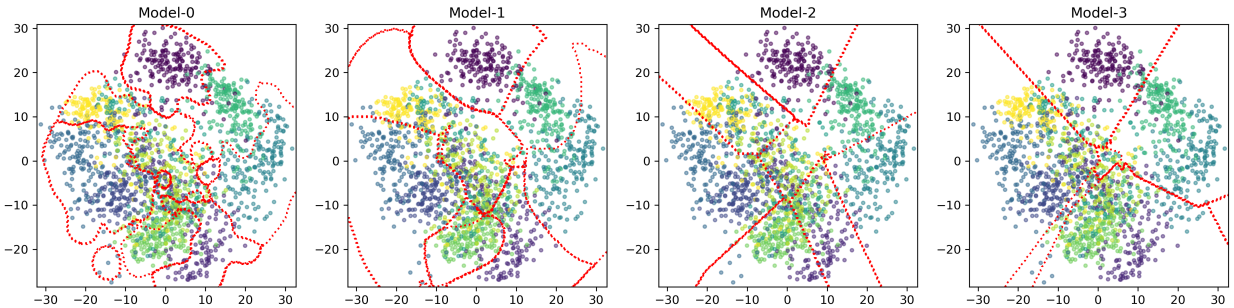
```
    acc = metrics.accuracy_score(expected, predicteds[i])
    print(f'Model-{i} (g={gamma_param[i]:.0e}) Accuracy={acc:.3f}')
```

```
Model-0 (g=1e-01) Accuracy=0.101
Model-1 (g=1e-02) Accuracy=0.697
Model-2 (g=1e-04) Accuracy=0.940
Model-3 (g=1e-05) Accuracy=0.798
```

In [13]:

```
from sklearn.decomposition import PCA

# Visualize the models above in 2D
Xpca = PCA(n_components=2).fit_transform(X)

# train and test datasets and their labels
Xtr, ytr = Xpca[:Xpca.shape[0]//2], digits.target[:digits.target.shape[0]//2]
Xts, yts = Xpca[Xpca.shape[0]//2:], digits.target[digits.target.shape[0]//2:]

for clf in Classifiers:
    clf.fit(Xtr, ytr)

ypreds = [clf.predict(Xts) for clf in Classifiers]

for i, clf in enumerate(Classifiers):
    acc = metrics.accuracy_score(yts, ypreds[i])
    print(f'M=2 (PCA), Model-{i} (g={gamma_param[i]:.0e}) Acc={acc:.3f}')

h = 0.3  # mesh granularity of the plot

def plot_decisionboundary(_X, _clf, _h, color_db='r'):  # _h = step size in the
    def get_minmax(_X, _m):  # _m = margin for visuals
        return _X[:,0].min()-_m, _X[:,0].max()+_m, _X[:,1].min()-_m, _X[:,1].ma
    x1_min, x1_max, x2_min, x2_max = get_minmax(_X, 1)
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, _h), np.arange(x2_min, x2_
    ypred = _clf.predict(np.c_[xx1.ravel(), xx2.ravel()]).reshape(xx1.shape)
    plt.contour(xx1, xx2, ypred, colors=color_db, linestyles='dotted')

plt.figure(figsize=(18, 4), dpi=300)
for i, clf in enumerate(Classifiers):
    plt.subplot(1, 4, i+1)
    plt.scatter(Xpca[:,0], Xpca[:,1], s=8, c=digits.target.tolist(), alpha=0.5)
    plot_decisionboundary(Xpca, clf, h)
    plt.title(f'Model-{i}')
```

```
M=2 (PCA), Model-0 (g=1e-01) Acc=0.598
M=2 (PCA), Model-1 (g=1e-02) Acc=0.626
M=2 (PCA), Model-2 (g=1e-04) Acc=0.587
M=2 (PCA), Model-3 (g=1e-05) Acc=0.349
```



As gamma decreased the SVM decision boundaries become linear.

Question: The performance dropped. Why?

References

1. Raschka, Sebastian. Python Machine Learning Ed. 3. Packt Publishing, 2019.
2. Examples - scikit-learn 1.1.1 documentation. https://scikit-learn.org/stable/auto_examples/index.html. Accessed Jun 2022.
3. GitHub. https://github.com/rasbt/python-machine-learning-book-3rd-edition. Accessed Jun 2022.

Exercises

Exercise 1. Inspect training data points indexed 100 and 101, what are their labels?

Exercise 2. Study the `scikit-learn` API for the Multi Layer Perceptron and apply it instead of the SVM. Can you match the SVM performance?

Exercise 3. Download PyCharm community version (ref: https://www.jetbrains.com/pycharm/download/#section=windows) and single-step the code above. Create a watch for the variable `acc` above. Then run the program and observe changes.

Exercise 4. Research about methods finding the *right* `gamma` parameter above? Hyperparameter tuning?
