Novel Classifier for a Smart Traffic Network

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I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Date _____ / _____ / _____

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Chapter 1

Introduction

Economies of the world have been industrializing for over two centuries [1] and the consequent advent of machines and factories has seen a great migration of humanity from farmlands to cities. Such a shift in population density has posed a plethora of infrastructural challenges and led to many iconic solutions to high density living, like the skyscraper, subway train and traffic light. One unfortaunte metropolitan trait, however, continues unabated and is in fact growing in size [2] - it is traffic congestion.

Road transport contributes 16.5% of global CO2 emissions [3] and costs the US $305 billion of productivity per year alone [4][5] thus even a small improvement in traffic efficiency will yield great benefit to society and the future of the planet. Unfortunately its persistence is only an indicator of its difficulty to solve.

There is no single solution to the problem of traffic congestion, whether it be the building of tunnels, the conversion of traffic lights to roundabouts or the widening of roads though several studies [6][7][8][9] have found that the integration of several lightweight and inexpensive techniques is a far more efficient and effective approach than the aforementioned heavyhanded methods. A 'Smart City' is such an approach, and part of its design is to deploy many devices in an urban area that collect data [10] which is then transmitted and processed to make useful conclusions about a system. This technology could be applied

to collect traffic data more completely and inexpensively than is currently the case. Data of interest includes traffic volume and vehicle speed.

Current widely employed methods of traffic data collection [11] have inherit weaknesses that justify a movement to new techniques that exploit advantages provided by the latest technology. For example, manual counting that requires a person be visually counting traffic is very expensive hence is can be used for short surveys limiting the completeness of the data collected and necessitating extrapolation at a cost to accuracy. Automatic methods of data collection such as inductive loops and piezo-electric sensors are able to measure speed and mass of vehicles due to the change in electric field that generate as they pass a sensor however these systems are embedded in roadways and thus have high installation and maintanence costs. Less invasive automatic methods of data collection include pneumatic road tubes that sense change in air pressure as a tire passes over them. These systems are often temporary and accuracy is subject to temperature and traffic conditions. Infra-red sensors are inexpensive but cannot provide coverage across multi-lane roads and magnetic sensors embdedded in roadways often cannot differentiate between closely placed traffic.

A single *modular* lightweight system capable of performing all the functions of the aforementioned devices would be advantaged by significantly lower maintenance fees, dyanmic installation capabilities and efficiency borne of the simplicity of relying on a single system set. Further, if many system modules were employed at key locations and data was trasnmitted in realtime to a central database for processing a complete picture of the state of the traffic system at anytime could be developed. A module running a computer vision algorithm with a small camera module would be able to complete such functions.

Computer vision is a versatile method by which image classification and object tracking may be achieved. An algorithm can be tailored to produce high accuracy real-time results requiring only images as input. Computer vision attempts mimic human vision's ability to rapidly identify objects like separating a vehicle from its surroundings and tracking its

movement. An increasingly effective method of image classification utilizes machine learning and trains a neural network to recognise objects in an image, however, this method is hindered by the large amounts of computational power required to train the network and the many thousands of data samples to train the network on. In a specific use-case like traffic monitoring a specialized algorithm that does not depend on a neural network but image processing techniques alone can yield high quality results. The implementation of a robust computer vision algorithm for traffic monitoring is not trivial however, and many techniques may have to be choreographed for the algorithm to behave as intended.

It is the objective of this report to explain the design and operation of a lightweight and discrete traffic data collection module whose capabilities to estimate traffic speed and volume depend on an underlying computer vision algorithm. Further the module will trasnmit real-time results to a central database.

Chapter 2 explores the relevant theoretical background undpinning the computer vision techniques implemented by the algorithm. This begins with the fundamental qualities of a digital image and ends with an explaination of the probabilistic model that is used to determine what is a car and what is not in the algorithm.

Chapter 3 details the system's overall design and how its susbsytems interface with each other to produce a functional data collection product. Subsystems include the Computer Vision, Networking, Hardware, Data Storage and Organization and The User Interface. The Computer Vision section in particular explains how the theoretical principles discussed in Chapter 2 are employed.

Chapter 4 outlines the capabilities of the system and the results it is able to produce whose analysis helps identify the strengths and weaknesses of the system.

Chapter 5 summarises how well the system satisfied the requirements it was designed to meet and also suggests augmentations that could be made to the system to imrprove its performance and applicability.

Chapter 2

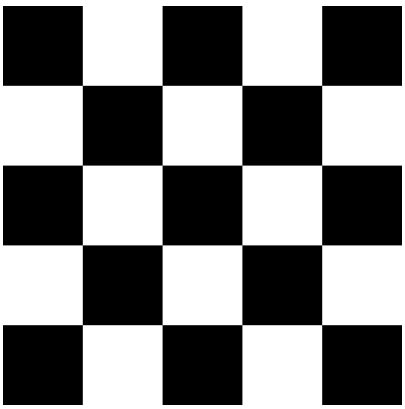
Theoretical Background

This section of the report expands upon the theory behind the design of the system. Digital image processing and computer vision are broad fields and so only concepts relevant to the system are explored.

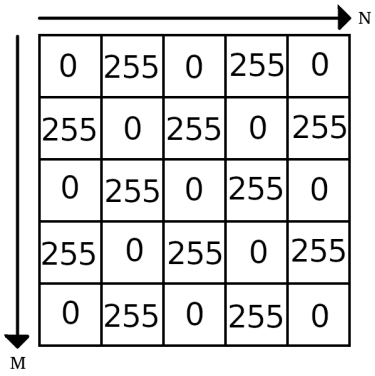
2.1 Digital Images

Digital images consist of discrete valued data points called pixels arranged in a grid where it is the value of these pixels that determine the colour of each cell. A pixel's value is also called its *intensity* and lies within a range of values determined by the image's encoding. For example an 8-bit image has pixel values in the range $[0, 255]$.

Digital images are often represented as a 2D array of values where each cell corresponds to an intesnity. In software in particular, digital images are stored and manipulated as arrays. An image's array is $M \times N$ pixels in size, which is also its resolution. Notice that in Figure 2.1 the lowest value is 0 (black) and the highest value is 255 (white). All other colors that can be represented by 8-bits are between these two values.



(a)



(b)

Figure 2.1: (a) A Simple 8-bit Image (b) Array Representation of Image.

2D array representation allows pixels to be referenced by their relative position in the M and N directions. Furthermore, M and N may be substituted for the x and y axes of the Cartesian plane. In fact, a digital image is just a two dimensional function where each pixel is described by a coordinate (x,y) and an intensity (z) at that point.

$$z = f(x, y) \tag{2.1}$$

This representation is extremely useful as it means that two dimnesional operations may be applied to a images. Rates of change, derivatives, of a digital images are important in computer vision because they help to identify features like lines and object edges. Figure 2.2 is a 3D plot of a 2D image where you can see that there is a rapid change in value between different coloured squares, shown as steep cliff edges.

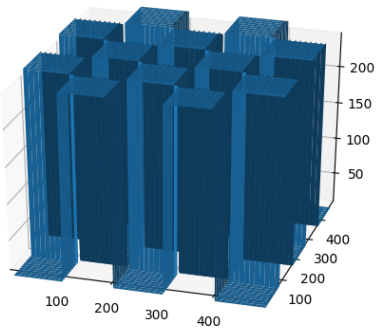


Figure 2.2: Surface Plot of Figure 2.1a

2.2 Linear Filtering

Filtering an image is a way to augment or extract information from it. Linear filtering is a mathematical operation on a neighbourhood of pixels in an image that outputs a weighted average of the pixels in that neighbourhood. It is the weightings of a filter, known as filter coefficients, that determine the effect of the filter. These weights are stored in a matrix called a mask or kernel (see Figure 2.3) that's then convolved with an image (see sections 2.2.1 & 2.2.2).

$$Kernel = \frac{1}{\sum_{i=0}^{M}\sum_{j=0}^{N} c_{i,j}} \begin{bmatrix} c_{0,0} & c_{0,1} & \cdots & c_{0,n} \\ c_{1,0} & c_{1,1} & \cdots & c_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m,0} & c_{m,1} & \cdots & c_{m,n} \end{bmatrix}$$

Figure 2.3: General Form of a Linear Filter

2.2.1 Correlation

The application of a linear filter $h(u, v)$ to an image $f(i, j)$ may be described as follows

$$g(i,j) = \sum_{u=-k}^{k}\sum_{v=-l}^{l} f(i+u, j+v)h(u,v) \tag{2.2}$$

$g(i, j)$ is the output image. Performing correlation with a filter may be notated more concisely by the correlation operator.

$$g = f \otimes h$$

Correlation measures the *similarity* between two signals and as both digital images and linear filters are two dimensional signals by correlating them we can see where they are most similar. Performing correlation between them will produce an output image whose

highest values correspond to where the image and filter were most similar [12]. This is an important operation in image classification as it can be used to highlight features in an image and diminish everything else by correlating a filter that describes the desired feature. The feature could be as simple as a straight line as in a Sobel filter (Figure 2.4) or as specific as the outline of a car wheel. This method of feature detection is called *templating*.

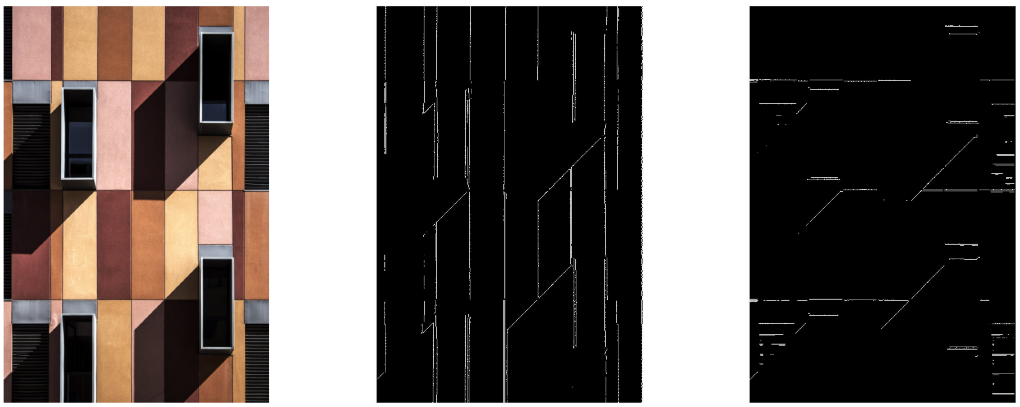
In Figure 2.5 vertical and horizontal Sobel filters are applied to produce images that emphasise lines that match the orientation in the respective filter, the lines that are most similar. The result is black and white as the initial output image's intensities have been thresholded to either be 1 or 0. I.e. where initial output image is $F(x, y) = z$ and T is the threshold intensity:

$$BinaryOutput = \begin{cases} 1 & \text{if } z >= T \\ 0 & \text{if } z < T \end{cases} \tag{2.3}$$

$$\begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix} \qquad \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix}$$

(a) Horizontal Sobel Filter Mask (b) Vertical Sobel Filter Mask

Figure 2.4: Sobel Filters



(a) Image by Simone Hutsch (b) Vertical Sobel Filter (c) Horizontal Sobel Filter

Figure 2.5: Application of Sobel filters to exagerate lines.

Correlation is *shift invariant*, which means that it does the same thing no matter where in an image it is applied. To satisfy this property correlation may be superpositioned

$$a(f_1 + f_2) = af_1 + af_2$$

and abides by the shift invariance principle

$$g(i,j) = f(i+k, j+l) \Leftrightarrow \ (h \circ g)(i,j) = (h \circ f)(i+k, j+l)$$

Correlation has the side effect of flipping both horizontally and vertically the location of output points relative to the center point (*reference point*) in the original image which may be undesirable as can be observed in Figure 2.6.

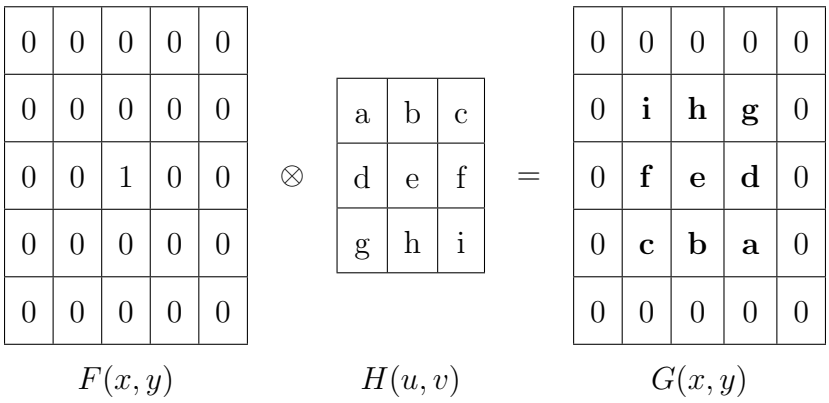


Figure 2.6: Correlation of a filter and an image.

2.2.2 Convolution

Convolution is also a linear operation that is shift invariant. It is very similar to correlation except that where correlation measure similarity between signals convolution measures the effect of one signal on another. It is described mathematically by the expression,

$$g(i,j) = \sum_{u=-k}^{k} \sum_{v=-l}^{l} f(u,v)h(i-u, j-v)$$

Notice that the filter $h(i,j)$ is rotated 180 degrees. This causes the output's orientation to match the original image. Convolution may be notated as follows,

$$g = f * h$$

Convolution is essentially the same as correlation except that it doesn't flip the output relative to the original image as can be seen in Figure 2.7 and it is the operation that is performed when a linear filter is applied to a digital image.

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0

$F(x, y)$

$*$

a	b	c
d	e	f
g	h	i

$H(u, v)$

$=$

0	0	0	0	0
0	**a**	**b**	**c**	0
0	**d**	**e**	**f**	0
0	**g**	**h**	**i**	0
0	0	0	0	0

$G(x, y)$

Figure 2.7: Convolution of a filter and an image.

2.2.3 Kernels

Kernels are just the weightings that define the characteristics of a filter, also known as a filter's mask. A filter kernel is nearly always square so as to have a center cell which sits atop a reference pixel. The result of the filter's application at that reference pixel will be stored in the output image at the location of the reference pixel. Notice in Figure 2.8 how the mask sits over the reference pixel.

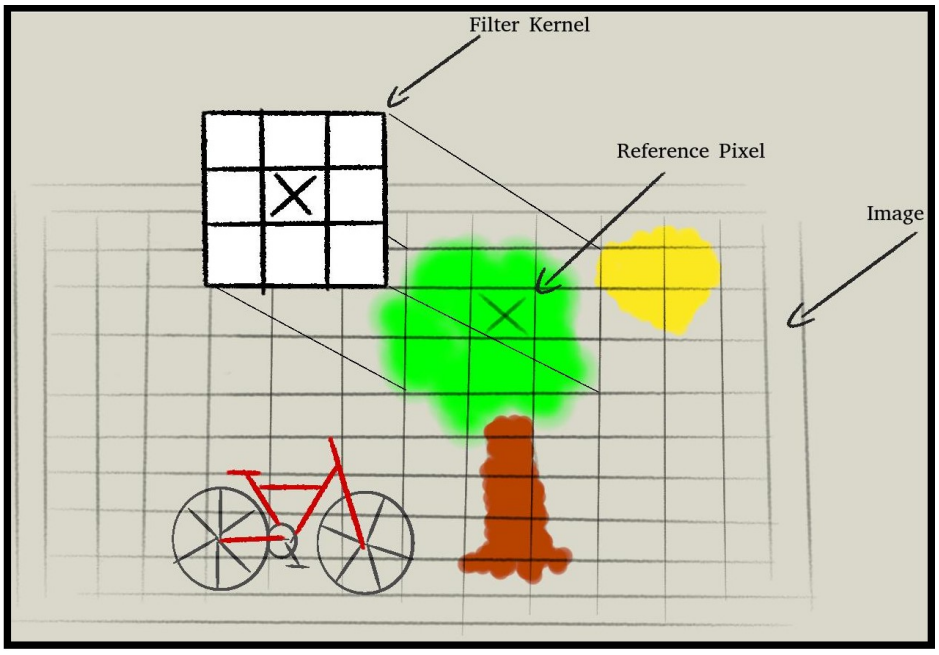
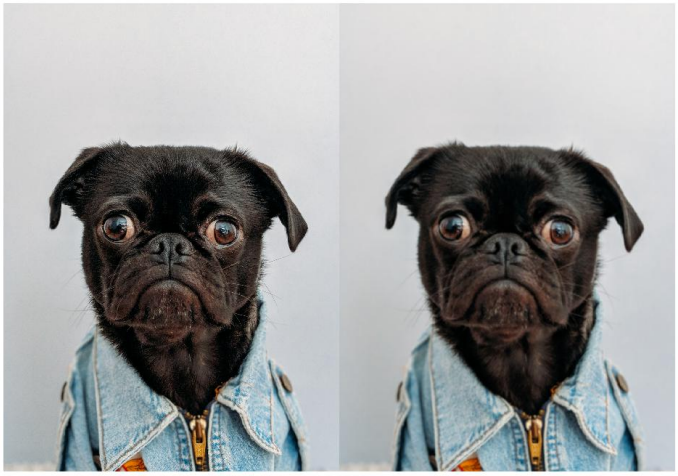


Figure 2.8: Visualization of a Filter Kernel Application

Box Filter

A box filter also known as a moving average filter simply outputs the average of its inputs because the filter weights are evenly distributed. By passing this filter over an image its sharpness is reduced giving a smoothing or blurring effect which can sometime be useful in image processing for filtering out noise. This can be observed in Figure 2.9a.



(a) Left: Photo by Charles Deluvio. Right: Application of 16×16 box filter.

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

(b) Box Filter Kernel.

Figure 2.9: Box Filter application and kernel.

Gaussian Kernel

The Gaussian is a rather important kernel in image processing as it models the Gaussian function (see Section 2.3) or normal distribution. This filter is perhaps most well known for filtering noise but retaining edge sharpness better than other denoising filters. It works

in a similar fashion to the moving average filter but as you can see in Figure XXX it is superior at filtering out the noise in comparison as it retains better edge definition. The reason the Gaussian filter is superior is because it addresses two properties about images that a generally true,

1. The actual value of a pixel is probably the same or similar to its neighbors.

2. Each pixel of noise in an image is added independently.

The Gaussian which models the Normal distribution addresses both of these qualities by having high value cooefficients at the filter's center and lower values tapering out to the edges of the filter. Which essentially means values closer together are more strongly correlated than those further away from the reference pixel as can be observed in the 16x16 Gaussian filter kernel in Figure XXX.

[Add Denoising using Gaussian Example] [Add matrix of kernel filter.]

2.3 The Gaussian

The Gaussian provides a consistent model for normal distributions, aka the bell curve, as in Figure 2.10 & 2.11. Normal distributions follow the *central limit theorem* where in if a histogram is taken of a sufficiently large number of independent random variables they will distribute with a central most probable value and symmetrically fall away either side of this value. Many datasets follow this trend closely enough that the Gaussian can be used to approximate a probability distribution for them.

The Gaussian function is defined by three parameters, its mean μ, standard deviation σ and amplitude A.

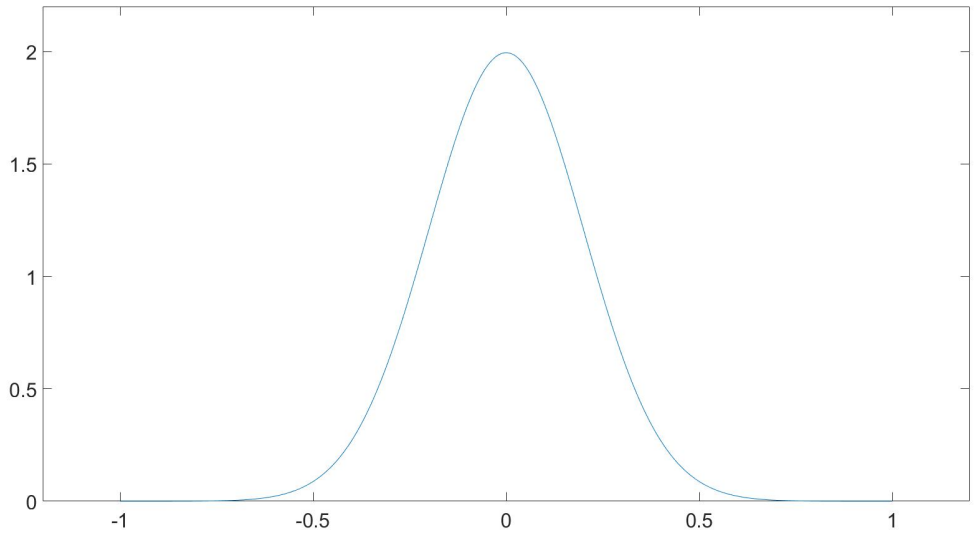


Figure 2.10: The Gaussian Function in 2D with μ=0, σ=0.2 and $A = 2$.

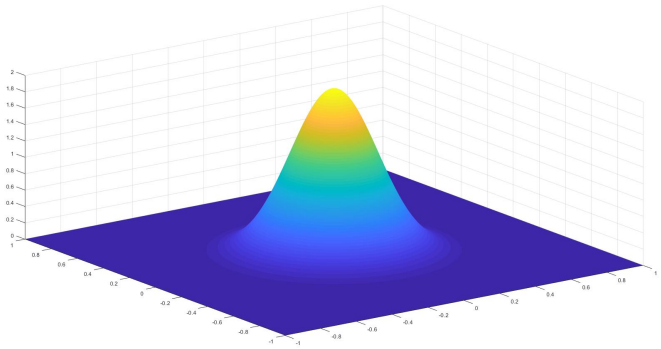


Figure 2.11: The Gaussian Function in 1D with μ=0, σ=0.2 and $A = 2$.

The general one dimensional Gaussian is described:

$$f(x) = \frac{A}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \tag{2.4}$$

The mean value, the central limit, of the sample distribution is the value that has the greatest likelihood[1] in the distribution. The standard deviation is how much the distribution is spread out, the greater the standard deviation the fatter the distribution. The

[1]Likelihood is the value of the distribution given a fixed sample. Probability is the value of a sample given a fixed distribution.

amplitude is the likelihood at the mean of the distribution. In Figure 2.10, for example, the likelihood of a value being 0 is 2. Generally, the curve is used to determine a sample's probability density within a value range. This is the area under the distribution given an interval and is calculated using integration, as shown in 2.5.

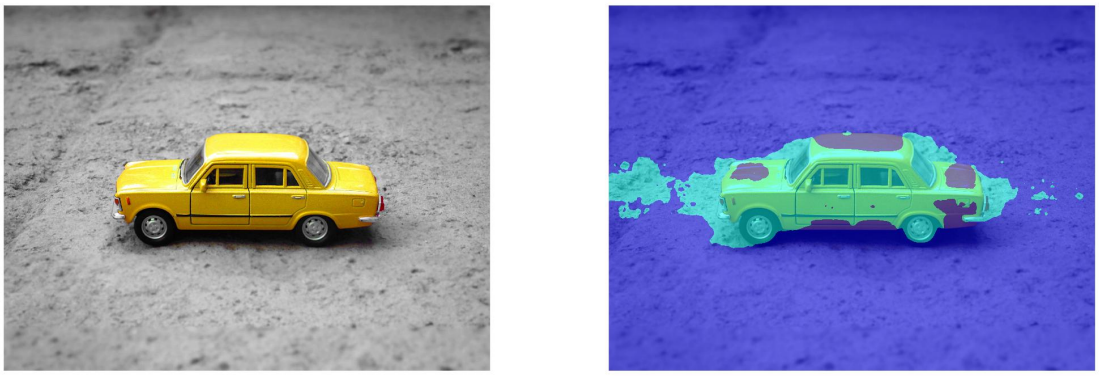
$$P(x) = \int_a^b \frac{A}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx \tag{2.5}$$

Data sets can have many dimensions and distributions need to be able to express all of them. The notation for a multi-variate Gaussian distribution, for a k-dimensional random vector $\boldsymbol{X} = (X_1, \ldots, X_k)^T$, is

$$\boldsymbol{X} \sim \mathcal{N}_k(\mu, \sigma^2) \tag{2.6}$$

2.4 Clustering

Clustering is a method of segmenting an image into disjoint sets known as classes. This is useful for separating types of features or objects in an image. For example in Figure 2.12 the toy car has been segmented from the background.



(a) Image by Gustavo, Upsplash. (b) Segmentation of car from background.

Figure 2.12: Segmentation of toy cars using K-Means Clustering.

In an image every pixel can be individually classified or groups of pixels known as super-pixels may be treated as single entities. Entities are sorted based on their similarity. For example, a pixel's intensity is a feature that could be used to cluster it with other pixels of similar intensity. As seen in (2.7) an entity's comparable traits may be represented by a feature vector. An entity may have any number of features which as also regarded as dimensions, d.

$$\vec{v} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix} \tag{2.7}$$

2.4.1 K-Means

There are many methods by which to cluster, K-Means is a popular method due to its speed and simplicity. Data points are sorted into one of K clusters where the average value of the cluster is stored in a central data point known as the cluster centroid. Centroids may initially be randomly generated or selected from the given data set.

Data points or samples are placed in the class of the centroid that is closest to them. The distance between them is the Euclidean Distance between their feature vectors as in 2.8.

$$D(\vec{p}, \vec{q}) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots + (p_n - q_n)^2} \tag{2.8}$$

K-Mean's algorithm proceeds as follows:

1. Place the initial K centroids.
2. Assign all data points to their nearest centroid.
3. Update the centroids' values to be the mean of all data points in their cluster.

4. Repeat steps 2 and 3 until a criteria is met, for example until cluster centroids no longer move (converge).

K-means benefits greatly from its low computational cost such that it is oten performed a number of times with different initial centroids and the instance best result is used. The best result is defined as having the smallest intracluster variance. K-Means is disadvantaged by the implicit trait that it formulates clusters of similar sizes. This happens because the algorithm seeks to minimize variance (spread) in each cluster hence the 'ideal' centroid placement will form distributions spherically about centroids. This method cannot disentangle overlapping samples that belong in different classes. In Figure 2.13 clear edges between clusters and sphereical distributions can be observed. The algorithm can only implement *hard assignments*, as opposed to a *soft assignment* that consider the probability of a sample's class membership.

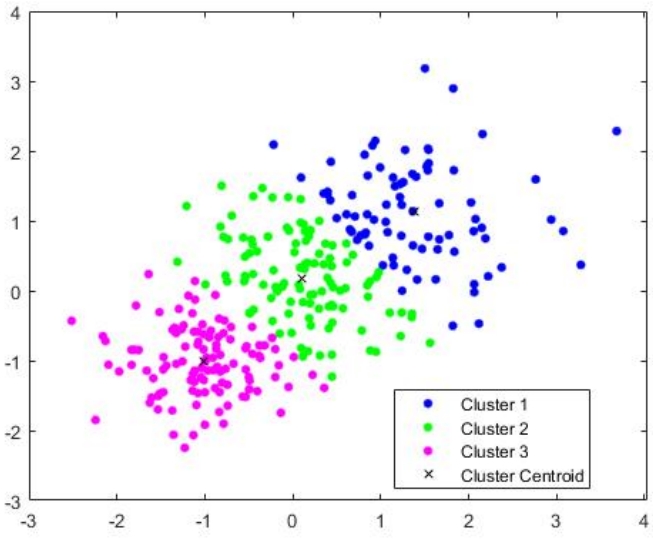


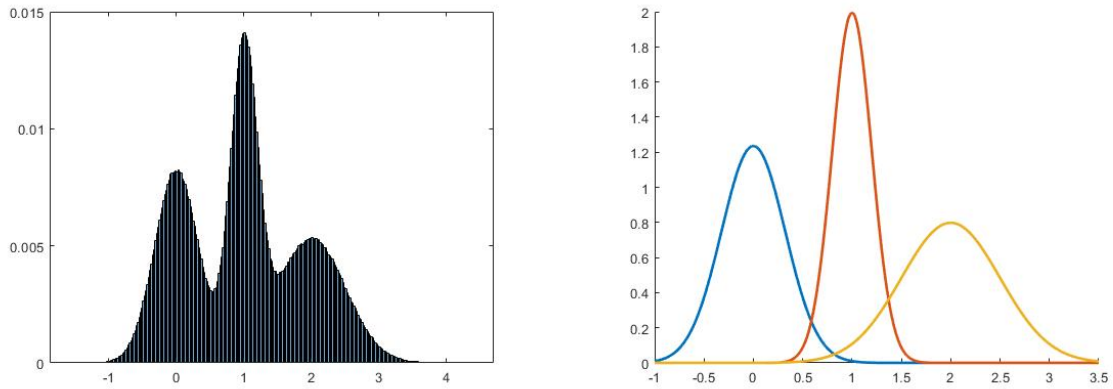
Figure 2.13: K-Means clustering performed on random data.

2.4.2 Mixtures of Gaussians

Mixtures of Gaussian or the Gaussian Mixture Model (GMM) is a method of clustering data that's able to disentangle ambiguous samples by considering a sample's probability

of belonging to a class, known as a soft assignment.

Initially, K Gaussian functions are randomly generated corresponding to K clusters. If a dataset has low dimensionality, by taking a histogram of its values the Gasussians' initial conditions can be approximated, as in Figure 2.14a. By superpositioning all of the Gaussians a sample's complete probabilistic model is created, i.e. a model for *all* clusters, see Figure 2.14b.



(a) Normalized Histogram of 1D samples. (b) Gaussians derived from 1D histogram.

Figure 2.14: Formulation of Mixture of Gaussians.

With each iteration of the GMM algorithm the parameters of the model's component Gaussians are tuned according to the covariance between samples in each cluster. In 2.9 X and Y are the variables being compared, $\overline{X}$ and $\overline{Y}$ are variable means and n is the number of samples. For a multidimensional dataset a covariance matrix $\boldsymbol{\Sigma_k}$ will be generated and each Gaussian will require a mean vector $\boldsymbol{\mu_k}$ as opposed to a scalar.

$$Cov(X,Y) = \frac{\Sigma(X_i - \overline{X})(Y_j - \overline{Y})}{n} \tag{2.9}$$

The algorithm seeks the highest covariance possible in each of its clusters. It is by considering the covariance of samples that the GMM is able to best classify ambiguous samples. The higher the covariance (aka correlation) between sample dimensions the more likely it is they belong in the same cluster. This can observed in Figure 2.15, the data being

clustered is the same as in Figure 2.13 but notice the elliptical shape of the Gaussian cluster distributions as opposed to the spherical shape of K-Means clustering.

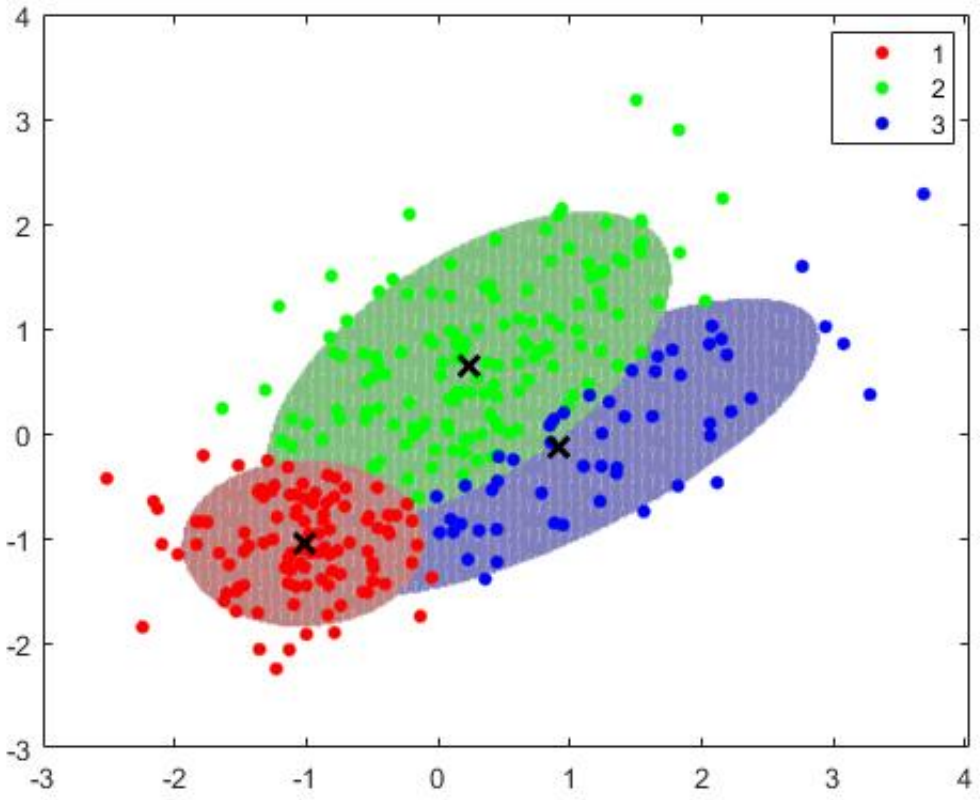


Figure 2.15: Clustering using GMM. X marks cluster mean.

In Figure 2.16 the Gaussians from Figure 2.14b have been scaled to have the amplitudes $\pi_1 = 0.3$, $\pi_1 = 0.5$ and $\pi_1 = 0.2$. These are weightings that give the mixing ratio of the GMM and represent each cluster's proportion of the total samples. The more samples a cluster contains the more likely it is a sample belongs to it. The sum of ratios must add to one because the probability a sample belongs to at least one cluster is one, as defined in 2.10 and 2.11.

$$0 \leq \pi_k \leq 1 \tag{2.10}$$

$$\sum_{k=1}^{K} \pi_k = 1 \tag{2.11}$$

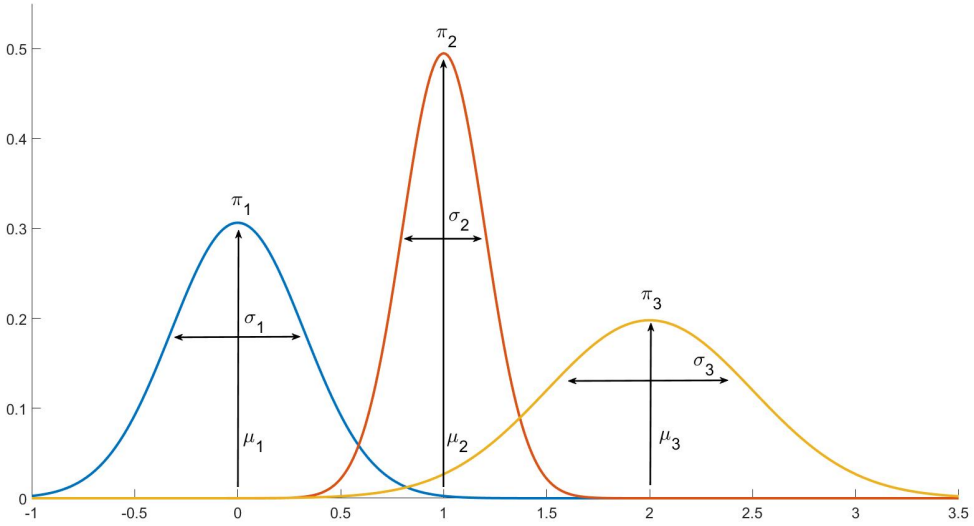


Figure 2.16: Individual Gaussians with scaled weightings.

Each Gaussian's three parameters, mean $\boldsymbol{\mu}_k$, ampltidue π_k and covariance $\boldsymbol{\Sigma}_k$ are updated following each iteration of the algorithm according to the 'Expectation Maximization' algorithm.

Expectation Maximization

Expectation Maximization (EM) is a method of updating the parameters of cluster Gaussians that seeks to maximize a sample's likelihood of belonging to said Gaussians (2.12).

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{2.12}$$

A binary indicator z_i exists for every sample x_i, it is 1 if the sample belongs in the cluster k and 0 otherwise such that $z_{ik} \in \{0, 1\}$ and $\sum_k z_{ik} = 1$. If the data is multidimensional then the sample and inidicator are both vectors, $\boldsymbol{x}$ and $\boldsymbol{z}$. The marginal probability $p(\boldsymbol{z}_k = 1)$ is the probability that a sample $\boldsymbol{x}$ is in cluster k. This quantity is completely specified by the mixture weight π_k for each Gaussian because the area under a Gaussian

component is equal to its mixing ratio, i.e.

$$p(\boldsymbol{z}_k = 1) = \pi_k \tag{2.13}$$

If we know that a sample $\boldsymbol{x}$ is from cluster k the *likelihood* of seeing it in the associated Gaussian is the value of the Gaussian at that point,

$$p(\boldsymbol{x} \mid \boldsymbol{z}_k = 1) = \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k}) \tag{2.14}$$

The conditional probability of $\boldsymbol{z}_{ik}$ given the value of sample, $\boldsymbol{x}_i$ is denoted as $\gamma(\boldsymbol{z}_{ik})$. This is the probability that a sample belongs to cluster k given its value $\boldsymbol{x}_i$ and is the quantity of interest when trying to classify a sample. Using Bayes Theorem [REF APPENDIX] quantity can be found

$$\gamma(\boldsymbol{z}_{ik}) \equiv p(\boldsymbol{z}_{ik} = 1|\boldsymbol{x}_i) = \frac{p(\boldsymbol{z}_{ik} = 1)p(\boldsymbol{x}_i \mid \boldsymbol{z}_{ik} = 1)}{\sum_{j=1}^{K} p(\boldsymbol{z}_{jk} = 1)p(\boldsymbol{x}_j \mid \boldsymbol{z}_{jk} = 1)} \tag{2.15}$$

$$= \frac{\pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})}{\sum_{j=1}^{K} \pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})} \tag{2.16}$$

To maximize the likelihood of each sample being in each Gaussian the distribution parameters are modified. This is achieved by taking derivatives of the log of the likelihood function (2.12) with respect to each Gaussian parameter and setting the result to 0 to find local maxima. To take the log of the likelihood function assume all samples in are in an $N \times D$ matrix $\boldsymbol{X}$ and the corresponding indicators are in an $N \times K$ matrix $\boldsymbol{Z}$.

$$ln\, p(X|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{n=1}^{N} ln\left\{ \sum_{k=1}^{K} \pi_k(N)(\boldsymbol{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\} \tag{2.17}$$

The EM algorithm is comprised of [X] steps

1. Generate the initial K Gaussian parameters mean $\boldsymbol{\mu}_k$, covariance $\boldsymbol{\Sigma}_k$ and mixing ratios π_k either randomly or informed by a histogram.

2. Estimate the likelihood sample n was generated by cluster k for all samples.

$$\gamma(\boldsymbol{z}_{ik}) = \frac{\pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})}{\sum_{j=1}^{K} \pi_k \mathcal{N}(\boldsymbol{x} \mid \boldsymbol{\mu_k}, \boldsymbol{\Sigma_k})} \tag{2.18}$$

3. Maximize the Gaussian parameter using derivatives of log likelihood for each parameter.

$$\boldsymbol{\mu}_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) \boldsymbol{x}_n \tag{2.19}$$

$$\boldsymbol{\Sigma}_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(\boldsymbol{x}_n - \boldsymbol{\mu}_k^{new})(\boldsymbol{x}_n - \boldsymbol{\mu}_k^{new})^T \tag{2.20}$$

$$\pi_k = \frac{N_k}{N} \tag{2.21}$$

where

$$N_k = \sum_i z_{ik}$$

4. Repeat steps 2 and 3 until convergence of log likelihood (2.12) or parameters.

The Gaussian Mixture Model method of clustering is computationally complex compared to K-Means however it's ability to differentiate ambiguous samples by considering covariance is superior.

Chapter 3

Design

The design of the system is compromised of a number of submodules.

[Insert Block Diagram of Submodules Comprising Whole System]

[Then Breakdown Each Submodule]

[Why was a CNN not used?]

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