Assignment 1

BFS

```
#include <iostream>
#include <queue>
#include <omp.h>

class node {
public:
    node* left;
    node* right;
    int data;
};

class Breadthfs {
private:
    node* root;

public:
    Breadthfs() : root(nullptr) {}  // Constructor to initialize root
    node* insert(int);
    void bfs();
};


node* Breadthfs::insert(int data) {
    if (!root) {
        root = new node;
        root->left = nullptr;
        root->right = nullptr;
        root->data = data;
```

```
        return root;
    }

    std::queue<node*> q;
    q.push(root);

    while (!q.empty()) {
        node* temp = q.front();
        q.pop();

        if (temp->left == nullptr) {
            temp->left = new node;
            temp->left->left = nullptr;
            temp->left->right = nullptr;
            temp->left->data = data;
            return root;
        } else {
            q.push(temp->left);
        }

        if (temp->right == nullptr) {
            temp->right = new node;
            temp->right->left = nullptr;
            temp->right->right = nullptr;
            temp->right->data = data;
            return root;
        } else {
            q.push(temp->right);
        }
    }
}
```

```
void Breadthfs::bfs() {
    if (!root) {
        std::cout << "Tree is empty." << std::endl;
        return;
    }

    std::queue<node*> q;
    q.push(root);

    int qSize;

    while (!q.empty()) {
        qSize = q.size();
        #pragma omp parallel for
        for (int i = 0; i < qSize; i++) {
            node* currNode;
            #pragma omp critical
            {
                currNode = q.front();
                q.pop();
                std::cout << "\t" << currNode->data;
            }
            #pragma omp critical
            {
                if (currNode->left)
                    q.push(currNode->left);
                if (currNode->right)
                    q.push(currNode->right);
            }
        }
```

```
    }
}



int main() {
    Breadthfs tree;
    int data;
    char ans;

    do {
        std::cout << "\nEnter data => ";
        std::cin >> data;

        tree.insert(data);

        std::cout << "Do you want to insert one more node? (y/n): ";
        std::cin >> ans;

    } while (ans == 'y' || ans == 'Y');

    tree.bfs();

    return 0;
}
```

```
Enter data => 5
Do you want to insert one more node? (y/n): y

Enter data => 3
Do you want to insert one more node? (y/n): y

Enter data => 6
Do you want to insert one more node? (y/n): y

Enter data => 0
Do you want to insert one more node? (y/n): y

Enter data => 1
Do you want to insert one more node? (y/n): n
        5       3       6       0       1
PS C:\Users\Atharv Kulkarni\Desktop\LP5\A1>
```

DFS

```
#include <iostream>
#include <vector>
#include <stack>
#include <omp.h>

using namespace std;

const int MAX = 100000;
vector<int> graph[MAX];
bool visited[MAX];

void dfs(int node) {
	stack<int> s;
	s.push(node);

	while (!s.empty()) {
	int curr_node = s.top();
	s.pop();

	if (!visited[curr_node]) {
	visited[curr_node] = true;

	if (visited[curr_node]) {
	cout << curr_node << " ";
	}

	#pragma omp parallel for
	for (int i = 0; i < graph[curr_node].size(); i++) {
```

```
                    int adj_node = graph[curr_node][i];
                    if (!visited[adj_node]) {
                    s.push(adj_node);
                    }
          }
          }
          }
}

int main() {
          int n, m, start_node;
          cout << "Enter No of Node,Edges,and start node:" ;
          cin >> n >> m >> start_node;
        //n: node,m:edges

cout << "Enter Pair of edges:" ;
          for (int i = 0; i < m; i++) {
          int u, v;

          cin >> u >> v;
//u and v: Pair of edges
          graph[u].push_back(v);
          graph[v].push_back(u);
          }

          #pragma omp parallel for
          for (int i = 0; i < n; i++) {
          visited[i] = false;
          }

          dfs(start_node);

/*        for (int i = 0; i < n; i++) {
          if (visited[i]) {
          cout << i << " ";
          }
          }*/

          return 0;
}
```

```
PS C:\Users\Atharv Kulkarni> cd "c:\Users\Atharv
 if ($?) { .\DFS }
Enter No of Node,Edges,and start node:4 3 0
Enter Pair of edges:0 1
0 2
2 4
0 2 4 1
```

Assignment 2

Bubble Sort

```
#include<iostream>
#include<stdlib.h>
#include<omp.h>
using namespace std;

void bubble(int *, int);
void swap(int &, int &);


void bubble(int *a, int n)
{
   for(  int i = 0;  i < n;  i++ )
    {
          int first = i % 2;

          #pragma omp parallel for shared(a,first)
          for(  int j = first;  j < n-1;  j += 2  )
            {
                   if(  a[ j ]  >  a[ j+1 ]  )
                    {
                            swap(  a[ j ],  a[ j+1 ]  );
                    }
                     }
    }
}


void swap(int &a, int &b)
{

   int test;
   test=a;
   a=b;
   b=test;

}

int main()
{

   int *a,n;
   cout<<"\n enter total no of elements=>";
   cin>>n;
   a=new int[n];
   cout<<"\n enter elements=>";
   for(int i=0;i<n;i++)
   {
```

```
        cin>>a[i];
  }

  bubble(a,n);

  cout<<"\n sorted array is=>";
  for(int i=0;i<n;i++)
  {
        cout<<a[i]<<endl;
  }


return 0;
}
```

```
PS C:\Users\Atharv Kulkarni\Downloads> cd "c
oads\" ; if ($?) { g++ main.cpp -o main } ;

 enter total no of elements=>5

 enter elements=>3 4 2 1 0

 sorted array is=>0
1
2
3
4
PS C:\Users\Atharv Kulkarni\Downloads>
```

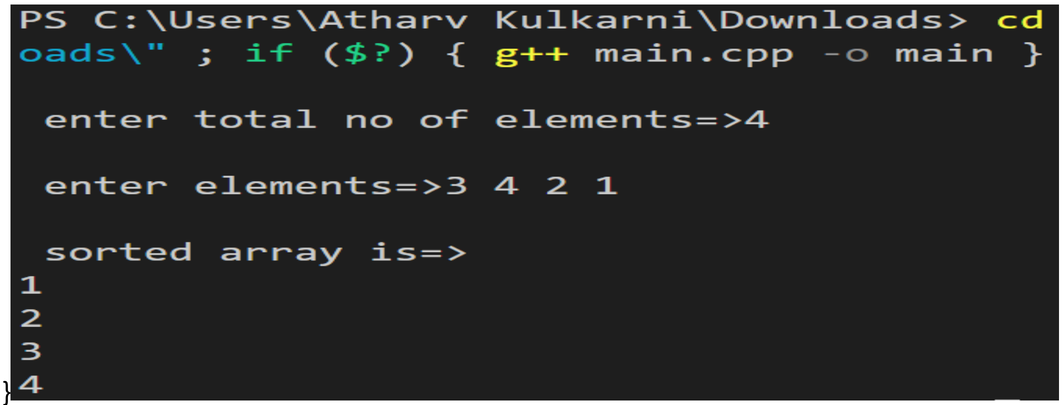
MergeSort

```
#include<iostream>

#include<stdlib.h>

#include<omp.h>

using namespace std;
```

```
void mergesort(int a[],int i,int j);
void merge(int a[],int i1,int j1,int i2,int j2);

void mergesort(int a[],int i,int j)
{
	int mid;
	if(i<j)
	{
	mid=(i+j)/2;

	#pragma omp parallel sections
	{

	#pragma omp section
	{
	mergesort(a,i,mid);
	}

	#pragma omp section
	{
	mergesort(a,mid+1,j);
	}
	}

	merge(a,i,mid,mid+1,j);
	}

}
```

```
void merge(int a[],int i1,int j1,int i2,int j2)
{
        int temp[1000];
        int i,j,k;
        i=i1;
        j=i2;
        k=0;
        while(i<=j1 && j<=j2)
        {
        if(a[i]<a[j])
        {
        temp[k++]=a[i++];
        }
        else
        {
        temp[k++]=a[j++];
  }
        }

        while(i<=j1)
        {
        temp[k++]=a[i++];
        }

        while(j<=j2)
        {
        temp[k++]=a[j++];
        }

        for(i=i1,j=0;i<=j2;i++,j++)
        {
```

```
            a[i]=temp[j];
            }
}
int main()
{
            int *a,n,i;
            cout<<"\n enter total no of elements=>";
            cin>>n;
            a= new int[n];

            cout<<"\n enter elements=>";
            for(i=0;i<n;i++)
            {
            cin>>a[i];
            }
            mergesort(a, 0, n-1);
            cout<<"\n sorted array is=>";
            for(i=0;i<n;i++)
            {
            cout<<"\n"<<a[i];
            }
            return 0;
```



```
PS C:\Users\Atharv Kulkarni\Downloads> cd
oads\" ; if ($?) { g++ main.cpp -o main }

 enter total no of elements=>4

 enter elements=>3 4 2 1

 sorted array is=>
1
2
3
4
```

```
}
```

Assignment 3

```
#include <iostream>

//#include <vector>

#include <omp.h>

#include <climits>

using namespace std;

void min_reduction(int arr[], int n) {

  int min_value = INT_MAX;

  #pragma omp parallel for reduction(min: min_value)

  for (int i = 0; i < n; i++) {

            if (arr[i] < min_value) {

            min_value = arr[i];

            }

  }

  cout << "Minimum value: " << min_value << endl;

}


void max_reduction(int arr[], int n) {

  int max_value = INT_MIN;

  #pragma omp parallel for reduction(max: max_value)

  for (int i = 0; i < n; i++) {

            if (arr[i] > max_value) {

            max_value = arr[i];

            }

  }

  cout << "Maximum value: " << max_value << endl;

}


void sum_reduction(int arr[], int n) {

  int sum = 0;

   #pragma omp parallel for reduction(+: sum)
```

```
  for (int i = 0; i < n; i++) {
            sum += arr[i];
  }
  cout << "Sum: " << sum << endl;
}

void average_reduction(int arr[], int n) {
  int sum = 0;
  #pragma omp parallel for reduction(+: sum)
  for (int i = 0; i < n; i++) {
            sum += arr[i];
  }
  cout << "Average: " << (double)sum / (n-1) << endl;
}

int main() {
    int *arr,n;
    cout<<"\n enter total no of elements=>";
    cin>>n;
    arr=new int[n];
    cout<<"\n enter elements=>";
    for(int i=0;i<n;i++)
    {
             cin>>arr[i];
    }

  min_reduction(arr, n);
  max_reduction(arr, n);
  sum_reduction(arr, n);
  average_reduction(arr, n);
}
```

```
PS C:\Users\Atharv Kulkarni\Downlo
oads\" ; if ($?) { g++ main.cpp -o

 enter total no of elements=>4

 enter elements=>3 1 5 3
Minimum value: 1
Maximum value: 5
Sum: 12
Average: 4
```

Assignment 4

Addition of two large vector

```
#include <iostream>
#include <cuda_runtime.h>
#include /usr/local/cuda/include/cuda_runtime.h

_global_void addVectors(int* A, int* B, int* C, int n)
{
	int i = blockIdx.x * blockDim.x + threadIdx.x;
	if (i < n)
	{
	C[i] = A[i] + B[i];
	}
}

int main()
{
	int n = 1000000;
	int* A, * B, * C;
	int size = n * sizeof(int);

	// Allocate memory on the host
	cudaMallocHost(&A, size);
	cudaMallocHost(&B, size);
	cudaMallocHost(&C, size);

	// Initialize the vectors
	for (int i = 0; i < n; i++)
	{
	A[i] = i;
	B[i] = i * 2;
	}
	// Allocate memory on the device
	int* dev_A, * dev_B, * dev_C;
	cudaMalloc(&dev_A, size);
	cudaMalloc(&dev_B, size);
	cudaMalloc(&dev_C, size);

	// Copy data from host to device
	cudaMemcpy(dev_A, A, size, cudaMemcpyHostToDevice);
	cudaMemcpy(dev_B, B, size, cudaMemcpyHostToDevice);

	// Launch the kernel
	int blockSize = 256;
	int numBlocks = (n + blockSize - 1) / blockSize;
	// Copy data from device to host
	cudaMemcpy(C, dev_C, size, cudaMemcpyDeviceToHost);

	// Print the results
```

```
	for (int i = 0; i < 10; i++)
	{
	cout << C[i] << " ";
	}
	cout << endl;

	// Free memory
	cudaFree(dev_A);
	cudaFree(dev_B);
	cudaFree(dev_C);
	cudaFreeHost(A);
	cudaFreeHost(B);
	cudaFreeHost(C);

	return 0;
}
```

```
C:\Users\Atharv Kulkarni\Downloads>nvcc -o main main.cu -allow-unsupported-compiler
main.cu
tmpxft_00005b3c_00000000-10_main.cudafe1.cpp
   Creating library main.lib and object main.exp

C:\Users\Atharv Kulkarni\Downloads>main.exe
0 3 6 9 12 15 18 21 24 27
```

Matrix Multiplication using CUDA C

```
#include <cuda_runtime.h>

#include <iostream>


__global__ void matmul(int* A, int* B, int* C, int N) {

  int Row = blockIdx.y*blockDim.y+threadIdx.y;

  int Col = blockIdx.x*blockDim.x+threadIdx.x;

  if (Row < N && Col < N) {

    int Pvalue = 0;

    for (int k = 0; k < N; k++) {

      Pvalue += A[Row*N+k] * B[k*N+Col];

    }

    C[Row*N+Col] = Pvalue;

  }

}
```

```
int main() {
    int N = 512;
    int size = N * N * sizeof(int);
    int* A, * B, * C;
    int* dev_A, * dev_B, * dev_C;
    cudaMallocHost(&A, size);
    cudaMallocHost(&B, size);
    cudaMallocHost(&C, size);
    cudaMalloc(&dev_A, size);
    cudaMalloc(&dev_B, size);
    cudaMalloc(&dev_C, size);

    // Initialize matrices A and B
    for (int i = 0; i < N; i++) {
        for (int j = 0; j < N; j++) {
            A[i*N+j] = i*N+j;
            B[i*N+j] = j*N+i;
        }
    }

    cudaMemcpy(dev_A, A, size, cudaMemcpyHostToDevice);
    cudaMemcpy(dev_B, B, size, cudaMemcpyHostToDevice);

    dim3 dimBlock(16, 16);
    dim3 dimGrid(N/dimBlock.x, N/dimBlock.y);

    matmul<<<dimGrid, dimBlock>>>(dev_A, dev_B, dev_C, N);

    cudaMemcpy(C, dev_C, size, cudaMemcpyDeviceToHost);
```

```
    // Print the result
    for (int i = 0; i < 10; i++) {
        for (int j = 0; j < 10; j++) {
            std::cout << C[i*N+j] << " ";
        }
        std::cout << std::endl;
    }

    // Free memory
    cudaFree(dev_A);
    cudaFree(dev_B);
    cudaFree(dev_C);
    cudaFreeHost(A);
    cudaFreeHost(B);
    cudaFreeHost(C);

    return 0;
}
```

```
C:\Users\Atharv Kulkarni\Downloads>nvcc -o new new.cu -allow-unsupported-compiler
new.cu
tmpxft_00006b8c_00000000-10_new.cudafe1.cpp
   Creating library new.lib and object new.exp

C:\Users\Atharv Kulkarni\Downloads>new.exe
44608256 111586048 178563840 245541632 312519424 379497216 446475008 513452800 580430592 647408384
111586048 312781568 513977088 715172608 916368128 1117563648 1318759168 1519954688 1721150208 1922345728
178563840 513977088 849390336 1184803584 1520216832 1855630080 -2103923968 -1768510720 -1433097472 -1097684224
245541632 715172608 1184803584 1654434560 2124065536 -1701270784 -1231639808 -762008832 -292377856 177253120
312519424 916368128 1520216832 2124065536 -1567053056 -963204352 -359355648 244493056 848341760 1452190464
379497216 1117563648 1855630080 -1701270784 -963204352 -225137920 512928512 1250994944 1989061376 -1567839488
446475008 1318759168 -2103923968 -1231639808 -359355648 512928512 1385212672 -2037470464 -1165186304 -292902144
513452800 1519954688 -1768510720 -762008832 244493056 1250994944 -2037470464 -1030968576 -24466688 982035200
580430592 1721150208 -1433097472 -292377856 848341760 1989061376 -1165186304 -24466688 1116252928 -2037994752
647408384 1922345728 -1097684224 177253120 1452190464 -1567839488 -292902144 982035200 -2037994752 -763057408
```

HPC Mini Project

Problem Statement:

Implement Huffman Encoding on GPU

Theory:

Huffman encoding is a technique used for lossless data compression, primarily in the context of encoding text or binary data. It was developed by David A. Huffman in 1952 while he was a graduate student at MIT. Huffman encoding works by assigning variable-length codes to input characters, with shorter codes assigned to more frequent characters and longer codes assigned to less frequent characters. This results in a more efficient representation of the data, where frequently occurring characters are represented using fewer bits, thereby reducing the overall size of the encoded data.

Here's how Huffman encoding typically works:

1. **Frequency Analysis:** The first step in Huffman encoding is to analyze the input data and determine the frequency of occurrence of each character or symbol. This can be done by scanning the input data and counting the occurrences of each character.
2. **Build Huffman Tree:** Based on the frequency analysis, a Huffman tree is constructed. This is a binary tree where each leaf node represents a character/symbol and each non-leaf node represents a combined set of characters/symbols. The frequencies of the characters determine the placement of nodes in the tree, with lower frequency characters generally placed higher up in the tree.
3. **Assign Codes:** Starting from the root of the Huffman tree, traverse the tree to assign binary codes to each character. This is done by assigning a '0' for each left branch and a '1' for each right branch encountered during the traversal. The resulting binary codes are unique for each character and are determined by the path from the root to the leaf node representing that character.
4. **Encode Data:** With the Huffman tree constructed and the codes assigned, the input data is encoded by replacing each character with its corresponding Huffman code. The encoded data will typically be a sequence of bits, where each character is represented by its Huffman code.
5. **Compression:** The encoded data is usually more compact than the original data, especially if the input data has repetitive patterns or contains frequently occurring characters. This compression is achieved by representing common characters with shorter codes and less common characters with longer codes.
6. Implementing Huffman encoding on a GPU can be done using parallel processing techniques. Here's a basic outline of how you can approach it:
7. **Generate Huffman Tree**:
    a. Start by building the Huffman tree on the CPU. This involves calculating the frequency of each symbol in the input data and constructing the tree based on these frequencies.
    b. You can parallelize the frequency counting step by dividing the input data into chunks and processing each chunk in parallel.
    c. Once you have the frequency information, construct the Huffman tree. This part can be done efficiently on the CPU since it typically involves sorting and merging nodes based on their frequencies, which isn't as easily parallelizable on a GPU.
8. **Encode Symbols**:

    a. Once you have the Huffman tree constructed, you can move to encoding symbols using the tree.
    b. Break down the input data into chunks and encode each chunk in parallel on the GPU.
    c. Traverse the Huffman tree for each symbol in the input data and generate the corresponding Huffman codes.
9. **Write GPU Kernels**:
    a. Write GPU kernels (CUDA or OpenCL) for encoding symbols. Each thread can handle encoding one symbol or a small chunk of symbols.
    b. The kernels would traverse the Huffman tree to determine the code for each symbol.
    c. Utilize shared memory for efficient access to the Huffman tree and input data.
10. **Output Compression**:
    a. Once the encoding is done, you can write the encoded data back to CPU memory for further processing or storage.
    b. Depending on your application, you might want to compress the encoded data further using techniques like run-length encoding or LZ77/LZ78.
11. **Considerations**:
    a. Balancing workload across GPU threads is crucial for optimal performance.
    b. Ensure proper synchronization where needed, especially during tree traversal.
    c. Minimize memory transfers between CPU and GPU to avoid bottlenecks.

Conclusion:

Implementing Huffman encoding on a GPU can significantly accelerate the compression process due to the parallel nature of GPU architectures. By leveraging the massive parallelism offered by GPUs, Huffman encoding can be executed more efficiently, resulting in faster compression speeds compared to traditional CPU implementations. Additionally, utilizing GPU resources for Huffman encoding can lead to improved performance and throughput, making it a promising approach for high-performance compression tasks.

Code

```
#include <stdio.h>
#include <stdlib.h>
#include <stdint.h>
#include <string.h>

// Node structure for Huffman tree
typedef struct Node
{
    uint8_t data;
    int frequency;
    struct Node *left, *right;
} Node;

// Structure to hold information about each symbol in the input data
typedef struct
{
    uint8_t symbol;
    int frequency;
} SymbolInfo;

// Function prototypes
__global__ void encodeData(const uint8_t *__restrict__ input, int *output, int
dataSize, Node *huffmanTree);
__device__ void traverseTree(Node *root, uint8_t symbol, int *encodedData, int
*index);

// Function to create a new node
Node *newNode(uint8_t symbol, int frequency)
{
    Node *temp = (Node *)malloc(sizeof(Node));
    temp->left = temp->right = NULL;
    temp->data = symbol;
    temp->frequency = frequency;
    return temp;
}

// Comparator function for sorting SymbolInfo array based on frequency
int compare(const void *a, const void *b)
{
    return (((SymbolInfo *)a)->frequency - ((SymbolInfo *)b)->frequency);
}

// Function to build Huffman tree
Node *buildHuffmanTree(SymbolInfo *symbols, int n)
```

```
{
    Node *left, *right, *top;
    // Create a priority queue to store nodes
    Node **queue = (Node **)malloc(n * sizeof(Node *));

    for (int i = 0; i < n; ++i)
    {
        queue[i] = newNode(symbols[i].symbol, symbols[i].frequency);
    }

    // Iterate until there is only one node in the queue, i.e., the root
    int size = n;
    while (size > 1)
    {
        left = queue[0];
        right = queue[1];
        top = newNode('$', left->frequency + right->frequency);
        top->left = left;
        top->right = right;

        // Remove the two nodes with the lowest frequency from the queue
        for (int i = 0; i < size - 2; ++i)
            queue[i] = queue[i + 2];
        queue[size - 2] = top;
        size--;
        qsort(queue, size, sizeof(Node *), compare);
    }
    return queue[0];
}

// Function to perform Huffman encoding on GPU
__global__ void encodeData(const uint8_t *__restrict__ input, int *output, int
dataSize, Node *huffmanTree)
{
    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    if (tid < dataSize)
    {
        int index = 0;
        traverseTree(huffmanTree, input[tid], output, &index);
    }
}

// Helper function for encoding data using Huffman tree
__device__ void traverseTree(Node *root, uint8_t symbol, int *encodedData, int
*index)
{
    if (root == NULL)
        return;

        if (root->left == NULL && root->right == NULL)
```

```
    {
        if (root->data == symbol)
        {
            encodedData[*index] = 1;
            *index += 1;
        }
        else
        {
            encodedData[*index] = 0;
            *index += 1;
            traverseTree(root, symbol, encodedData, index);
        }
    }
    else
    {
        traverseTree(root->left, symbol, encodedData, index);
        traverseTree(root->right, symbol, encodedData, index);
    }
}

int main()
{
    // Example input data
    uint8_t inputData[] = {'a', 'b', 'c', 'a', 'b', 'c', 'd', 'a', 'a', 'b'};
    int dataSize = sizeof(inputData) / sizeof(inputData[0]);

    // Calculate frequency of each symbol
    SymbolInfo symbols[256] = {0}; // Assuming ASCII characters

    for (int i = 0; i < dataSize; ++i)
    {
        symbols[inputData[i]].symbol = inputData[i];
        symbols[inputData[i]].frequency++;
    }

    // Sort symbols based on frequency
    qsort(symbols, 256, sizeof(SymbolInfo), compare);

    // Build Huffman tree
    Node *huffmanTree = buildHuffmanTree(symbols, 256);

    // Transfer Huffman tree to GPU memory

    // Allocate memory on GPU for encoded data
    int *d_encodedData;
    cudaMalloc((void **)&d_encodedData, dataSize * sizeof(int));

    // Allocate memory on GPU for Huffman tree
    Node *d_huffmanTree;
    cudaMalloc((void **)&d_huffmanTree, sizeof(Node));
```

```
    // Transfer Huffman tree from host to device
    cudaMemcpy(d_huffmanTree, huffmanTree, sizeof(Node), cudaMemcpyHostToDevice);

        // Define grid and block dimensions
    int blockSize = 256;
    int numBlocks = (dataSize + blockSize - 1) / blockSize;

    // Encode data on GPU
    encodeData<<<numBlocks, blockSize>>>(inputData, d_encodedData, dataSize,
d_huffmanTree);

    // Copy encoded data back to host memory
    int *encodedData = (int *)malloc(dataSize * sizeof(int));
    cudaMemcpy(encodedData, d_encodedData, dataSize * sizeof(int),
cudaMemcpyDeviceToHost);

      // Free allocated memory
    cudaFree(d_encodedData);
    cudaFree(d_huffmanTree);

    printf("Input Data: ");
    for (int i = 0; i < sizeof(inputData) / sizeof(uint8_t); i++)
    {
        printf("%d", inputData[i]);
    }
    printf("\n");

    // Print encoded data
    printf("Encoded Data: ");
    for (int i = 0; i < dataSize; ++i)
    {
        printf("%d", encodedData[i]);
    }
    printf("\n");

    // Free allocated memory
    free(encodedData);

    return 0;
}
```

Output

```
Command Prompt

(c) Microsoft Corporation. All rights reserved.

C:\Windows\System32> "C:\Program Files\Microsoft Visual Studio\2022\Community\VC\Auxiliary\Build\vcvarsall.bat" x64
**********************************************************************
** Visual Studio 2022 Developer Command Prompt v17.9.2
** Copyright (c) 2022 Microsoft Corporation
**********************************************************************
[vcvarsall.bat] Environment initialized for: 'x64'

C:\Windows\System32> cd "D:\Final Year Projects\BE_Project"

D:\Final Year Projects\BE_Project> nvcc huffman_encoding.cu -o huffman_encoding.exe

huffman_encoding.cu
ptxas warning : Stack size for entry function '_Z10encodeDataPKhPiiP4Node' cannot be statically determined

D:\Final Year Projects\BE_Project> ./huffman_encoding.exe
Input Data: abcabcdaab
Encoded Data: 0101110101111100010

D:\Final Year Projects\BE_Project>
```

Import Library

In [1]:
```
# Data analysis and visualization
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

# Preprocessing and evaluation
from sklearn.model_selection import train_test_split
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import MinMaxScaler
```

Load Data

In [2]:
```
(X_train , y_train), (X_test , y_test) = tf.keras.datasets.boston_housing.load_data(
                                            path = 'boston_housing_npz',
                                            test_split = 0.2,
                                            seed = 42
                                        )
```

Exploratory Data Analysis

Initial Observation

In [3]:
```
# Checking the data shape and type
(X_train.shape, type(X_train)), (X_test.shape, type(X_test)), (y_train.shape, type(y_train)), (y_test.shape, ty
```

Out[3]:
```
(((404, 13), numpy.ndarray),
 ((102, 13), numpy.ndarray),
 ((404,), numpy.ndarray),
 ((102,), numpy.ndarray))
```

In [4]:
```
# Converting Data to DataFrame
X_train_df = pd.DataFrame(X_train)
y_train_df = pd.DataFrame(y_train)

# Preview the training data
X_train_df.head(10)
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.09178	0.0	4.05	0.0	0.510	6.416	84.1	2.6463	5.0	296.0	16.6	395.50	9.04
1	0.05644	40.0	6.41	1.0	0.447	6.758	32.9	4.0776	4.0	254.0	17.6	396.90	3.53
2	0.10574	0.0	27.74	0.0	0.609	5.983	98.8	1.8681	4.0	711.0	20.1	390.11	18.07
3	0.09164	0.0	10.81	0.0	0.413	6.065	7.8	5.2873	4.0	305.0	19.2	390.91	5.52
4	5.09017	0.0	18.10	0.0	0.713	6.297	91.8	2.3682	24.0	666.0	20.2	385.09	17.27
5	0.10153	0.0	12.83	0.0	0.437	6.279	74.5	4.0522	5.0	398.0	18.7	373.66	11.97
6	0.31827	0.0	9.90	0.0	0.544	5.914	83.2	3.9986	4.0	304.0	18.4	390.70	18.33
7	0.29090	0.0	21.89	0.0	0.624	6.174	93.6	1.6119	4.0	437.0	21.2	388.08	24.16
8	4.03841	0.0	18.10	0.0	0.532	6.229	90.7	3.0993	24.0	666.0	20.2	395.33	12.87
9	0.22438	0.0	9.69	0.0	0.585	6.027	79.7	2.4982	6.0	391.0	19.2	396.90	14.33

In [5]:
```
# View summary of datasets
X_train_df.info()
```

```
print('_'*40)
y_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404 entries, 0 to 403
Data columns (total 13 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       404 non-null    float64
 1   1       404 non-null    float64
 2   2       404 non-null    float64
 3   3       404 non-null    float64
 4   4       404 non-null    float64
 5   5       404 non-null    float64
 6   6       404 non-null    float64
 7   7       404 non-null    float64
 8   8       404 non-null    float64
 9   9       404 non-null    float64
 10  10      404 non-null    float64
 11  11      404 non-null    float64
 12  12      404 non-null    float64
dtypes: float64(13)
memory usage: 41.2 KB
________________________________________
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404 entries, 0 to 403
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       404 non-null    float64
dtypes: float64(1)
memory usage: 3.3 KB
```

In [6]:

```
# distribution of numerical feature values across the samples
X_train_df.describe()
```

Out[6]:

	0	1	2	3	4	5	6	7	8	9
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000
mean	3.789989	11.568069	11.214059	0.069307	0.554524	6.284824	69.119307	3.792258	9.660891	408.960396
std	9.132761	24.269648	6.925462	0.254290	0.116408	0.723759	28.034606	2.142651	8.736073	169.685166
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.137000	1.000000	187.000000
25%	0.081960	0.000000	5.190000	0.000000	0.452000	5.878750	45.475000	2.097050	4.000000	281.000000
50%	0.262660	0.000000	9.690000	0.000000	0.538000	6.210000	77.500000	3.167500	5.000000	330.000000
75%	3.717875	12.500000	18.100000	0.000000	0.624000	6.620500	94.425000	5.118000	24.000000	666.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000

Preprocessing

In [7]:

```
# Create column transformer
ct = make_column_transformer(
    (MinMaxScaler(), [0, 1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12])
)

# Normalization and data type change
X_train = ct.fit_transform(X_train).astype('float32')
X_test = ct.transform(X_test).astype('float32')
y_train = y_train.astype('float32')
y_test = y_test.astype('float32')

# Distribution of X_train feature values after normalization
pd.DataFrame(X_train).describe()
```

Out[7]:

	0	1	2	3	4	5	6	7	8	9
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000
mean	0.042528	0.115681	0.394210	0.348815	0.521905	0.681970	0.241618	0.376560	0.423589	0.625737
std	0.102650	0.242696	0.253866	0.239522	0.138678	0.288719	0.194973	0.379829	0.323827	0.229502
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000850	0.000000	0.173387	0.137860	0.444098	0.438466	0.087361	0.130435	0.179389	0.510638
50%	0.002881	0.000000	0.338343	0.314815	0.507569	0.768280	0.184767	0.173913	0.272901	0.691489
75%	0.041717	0.125000	0.646628	0.491770	0.586223	0.942585	0.362255	1.000000	0.914122	0.808511
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

Model, Predict, Evaluation

In [8]:

```
# Reserve data for validation
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.1, random_state=42)
X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

Out[8]: ((363, 12), (41, 12), (363,), (41,))

Creating the Model and Optimizing the Learning Rate

learning rate = 0.01, batch_size = 32, dense_layers = 2, hidden_units for Dense_1 layer= 10, hidden_units for Dense_2 layer = 100

In [9]:

```
# Set random seed
tf.random.set_seed(42)

# Building the model
model = tf.keras.Sequential([
  tf.keras.layers.Dense(units=10, activation='relu', input_shape=(X_train.shape[1],), name='Dense_1'),
  tf.keras.layers.Dense(units=100, activation='relu', name='Dense_2'),
  tf.keras.layers.Dense(units=1, name='Prediction')
])

# Compiling the model
model.compile(
    loss = tf.keras.losses.mean_squared_error,
    optimizer = tf.keras.optimizers.RMSprop(learning_rate=0.01),
    metrics = ['mse']
)

# Training the model
history = model.fit(
    X_train,
    y_train,
    batch_size=32,
    epochs=50,
    validation_data=(X_val, y_val)
)
```

```
12/12 [==============================] - 0s 3ms/step - loss: 13.7454 - mse: 13.7454 - val_loss: 15.7261 - val_
mse: 15.7261
Epoch 49/50
12/12 [==============================] - 0s 4ms/step - loss: 14.7645 - mse: 14.7645 - val_loss: 9.9898 - val_m
se: 9.9898
Epoch 50/50
12/12 [==============================] - 0s 3ms/step - loss: 15.1951 - mse: 15.1951 - val_loss: 11.3679 - val_
mse: 11.3679
```

Model Evaluation

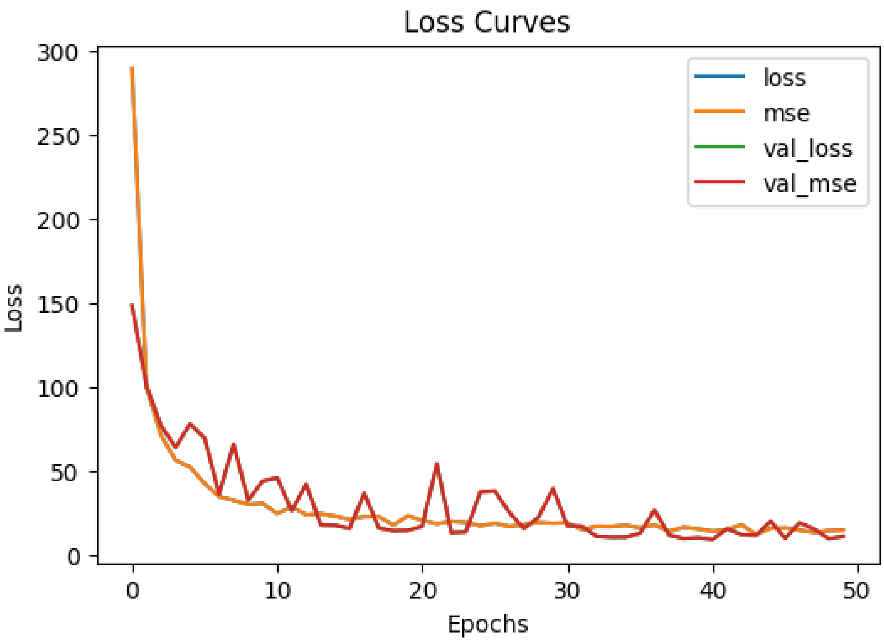
In [10]:
```
# Preview the mean value of training and validation data
y_train.mean(), y_val.mean()
```

Out[10]:
```
(22.235537, 24.89756)
```

In [11]:
```
# Evaluate the model on the test data
print("Evaluation on Test data \n")
loss, mse = model.evaluate(X_test, y_test, batch_size=32)
print(f"\nModel loss on test set: {loss}")
print(f"Model mean squared error on test set: {(mse):.2f}")
```

```
Evaluation on Test data

4/4 [==============================] - 0s 2ms/step - loss: 15.5170 - mse: 15.5170

Model loss on test set: 15.517014503479004
Model mean squared error on test set: 15.52
```

In [12]:
```
# Plot the loss curves
pd.DataFrame(history.history).plot(figsize=(6, 4), xlabel="Epochs", ylabel="Loss", title='Loss Curves')
plt.show()
```



Model Prediction

In [13]:
```
# Make predictions
y_pred = model.predict(X_test)

# View the first prediction
y_pred[0]
```

```
4/4 [==============================] - 0s 1ms/step
```

Out[13]:
```
array([19.093914], dtype=float32)
```

Classifying movie reviews: a binary classification example

Design a neural network to perform two-class classification or *binary classification* , of reviews form IMDB movie reviews dataset, to determine wether the reviews are positive or negative. We will use the Python library Keras to perform the classification

The IMDB Dataset

The IMDB dataset is a set of 50,000 highly polarized reviews from the Internet Movie Database. They are split into 25000 reviews each for training and testing. Each set contains equal number (50%) of positive and negative reviews.

The IMDB dataset comes packaged with Keras. It consists of reviews and their corresponding labels (0 for *negative* and 1 for *positive* review). The reviews are a sequence of words. They come preprocessed as sequence of integers, where each integer stands for a specific word in the dictionary.

The IMDB datset can be loaded directly from Keras and will usually download about 80 MB on your machine.

Import Packages

In [1]:
```
import numpy as np
from keras.datasets import imdb
from keras import models
from keras import layers
from keras import optimizers
from keras import losses
from keras import metrics


import matplotlib.pyplot as plt
%matplotlib inline
```

Loading the Data

In [2]:
```
# Load the data, keeping only 10,000 of the most frequently occuring words
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words = 10000)
```

In [3]:
```
# Check the first label
train_labels[0]
```

Out[3]:
```
1
```

In [4]:
```
# Since we restricted ourselves to the top 10000 frequent words, no word index should exceed
# we'll verify this below

# Here is a list of maximum indexes in every review --- we search the maximum index in this
print(type([max(sequence) for sequence in train_data]))

# Find the maximum of all max indexes
max([max(sequence) for sequence in train_data])
```

```
<class 'list'>
```

Out[4]:
```
9999
```

In [5]:
```
# Let's quickly decode a review

# step 1: load the dictionary mappings from word to integer index
word_index = imdb.get_word_index()

# step 2: reverse word index to map integer indexes to their respective words
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])

# Step 3: decode the review, mapping integer indices to words
#
# indices are off by 3 because 0, 1, and 2 are reserverd indices for "padding", "Start of se
decoded_review = ' '.join([reverse_word_index.get(i-3, '?') for i in train_data[0]])

decoded_review
```

Out[5]:
```
"? this film was just brilliant casting location scenery story direction everyone's really
suited the part they played and you could just imagine being there robert ? is an amazing a
ctor and now the same being director ? father came from the same scottish island as myself
so i loved the fact there was a real connection with this film the witty remarks throughout
the film were great it was just brilliant so much that i bought the film as soon as it was
released for ? and would recommend it to everyone to watch and the fly fishing was amazing
really cried at the end it was so sad and you know what they say if you cry at a film it mu
st have been good and this definitely was also ? to the two little boy's that played the ?
of norman and paul they were just brilliant children are often left out of the ? list i thi
nk because the stars that play them all grown up are such a big profile for the whole film
but these children are amazing and should be praised for what they have done don't you thin
k the whole story was so lovely because it was true and was someone's life after all that w
as shared with us all"
```

In [6]:
```
len(reverse_word_index)
```

Out[6]:
```
88584
```

Preparing the data

Vectorize input data

We cannot feed list of integers into our deep neural network. We will need to convert them into tensors.

To prepare our data we will One-hot Encode our lists and turn them into vectors of 0's and 1's. This would blow up all of our sequences into 10,000 dimensional vectors containing 1 at all indices corresponding to integers present in that sequence. This vector will have the element 0 at all indices which are not present in integer sequence.

Simply put, the 10,000 dimensional vector corresponding to each review, will have

- Every index corresponding to a word
- Every index vith value 1, is a word which is present in the review and is denoted by its integer counterpart
- Every index containing 0, is a word not present in the review

We will vectorize our data manually for maximum clarity. This will result in a tensors of shape (25000, 10000).

In [7]:
```
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))    # Creates an all zero matrix of shape
    for i,sequence in enumerate(sequences):
        results[i,sequence] = 1                        # Sets specific indices of results[i]
    return results

# Vectorize training Data
X_train = vectorize_sequences(train_data)

# Vectorize testing Data
X_test = vectorize_sequences(test_data)
```

In [8]:
```
X_train[0]
```
Out[8]:
```
array([0., 1., 1., ..., 0., 0., 0.])
```

In [9]:
```
X_train.shape
```
Out[9]:
```
(25000, 10000)
```

Vectorize labels

In [10]:
```
y_train = np.asarray(train_labels).astype('float32')
y_test  = np.asarray(test_labels).astype('float32')
```

Building the network

Our input data is vectors which needs to be mapped to scaler labels (0s and 1s). This is one of the easiest setups and a simple stack of *fully-connected*, *Dense* layers with *relu* activation perform quite well.

Hidden layers

In this network we will leverage *hidden layers*. we will define our layers as such.

```
Dense(16, activation='relu')
```

The argument being passed to each `Dense` layer, `(16)` is the number of *hidden units* of a layer.

The output from a *Dense* layer with *relu* activation is genrated after a chain of *tensor* operations. This chain of operations is implemented as

```
output = relu(dot(W, input) + b)
```

Where, `W` is the *Weight matrix* and `b` is the bias (tensor).

Having 16 hidden units means that the matrix W will be of the shape (*input_Dimension* , *16*). In this case where the dimension of input vector is 10,000; the shape of Weight matrix will be (10000, 16). If you were to represent this network as graph you would see 16 neurons in this hidden layer.

To put in in laymans terms, there will be 16 balls in this layer.

Each of these balls, or *hidden units* is a dimension in the representation space of the layer. Representaion space is the set of all viable representaions for the data. Every *hidden layer* composed of its *hidden units* aims to learns one specific transformation of the data, or one feature/pattern from the data.

Hidden layers, simply put, are layers of mathematical functions each designed to produce an output specific to an intended result. Hidden layers allow for the function of a neural network to be broken down into specific transformations of the data. Each hidden layer function is specialized to produce a defined output.For example, a hidden layer functions that are used to identify human eyes and ears may be used in conjunction by subsequent layers to identify faces in images. While the functions to identify eyes alone are not enough to independently recognize objects, they can function jointly within a neural network.

Model Architecture

1. For our model we will use
    - two intermediate layers with 16 hidden units each
    - Third layer that will output the scalar sentiment prediction
2. Intermediate layers will use *relu* activation function. *relu* or Rectified linear unit function will zero out the negative values.
3. Sigmoid activation for the final layer or *output layer*. A sigmoid function "*squashes*" arbitary values into the [0,1] range.

There are formal principles that guide our approach in selecting the architectural attributes of a model. These are not

Model defination

In [11]:
```python
model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

Compiling the model

In this step we will choose an *optimizer*, a *loss function*, and metrics to observe. We will go forward with

- *binary_crossentropy* loss function, commonlu used for Binary Classification
- *rmsprop* optimizer and
- *accuracy* as a measure of performance

We can pass our choices for optimizer, loss function and metrics as *strings* to the `compile` function because `rmsprop` , `binary_crossentropy` and `accuracy` come packaged with Keras.

```python
model.complie(
    optimizer='rmsprop',
    loss = 'binary_crossentropy',
    metrics = ['accuracy']
)
```

One could use a customized loss function or ortimizer by passing the custom *class instance* as argument to the `loss` , `optimizer` or `mertics` fields.

In this example, we will implement our default choices, but, we will do so by passing class instances. This is exactly how we would do it, if we had customized parameters.

In [12]:
```python
model.compile(
    optimizer=optimizers.RMSprop(learning_rate=0.001),
    loss = losses.binary_crossentropy,
    metrics = [metrics.binary_accuracy]
)
```

Setting up Validation

We will set aside a part of our training data for *validation* of the accuracy of the model as it trains. A *validation set* enables us to monitor the progress of our model on previously unseen data as it goes throug epochs during training.

Validation steps help us fine tune the training parameters of the `model.fit` function so as to avoid overfitting and under fitting of data.

In [13]:
```python
# Input for Validation
X_val = X_train[:10000]
partial_X_train = X_train[10000:]

# Labels for validation
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Training our model

Initially, we will train our models for 20 epochs in mini-batches of 512 samples. We will aslo pass our *validation set* to the `fit` method.

Calling the `fit` method returns a `History` object. This object contains a member `history` which stores all data

In [14]:
```
history = model.fit(
    partial_X_train,
    partial_y_train,
    epochs=20,
    batch_size=512,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/20
30/30 [==============================] - 2s 37ms/step - loss: 0.5156 - binary_accuracy: 0.7
949 - val_loss: 0.3994 - val_binary_accuracy: 0.8627
Epoch 2/20
30/30 [==============================] - 0s 16ms/step - loss: 0.3162 - binary_accuracy: 0.8
993 - val_loss: 0.3088 - val_binary_accuracy: 0.8886
Epoch 3/20
30/30 [==============================] - 0s 16ms/step - loss: 0.2303 - binary_accuracy: 0.9
267 - val_loss: 0.2881 - val_binary_accuracy: 0.8869
Epoch 4/20
30/30 [==============================] - 0s 15ms/step - loss: 0.1831 - binary_accuracy: 0.9
411 - val_loss: 0.2792 - val_binary_accuracy: 0.8897
Epoch 5/20
30/30 [==============================] - 0s 15ms/step - loss: 0.1514 - binary_accuracy: 0.9
501 - val_loss: 0.2767 - val_binary_accuracy: 0.8884
Epoch 6/20
30/30 [==============================] - 0s 15ms/step - loss: 0.1214 - binary_accuracy: 0.9
642 - val_loss: 0.3112 - val_binary_accuracy: 0.8781
Epoch 7/20
30/30 [==============================] - 0s 15ms/step - loss: 0.1041 - binary_accuracy: 0.9
694 - val_loss: 0.3267 - val_binary_accuracy: 0.8804
Epoch 8/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0830 - binary_accuracy: 0.9
779 - val_loss: 0.3235 - val_binary_accuracy: 0.8807
Epoch 9/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0707 - binary_accuracy: 0.9
798 - val_loss: 0.3542 - val_binary_accuracy: 0.8775
Epoch 10/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0553 - binary_accuracy: 0.9
858 - val_loss: 0.3724 - val_binary_accuracy: 0.8774
Epoch 11/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0457 - binary_accuracy: 0.9
889 - val_loss: 0.4186 - val_binary_accuracy: 0.8712
Epoch 12/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0381 - binary_accuracy: 0.9
915 - val_loss: 0.4310 - val_binary_accuracy: 0.8773
Epoch 13/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0305 - binary_accuracy: 0.9
941 - val_loss: 0.4663 - val_binary_accuracy: 0.8751
Epoch 14/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0242 - binary_accuracy: 0.9
953 - val_loss: 0.5045 - val_binary_accuracy: 0.8726
Epoch 15/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0192 - binary_accuracy: 0.9
966 - val_loss: 0.5289 - val_binary_accuracy: 0.8713
Epoch 16/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0162 - binary_accuracy: 0.9
971 - val_loss: 0.5600 - val_binary_accuracy: 0.8704
Epoch 17/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0111 - binary_accuracy: 0.9
987 - val_loss: 0.6111 - val_binary_accuracy: 0.8679
Epoch 18/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0082 - binary_accuracy: 0.9
995 - val_loss: 0.6720 - val_binary_accuracy: 0.8633
Epoch 19/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0106 - binary_accuracy: 0.9
978 - val_loss: 0.6709 - val_binary_accuracy: 0.8653
Epoch 20/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0039 - binary_accuracy: 0.9
999 - val_loss: 0.6942 - val_binary_accuracy: 0.8653
```

At the end of training we have attained a training accuracy of 99.85% and validation accuracy of 86.57%

Now that we have trained our network, we will observe its performance metrics stored in the `History` object.

Calling the `fit` method returns a `History` object. This object has an sttribute `history` which is a dictionary containing four enteries: one per monitored metric.

In [15]:
```
history_dict = history.history
history_dict.keys()
```

Out[15]:
```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

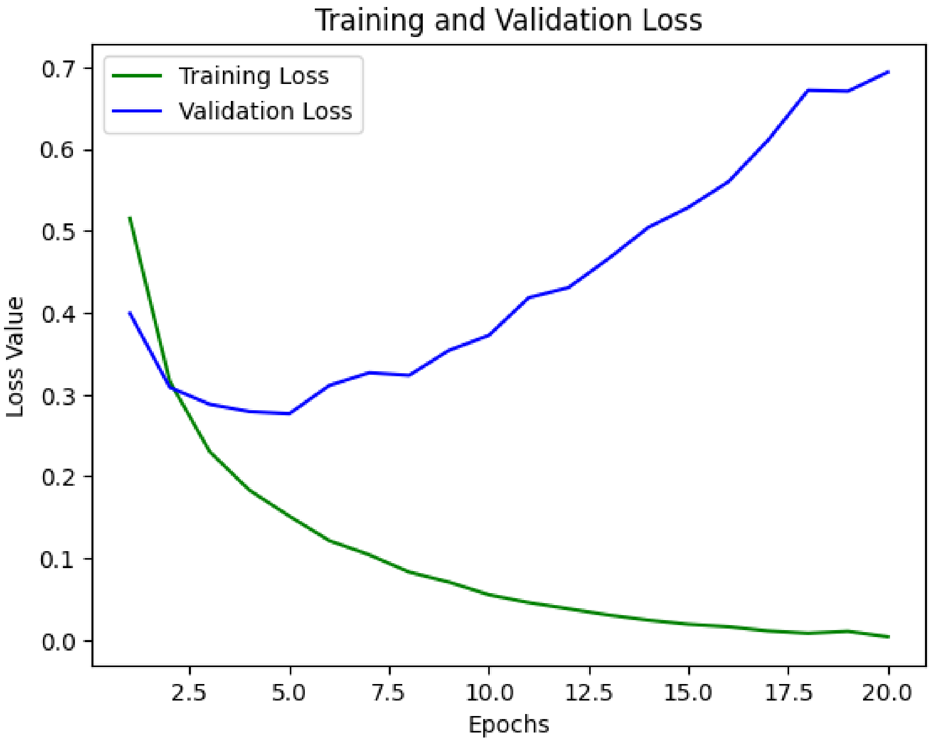
`history_dict` contains values of

- Training loss
- Trainining Accuracy
- Validation Loss
- Validation Accuracy

at the end of each epoch.

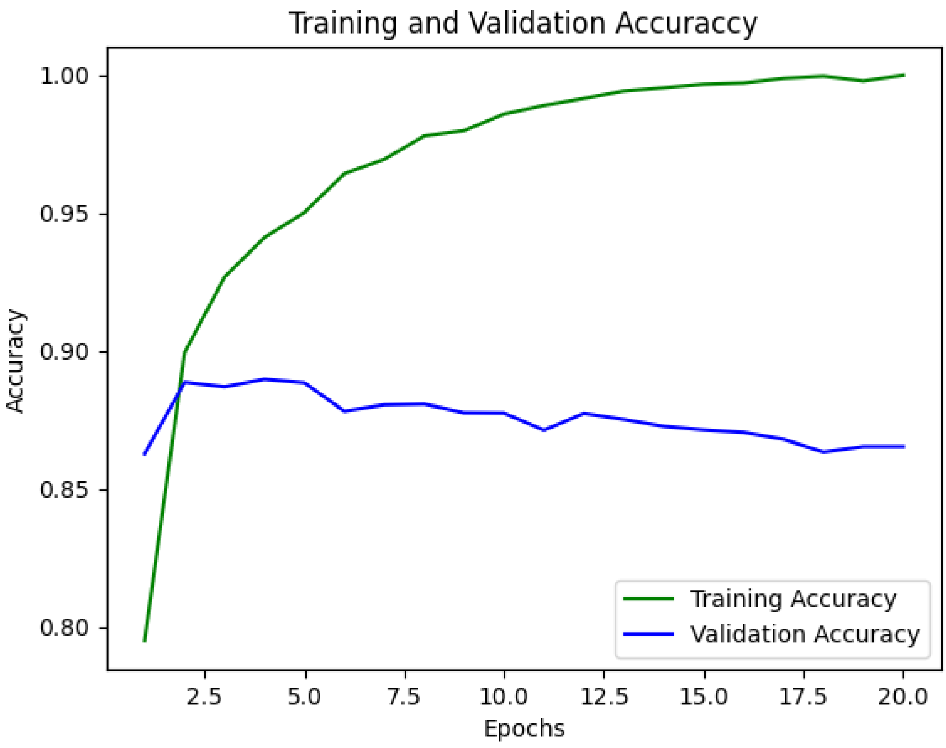
Let's use Matplotlib to plot Training and validation losses and Traing and Validation Accuracy side by side.

In [16]:
```
# Plotting losses
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, loss_values, 'g', label="Training Loss")
plt.plot(epochs, val_loss_values, 'b', label="Validation Loss")

plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss Value')
plt.legend()

plt.show()
```



In [17]:

```
# Training and Validation Accuracy

acc_values = history_dict['binary_accuracy']
val_acc_values = history_dict['val_binary_accuracy']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, acc_values, 'g', label="Training Accuracy")
plt.plot(epochs, val_acc_values, 'b', label="Validation Accuracy")

plt.title('Training and Validation Accuraccy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



We observe that *minimum validation loss* and *maximum validation Accuracy* is achived at around 3-5 epochs. After that we observe 2 trends:

- increase in validation loss and decrease in training loss
- decrease in validation accuracy and increase in training accuracy

This implies that the model is getting better at classifying the sentiment of the training data, but making consistently worse predictions when it encounters new, previously unseed data. This is the hallmark of *Overfitting*. After the 5th epoch the model begins to fit too closely to the trainning data.

To address overfitting, we will reduce the number of epochs to somewhere between 3 and 5. These results may vary depending on your machine and due to the very nature of the random assignment of weights that may vary from model to mode.

In our case we will stop training after 3 epochs.

Retraining our model

In [18]:
```
model.fit(
    partial_X_train,
    partial_y_train,
    epochs=3,
    batch_size=512,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/3
30/30 [==============================] - 2s 50ms/step - loss: 0.0053 - binary_accuracy: 0.9
996 - val_loss: 0.7299 - val_binary_accuracy: 0.8648
Epoch 2/3
30/30 [==============================] - 0s 15ms/step - loss: 0.0040 - binary_accuracy: 0.9
993 - val_loss: 0.7694 - val_binary_accuracy: 0.8659
Epoch 3/3
30/30 [==============================] - 0s 15ms/step - loss: 0.0019 - binary_accuracy: 0.9
999 - val_loss: 0.8005 - val_binary_accuracy: 0.8638
```

Out[18]:
```
<keras.callbacks.History at 0x7f1e00ba11e0>
```

In the end we achive a *training accuracy* of 99% and a *validation accuray* of 86%

Model Evaluation

In [19]:
```
# Making Predictions for testing data
np.set_printoptions(suppress=True)
result = model.predict(X_test)
```

```
782/782 [==============================] - 1s 1ms/step
```

In [20]:
```
result
```

Out[20]:
```
array([[0.00426335],
       [0.9999999 ],
       [0.99748594],
       ...,
       [0.000199  ],
       [0.02019035],
       [0.5236855 ]], dtype=float32)
```

In [21]:
```
y_pred = np.zeros(len(result))
for i, score in enumerate(result):
    y_pred[i] = np.round(score)
```

In [22]:
```
mae = metrics.mean_absolute_error(y_pred, y_test)
mae
```

Out[22]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=0.15012>
```

Basic classification: Classify images of clothing

In [1]:
```
# TensorFlow and tf.keras
import tensorflow as tf

# Helper libraries
import numpy as np
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
2.11.0
```

Import the Fashion MNIST dataset

This guide uses the [Fashion MNIST (https://github.com/zalandoresearch/fashion-mnist)](https://github.com/zalandoresearch/fashion-mnist) dataset which contains 70,000 grayscale images in 10 categories. The images show individual articles of clothing at low resolution (28 by 28 pixels), as seen here:

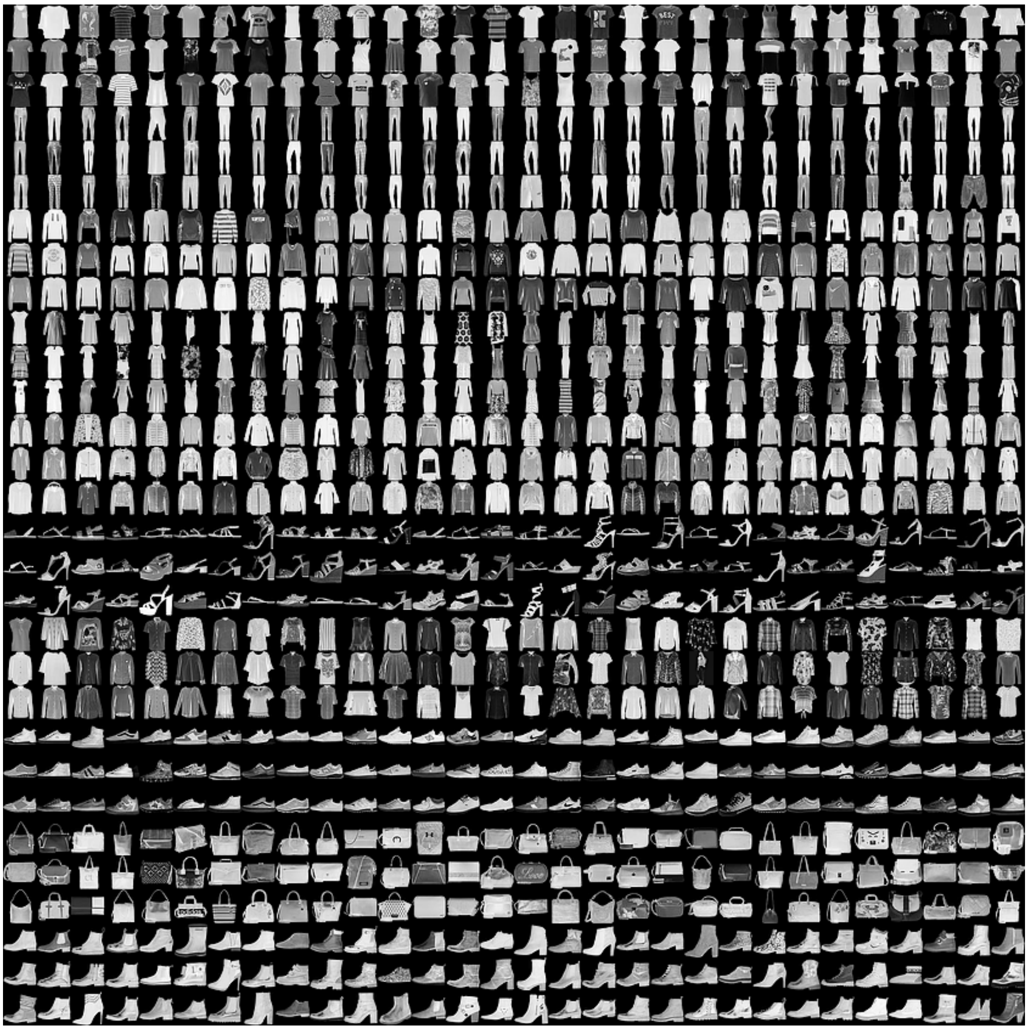


Figure 1. [Fashion-MNIST samples (https://github.com/zalandoresearch/fashion-mnist)](https://github.com/zalandoresearch/fashion-mnist) (by Zalando, MIT License).

Fashion MNIST is intended as a drop-in replacement for the classic [MNIST (http://yann.lecun.com/exdb/mnist/)](http://yann.lecun.com/exdb/mnist/) dataset—often used as the "Hello, World" of machine learning programs for computer vision. The MNIST dataset contains images of handwritten digits (0, 1, 2, etc.) in a format identical to that of the articles of clothing you'll use here.

This guide uses Fashion MNIST for variety, and because it's a slightly more challenging problem than regular MNIST. Both datasets are relatively small and are used to verify that an algorithm works as expected. They're good starting points to test and debug code.

Here, 60,000 images are used to train the network and 10,000 images to evaluate how accurately the network learned to

In [2]:
```
fashion_mnist = tf.keras.datasets.fashion_mnist

(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()
```

Loading the dataset returns four NumPy arrays:

- The `train_images` and `train_labels` arrays are the *training set*—the data the model uses to learn.
- The model is tested against the *test set*, the `test_images` , and `test_labels` arrays.

The images are 28x28 NumPy arrays, with pixel values ranging from 0 to 255. The *labels* are an array of integers, ranging from 0 to 9. These correspond to the *class* of clothing the image represents:

Label	Class
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

Each image is mapped to a single label. Since the *class names* are not included with the dataset, store them here to use later when plotting the images:

In [3]:
```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

Explore the data

Let's explore the format of the dataset before training the model. The following shows there are 60,000 images in the training set, with each image represented as 28 x 28 pixels:

In [4]:
```
train_images.shape
```

Out[4]:
```
(60000, 28, 28)
```

Likewise, there are 60,000 labels in the training set:

In [5]:
```
len(train_labels)
```

Out[5]:
```
60000
```

Each label is an integer between 0 and 9:

In [6]:
```
train_labels
```

Out[6]:
```
array([9, 0, 0, ..., 3, 0, 5], dtype=uint8)
```

There are 10,000 images in the test set. Again, each image is represented as 28 x 28 pixels:

In [7]:
```
test_images.shape
```

Out[7]:
```
(10000, 28, 28)
```

And the test set contains 10,000 images labels:

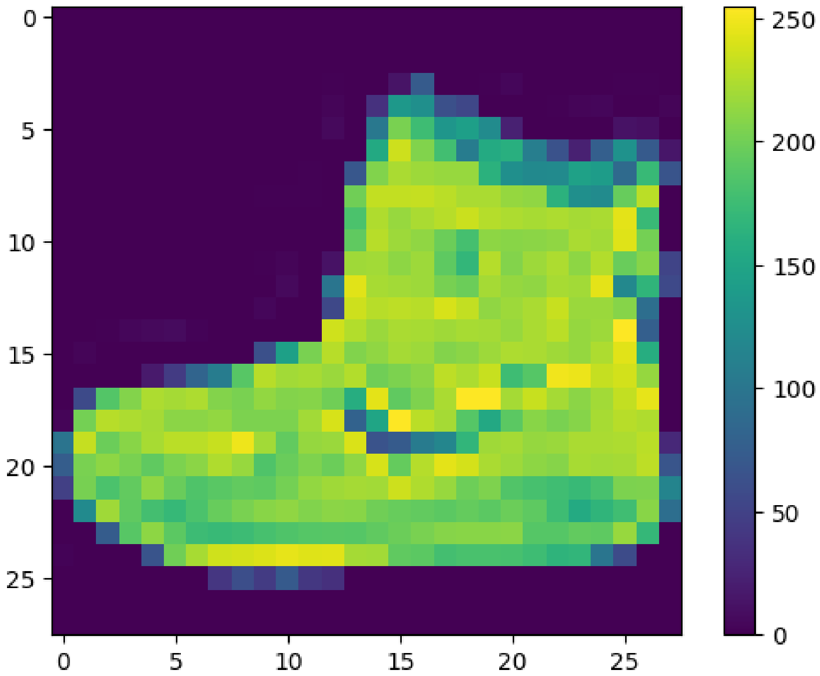
In [8]:
```
len(test_labels)
```

Out[8]:
```
10000
```

Preprocess the data

The data must be preprocessed before training the network. If you inspect the first image in the training set, you will see that the pixel values fall in the range of 0 to 255:

In [9]:
```
plt.figure()
plt.imshow(train_images[0])
plt.colorbar()
plt.grid(False)
plt.show()
```



Scale these values to a range of 0 to 1 before feeding them to the neural network model. To do so, divide the values by 255. It's important that the *training set* and the *testing set* be preprocessed in the same way:

In [10]:
```
train_images = train_images / 255.0

test_images = test_images / 255.0
```

To verify that the data is in the correct format and that you're ready to build and train the network, let's display the first 25 images from the *training set* and display the class name below each image.

In [11]:
```
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()
```

Build the model

Building the neural network requires configuring the layers of the model, then compiling the model.

Set up the layers

The basic building block of a neural network is the [*layer* (https://www.tensorflow.org/api_docs/python/tf/keras/layers)](https://www.tensorflow.org/api_docs/python/tf/keras/layers). Layers extract representations from the data fed into them. Hopefully, these representations are meaningful for the problem at hand.

Most of deep learning consists of chaining together simple layers. Most layers, such as `tf.keras.layers.Dense`, have parameters that are learned during training.

In [12]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(10)
])
```

The first layer in this network, `tf.keras.layers.Flatten`, transforms the format of the images from a two-dimensional array (of 28 by 28 pixels) to a one-dimensional array (of 28 * 28 = 784 pixels). Think of this layer as unstacking rows of pixels in the image and lining them up. This layer has no parameters to learn; it only reformats the data.

After the pixels are flattened, the network consists of a sequence of two `tf.keras.layers.Dense` layers. These are densely connected, or fully connected, neural layers. The first `Dense` layer has 128 nodes (or neurons). The second (and last) layer returns a logits array with length of 10. Each node contains a score that indicates the current image belongs to one of the 10 classes.

Compile the model

Before the model is ready for training, it needs a few more settings. These are added during the model's *compile* (https://www.tensorflow.org/api_docs/python/tf/keras/Model#compile) step:

- *Loss function* (https://www.tensorflow.org/api_docs/python/tf/keras/losses) —This measures how accurate the model is during training. You want to minimize this function to "steer" the model in the right direction.
- *Optimizer* (https://www.tensorflow.org/api_docs/python/tf/keras/optimizers) —This is how the model is updated based on the data it sees and its loss function.
- *Metrics* (https://www.tensorflow.org/api_docs/python/tf/keras/metrics) —Used to monitor the training and testing steps. The following example uses *accuracy*, the fraction of the images that are correctly classified.

In [13]:
```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Train the model

Training the neural network model requires the following steps:

1. Feed the training data to the model. In this example, the training data is in the `train_images` and `train_labels` arrays.
2. The model learns to associate images and labels.
3. You ask the model to make predictions about a test set—in this example, the `test_images` array.
4. Verify that the predictions match the labels from the `test_labels` array.

Feed the model

To start training, call the `model.fit` (https://www.tensorflow.org/api_docs/python/tf/keras/Model#fit) method—so called because it "fits" the model to the training data:

```
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1624 - accuracy: 0.938
8
Epoch 25/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1599 - accuracy: 0.940
2
Epoch 26/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1558 - accuracy: 0.941
9
Epoch 27/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1524 - accuracy: 0.943
1
Epoch 28/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1472 - accuracy: 0.944
4
Epoch 29/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1466 - accuracy: 0.945
2
Epoch 30/30
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1420 - accuracy: 0.946
9
```

Out[14]:

```
<keras.callbacks.History at 0x7f326fff3370>
```

As the model trains, the loss and accuracy metrics are displayed. This model reaches an accuracy of about 0.91 (or 91%) on the training data.

Evaluate accuracy

Next, compare how the model performs on the test dataset:

In [15]:

```
test_loss, test_acc = model.evaluate(test_images,  test_labels, verbose=2)

print('\nTest accuracy:', test_acc)
```

```
313/313 - 0s - loss: 0.4365 - accuracy: 0.8796 - 481ms/epoch - 2ms/step

Test accuracy: 0.8795999884605408
```

It turns out that the accuracy on the test dataset is a little less than the accuracy on the training dataset. This gap between training accuracy and test accuracy represents *overfitting*. Overfitting happens when a machine learning model performs worse on new, previously unseen inputs than it does on the training data. An overfitted model "memorizes" the noise and details in the training dataset to a point where it negatively impacts the performance of the model on the new data. For more information, see the following:

- [Demonstrate overfitting (https://www.tensorflow.org/tutorials/keras/overfit_and_underfit#demonstrate_overfitting)](https://www.tensorflow.org/tutorials/keras/overfit_and_underfit#demonstrate_overfitting)
- [Strategies to prevent overfitting (https://www.tensorflow.org/tutorials/keras/overfit_and_underfit#strategies_to_prevent_overfitting)](https://www.tensorflow.org/tutorials/keras/overfit_and_underfit#strategies_to_prevent_overfitting)

Make predictions

With the model trained, you can use it to make predictions about some images. Attach a softmax layer to convert the model's linear outputs—[logits (https://developers.google.com/machine-learning/glossary#logits)](https://developers.google.com/machine-learning/glossary#logits)—to probabilities, which should be easier to interpret.

In [16]:

```
probability_model = tf.keras.Sequential([model,
                                         tf.keras.layers.Softmax()])
```

In [17]:

```
predictions = probability_model.predict(test_images)
```

```
313/313 [==============================] - 0s 1ms/step
```

Here, the model has predicted the label for each image in the testing set. Let's take a look at the first prediction:

In [18]:
```
predictions[0]
```

Out[18]:
```
array([3.8219037e-12, 6.0263157e-12, 1.1343045e-19, 5.9180233e-16,
       1.9016950e-22, 4.5273669e-08, 5.1865828e-16, 1.9605557e-05,
       1.2793957e-13, 9.9998027e-01], dtype=float32)
```

A prediction is an array of 10 numbers. They represent the model's "confidence" that the image corresponds to each of the 10 different articles of clothing. You can see which label has the highest confidence value:

In [19]:
```
np.argmax(predictions[0])
```

Out[19]:
```
9
```

So, the model is most confident that this image is an ankle boot, or `class_names[9]`. Examining the test label shows that this classification is correct:

In [20]:
```
test_labels[0]
```

Out[20]:
```
9
```

Graph this to look at the full set of 10 class predictions.

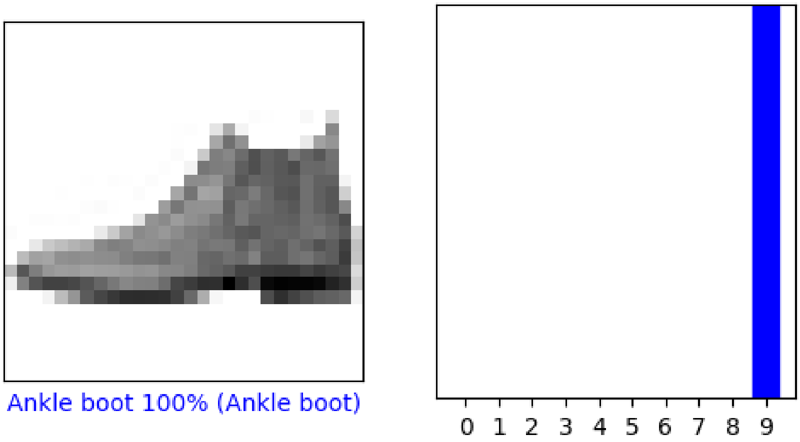
In [21]:
```
def plot_image(i, predictions_array, true_label, img):
  true_label, img = true_label[i], img[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])

  plt.imshow(img, cmap=plt.cm.binary)

  predicted_label = np.argmax(predictions_array)
  if predicted_label == true_label:
    color = 'blue'
  else:
    color = 'red'

  plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
                                100*np.max(predictions_array),
                                class_names[true_label]),
                                color=color)

def plot_value_array(i, predictions_array, true_label):
  true_label = true_label[i]
  plt.grid(False)
  plt.xticks(range(10))
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions_array)

  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

Verify predictions

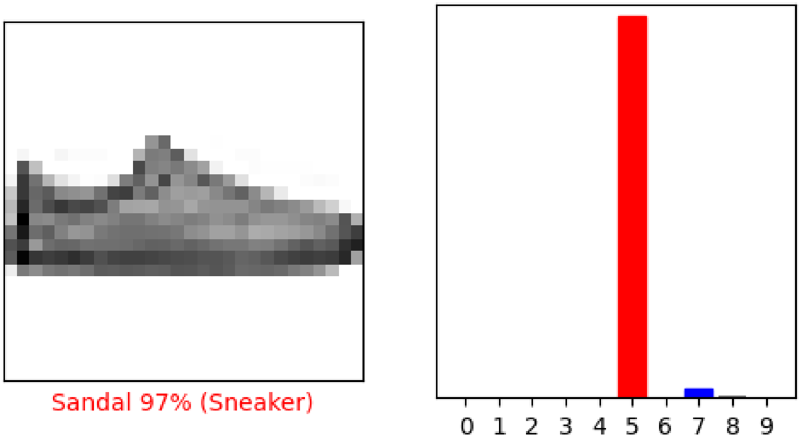
With the model trained, you can use it to make predictions about some images.

Let's look at the 0th image, predictions, and prediction array. Correct prediction labels are blue and incorrect prediction labels are red. The number gives the percentage (out of 100) for the predicted label.

In [22]:
```
i = 0
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions[i], test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions[i],  test_labels)
plt.show()
```

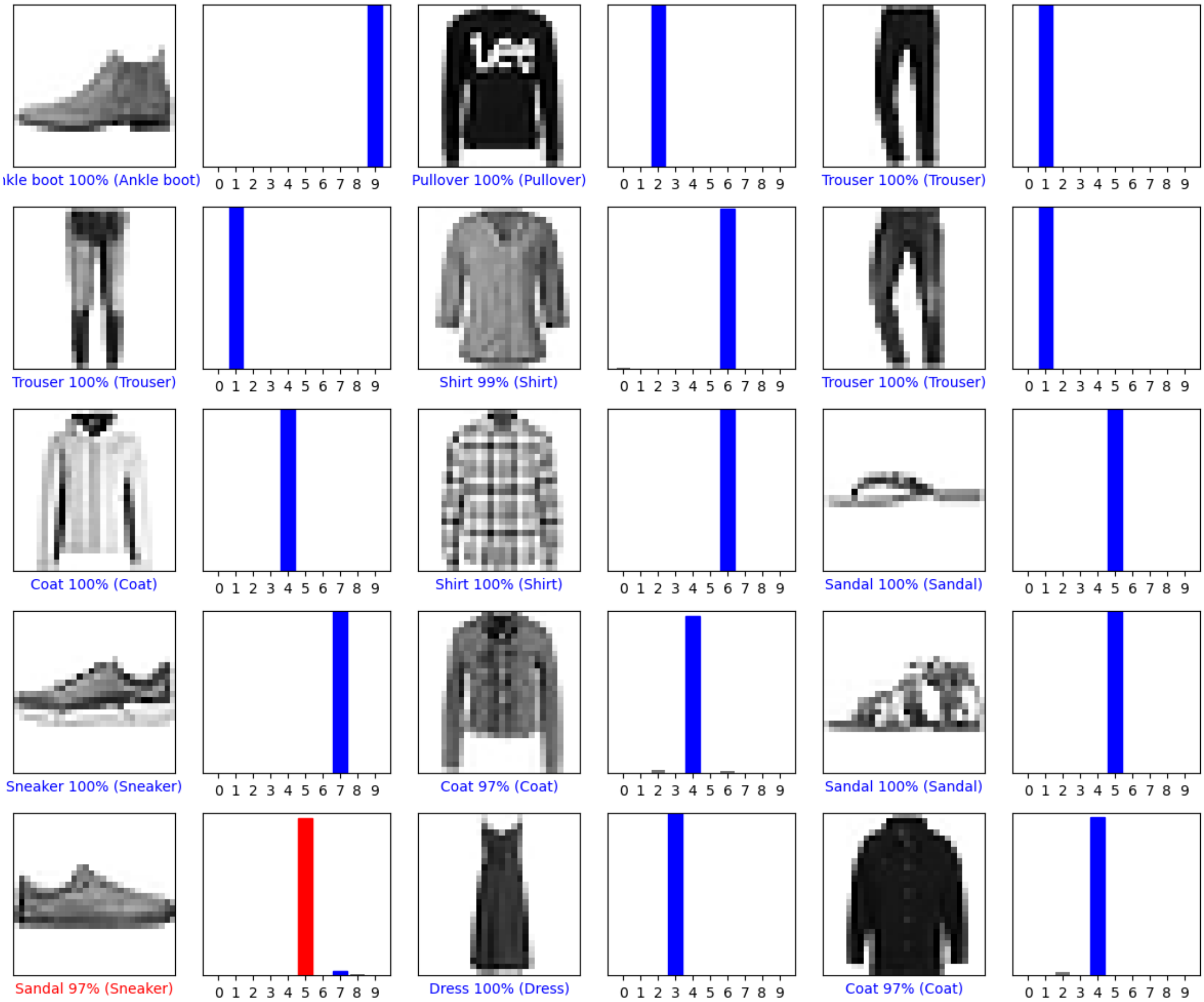


In [23]:
```
i = 12
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions[i], test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions[i],  test_labels)
plt.show()
```



Let's plot several images with their predictions. Note that the model can be wrong even when very confident.

```
In [24]: # Plot the first X test images, their predicted labels, and the true labels.
         # Color correct predictions in blue and incorrect predictions in red.
         num_rows = 5
         num_cols = 3
         num_images = num_rows*num_cols
         plt.figure(figsize=(2*2*num_cols, 2*num_rows))
         for i in range(num_images):
           plt.subplot(num_rows, 2*num_cols, 2*i+1)
           plot_image(i, predictions[i], test_labels, test_images)
           plt.subplot(num_rows, 2*num_cols, 2*i+2)
           plot_value_array(i, predictions[i], test_labels)
         plt.tight_layout()
         plt.show()
```



Use the trained model

Finally, use the trained model to make a prediction about a single image.

```
In [25]: # Grab an image from the test dataset.
         img = test_images[1]

         print(img.shape)
```

```
(28, 28)
```

`tf.keras` models are optimized to make predictions on a *batch*, or collection, of examples at once. Accordingly, even though you're using a single image, you need to add it to a list:

In [26]:
```
# Add the image to a batch where it's the only member.
img = (np.expand_dims(img,0))

print(img.shape)
```

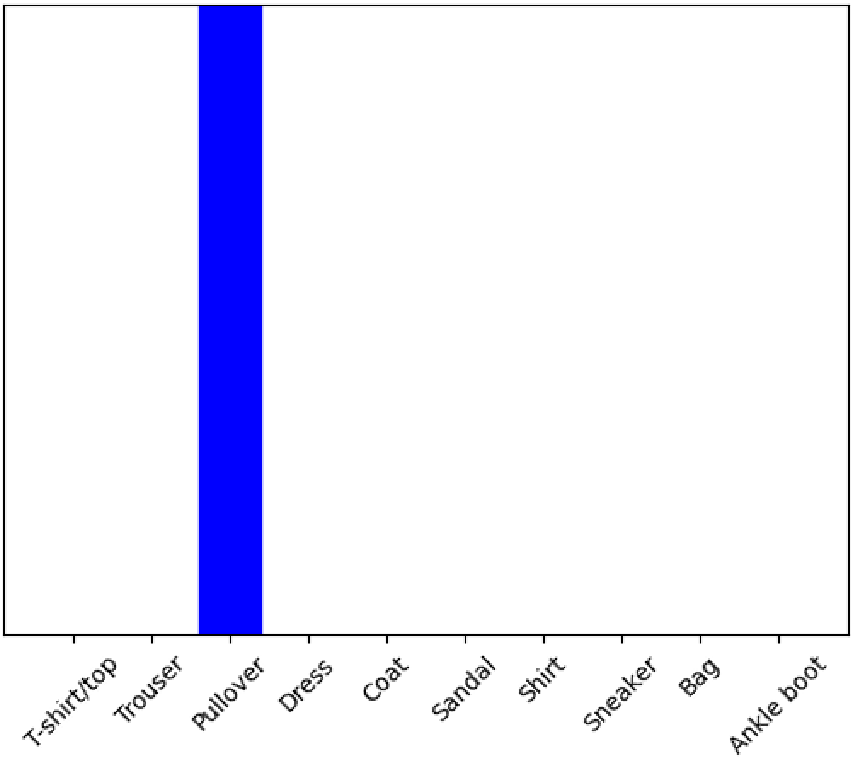
```
(1, 28, 28)
```

Now predict the correct label for this image:

In [27]:
```
predictions_single = probability_model.predict(img)

print(predictions_single)
```

```
1/1 [==============================] - 0s 19ms/step
[[2.3126481e-06 1.3403139e-21 9.9972457e-01 6.3178419e-14 2.6131392e-04
  7.6748816e-20 1.1800360e-05 6.7637641e-20 1.6529707e-15 6.0258504e-21]]
```

In [28]:
```
plot_value_array(1, predictions_single[0], test_labels)
_ = plt.xticks(range(10), class_names, rotation=45)
plt.show()
```



`tf.keras.Model.predict` returns a list of lists—one list for each image in the batch of data. Grab the predictions for our (only) image in the batch:

In [29]:
```
np.argmax(predictions_single[0])
```

Out[29]: 2

And the model predicts a label as expected.

Deep Learning Mini Project

Title : Gender and Age Detection: Predict if a person is male or female and also their age

Theory:

Gender and age detection in a Python project typically involves using computer vision techniques, machine learning models, and sometimes deep learning. Here are the key concepts and steps commonly used in such projects:

Face Detection:

- Utilize a face detection algorithm to locate faces in images or video frames. Popular choices include Haar cascades or deep learning-based methods like MTCNN (Multi-Task Cascaded Convolutional Networks) or Single Shot Multibox Detector (SSD).

Face Alignment:

- Align detected faces to a standard position to ensure consistency in subsequent analysis. This step helps in normalizing facial features across different images.

Feature Extraction:

- Extract relevant features from the face regions, such as facial landmarks, texture, or color information. Landmarks can be extracted using facial landmark detection models like dlib or facial feature extraction using deep learning models like FaceNet.

Gender Classification:

- Train a gender classification model using the extracted features. Common approaches include using traditional machine learning classifiers like Support Vector Machines (SVM), Random Forests, or more advanced techniques like deep learning with convolutional neural networks (CNNs).

Age Estimation:

- Train an age estimation model using the features extracted from faces. This can involve regression models, where the target is the estimated age, or classification models with age groups as classes.

Data Collection and Preprocessing:

- Gather a labeled dataset containing images with corresponding gender and age labels. Preprocess the data by normalizing images, resizing, and augmenting if necessary.

Model Training:

- Train the gender and age detection models on the preprocessed dataset. This step involves splitting the data into training and testing sets to evaluate model performance accurately.

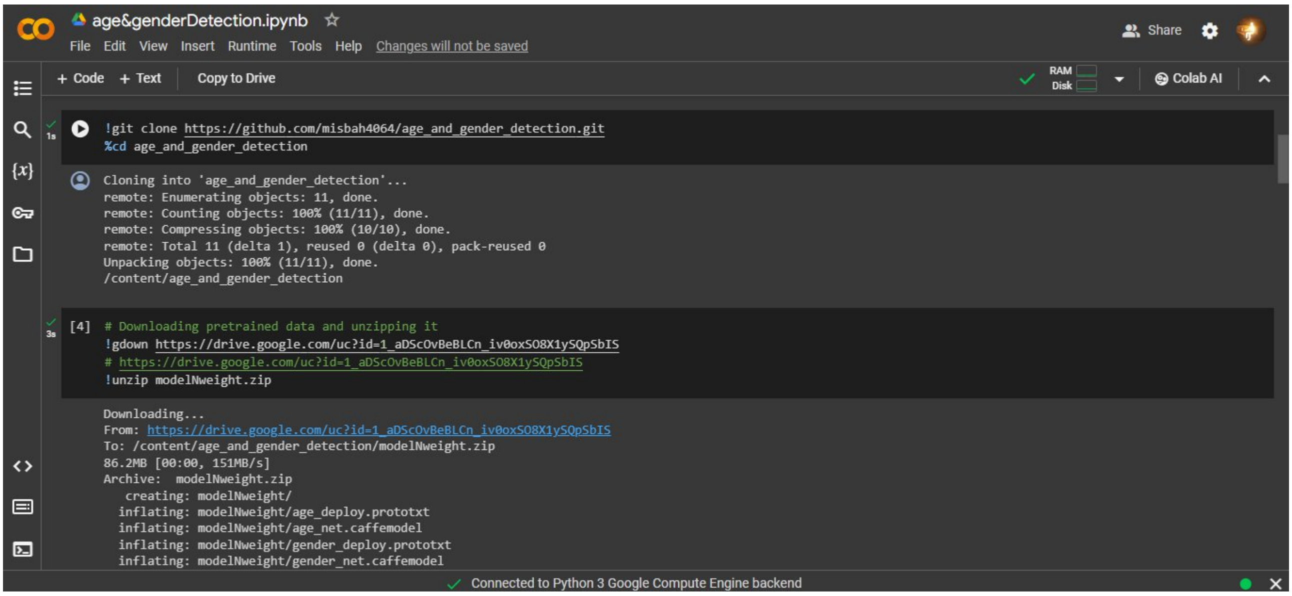
OpenCV (Open Source Computer Vision Library) is a widely used open-source computer vision and machine learning library. It provides a variety of tools and functions for image and video processing. In the context of a gender and age detection project, OpenCV can be used for face detection and image manipulation

Conclusion:

In conclusion, the gender and age detection Python project successfully demonstrates the capabilities of leveraging computer vision techniques and machine learning models to infer gender and age from facial images. The project utilized pre-trained deep learning models, such as Convolutional Neural Networks (CNNs), to extract features from facial data and make predictions.

DL Code and Outputs

Code :

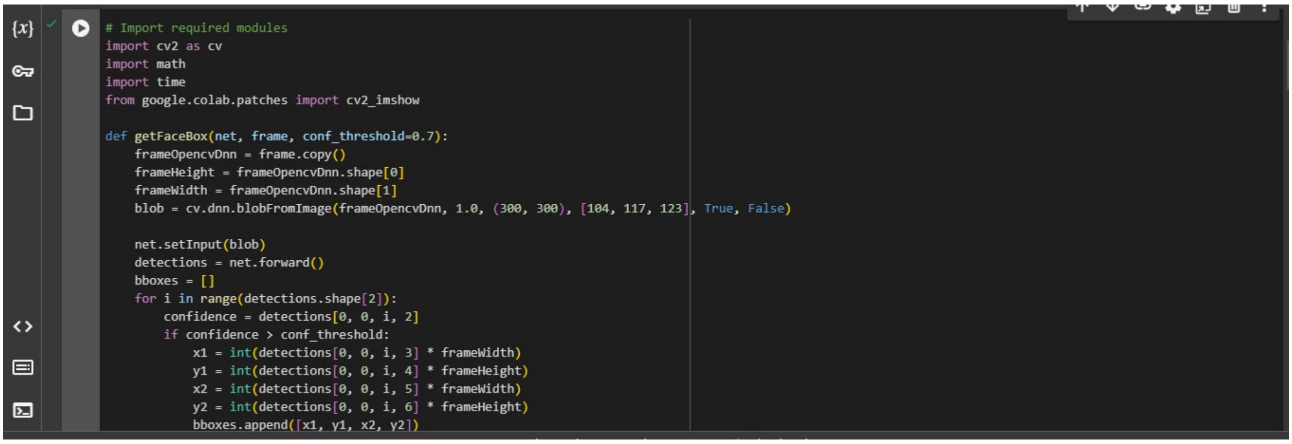



```
!git clone https://github.com/misbah4064/age_and_gender_detection.git
%cd age_and_gender_detection
```

```
Cloning into 'age_and_gender_detection'...
remote: Enumerating objects: 11, done.
remote: Counting objects: 100% (11/11), done.
remote: Compressing objects: 100% (10/10), done.
remote: Total 11 (delta 1), reused 0 (delta 0), pack-reused 0
Unpacking objects: 100% (11/11), done.
/content/age_and_gender_detection
```

```
[4] # Downloading pretrained data and unzipping it
!gdown https://drive.google.com/uc?id=1_aDScOvBeBLCn_iv0oxSO8X1ySQpSbIS
# https://drive.google.com/uc?id=1_aDScOvBeBLCn_iv0oxSO8X1ySQpSbIS
!unzip modelNweight.zip
```

```
Downloading...
From: https://drive.google.com/uc?id=1_aDScOvBeBLCn_iv0oxSO8X1ySQpSbIS
To: /content/age_and_gender_detection/modelNweight.zip
86.2MB [00:00, 151MB/s]
Archive:  modelNweight.zip
   creating: modelNweight/
  inflating: modelNweight/age_deploy.prototxt
  inflating: modelNweight/age_net.caffemodel
  inflating: modelNweight/gender_deploy.prototxt
  inflating: modelNweight/gender_net.caffemodel
```



```python
# Import required modules
import cv2 as cv
import math
import time
from google.colab.patches import cv2_imshow

def getFaceBox(net, frame, conf_threshold=0.7):
    frameOpencvDnn = frame.copy()
    frameHeight = frameOpencvDnn.shape[0]
    frameWidth = frameOpencvDnn.shape[1]
    blob = cv.dnn.blobFromImage(frameOpencvDnn, 1.0, (300, 300), [104, 117, 123], True, False)

    net.setInput(blob)
    detections = net.forward()
    bboxes = []
    for i in range(detections.shape[2]):
        confidence = detections[0, 0, i, 2]
        if confidence > conf_threshold:
            x1 = int(detections[0, 0, i, 3] * frameWidth)
            y1 = int(detections[0, 0, i, 4] * frameHeight)
            x2 = int(detections[0, 0, i, 5] * frameWidth)
            y2 = int(detections[0, 0, i, 6] * frameHeight)
            bboxes.append([x1, y1, x2, y2])
```

```python
            cv.rectangle(frameOpencvDnn, (x1, y1), (x2, y2), (0, 255, 0), int(round(frameHeight/150)), 8)
    return frameOpencvDnn, bboxes

faceProto = "modelNweight/opencv_face_detector.pbtxt"
faceModel = "modelNweight/opencv_face_detector_uint8.pb"

ageProto = "modelNweight/age_deploy.prototxt"
ageModel = "modelNweight/age_net.caffemodel"

genderProto = "modelNweight/gender_deploy.prototxt"
genderModel = "modelNweight/gender_net.caffemodel"

MODEL_MEAN_VALUES = (78.4263377603, 87.7689143744, 114.895847746)
ageList = ['(0-2)', '(4-6)', '(8-12)', '(15-20)', '(25-32)', '(38-43)', '(48-53)', '(60-100)']
genderList = ['Male', 'Female']

# Load network
ageNet = cv.dnn.readNet(ageModel, ageProto)
genderNet = cv.dnn.readNet(genderModel, genderProto)
faceNet = cv.dnn.readNet(faceModel, faceProto)

padding = 20

def age_gender_detector(frame):
    # Read frame
    t = time.time()
```

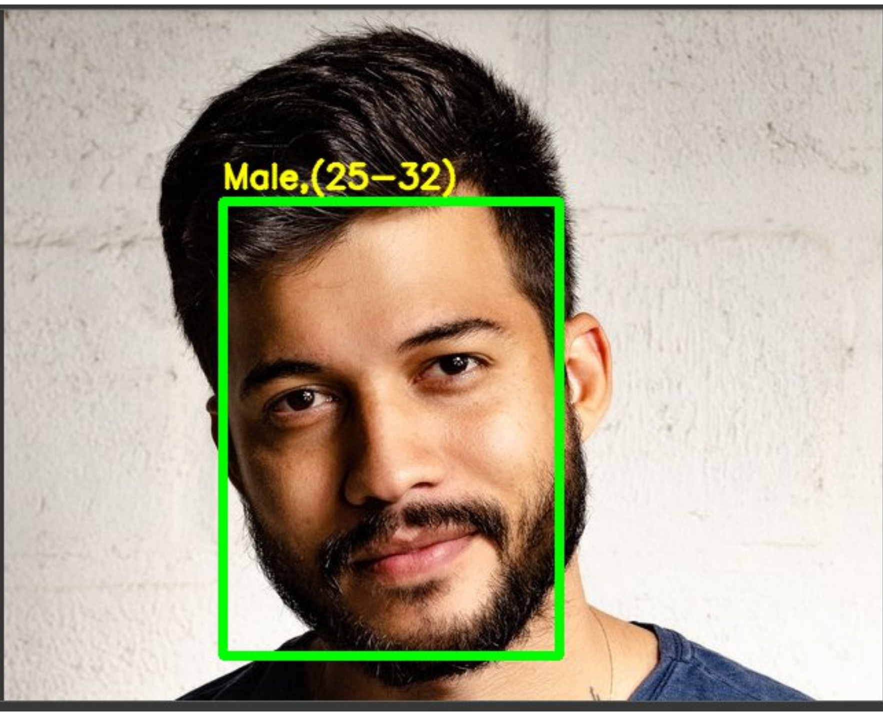
DL Code and Outputs

Code :

```
    frameFace, bboxes = getFaceBox(faceNet, frame)
    for bbox in bboxes:
        # print(bbox)
        face = frame[max(0,bbox[1]-padding):min(bbox[3]+padding,frame.shape[0]-1),max(0,bbox[0]-padding):min(bbox[2]+padding, frame.shape[1]-1)]

        blob = cv.dnn.blobFromImage(face, 1.0, (227, 227), MODEL_MEAN_VALUES, swapRB=False)
        genderNet.setInput(blob)
        genderPreds = genderNet.forward()
        gender = genderList[genderPreds[0].argmax()]
        ageNet.setInput(blob)
        agePreds = ageNet.forward()
        age = ageList[agePreds[0].argmax()]

        label = "{},{}".format(gender, age)
        cv.putText(frameFace, label, (bbox[0], bbox[1]-10), cv.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 255), 2, cv.LINE_AA)
    return frameFace
```

```
[6] input = cv.imread("image.jpg")
    output = age_gender_detector(input)
    cv2_imshow(output)
```

Output :




```
input = cv.imread("image1.jpg")
output = age_gender_detector(input)
cv2_imshow(output)
```