Absolutely! Let's walk through both CUDA kernel functions: assign_clusters and update_centroids, line by line, to explain exactly what each piece does and why it's needed for the K-Means clustering algorithm.

assign_clusters — Assigns each data point to the nearest centroid

__global__ void assign_clusters(float *data, float *centroids, int *labels)

- This is a **CUDA kernel** that runs in parallel.
- Each thread is responsible for one data point (from the dataset data).
- labels will store which cluster (0, 1, or 2) each point belongs to.

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

- idx is the **global index** of the thread. It maps each thread to a unique data point.
- For example, if we launch 256 threads per block, the second block's first thread will have idx =
 256.

if (idx < N)

• Ensures that the thread only processes valid indices (up to N = 150).

```
float min_dist = FLT_MAX;
int closest = -1;
```

- min_dist: initialized to the largest possible float value (to find the minimum distance).
- closest: will eventually hold the index of the closest centroid.

for (int k = 0; k < K; k++)

• Loop over each of the K centroids (3 clusters in this case).

float dist = 0.0f;

```
for (int d = 0; d < D; d++) {
    float diff = data[idx * D + d] - centroids[k * D + d];
    dist += diff * diff;
}</pre>
```

- Calculate the Euclidean distance squared between the current data point (data[idx]) and the k-th centroid.
- data and centroids are 1D arrays, so we use idx * D + d to access features correctly.

```
if (dist < min_dist) {
    min_dist = dist;
    closest = k;
}</pre>
```

• Update min_dist and closest if we find a closer centroid.

```
labels[idx] = closest;
```

After finding the closest centroid, we assign its index to the labels array for that data point.

update_centroids — Recomputes centroids based on cluster assignments

```
__global__ void update_centroids(float *data, float *centroids, int *labels)
```

• This kernel updates the centroids array based on the average of the assigned data points.

```
__shared__ float centroid_sums[K][D];
_ shared__ int counts[K];
```

- These are **shared memory arrays**, accessible by all threads in the block.
- centroid_sums accumulates the sum of all vectors for each cluster.
- counts keeps track of how many points were assigned to each cluster.

```
int tid = threadldx.x + blockldx.x * blockDim.x;
```

• Same as before: global thread index.

Step 1: Initialization by the first thread in the block

```
if (threadIdx.x == 0) {
   for (int k = 0; k < K; k++) {
      counts[k] = 0;
      for (int d = 0; d < D; d++) {
       centroid_sums[k][d] = 0.0f;
      }
   }
}
__syncthreads();</pre>
```

- Thread 0 initializes the shared memory arrays.
- __syncthreads() ensures all threads wait until initialization is complete.

Step 2: Accumulate sums of assigned data points

```
if (tid < N) {
  int label = labels[tid];
  for (int d = 0; d < D; d++) {
     atomicAdd(&centroid_sums[label][d], data[tid * D + d]);
  }
  atomicAdd(&counts[label], 1);
}</pre>
```

- Each thread (representing a data point) adds its values to the centroid it was assigned to.
- We use atomicAdd() to safely update shared memory from multiple threads (avoids race conditions).

Step 3: Compute the mean to get new centroids

```
_syncthreads();
```

Wait for all threads to finish updating the sums.

```
if (threadIdx.x == 0) {
    for (int k = 0; k < K; k++) {
```

```
if (counts[k] > 0) {
    for (int d = 0; d < D; d++) {
        centroids[k * D + d] = centroid_sums[k][d] / counts[k];
    }
}
}</pre>
```

- Only thread 0 now computes the **average** to update the actual centroids.
- For each cluster k, we divide the accumulated sum by the number of points assigned to that cluster.

Summary

Kernel Function	Responsibility	Key CUDA Feature Used
assign_cluster s	Assign each data point to the closest centroid	Thread-wise parallelism
update_centroi ds	Compute new centroid positions	Shared memory + atomicAdd

Would you like me to visualize the flow or help you with enhancements like multi-block/grid support or dynamic cluster count (K)?

Great question! Let's break down how the formula π / 4 comes into play when estimating π using the **Monte Carlo method**.

\odot The Idea Behind the $\pi/4$ Formula

We use **geometry** to estimate π by comparing the area of a **quarter circle** with the area of a **square** that contains it.

The Square

We consider a unit square:

- Its sides go from 0 to 1 on both axes.
- So its area is: Asquare=1×1=1A_{\text{square}} = 1 \times 1 = 1

The Quarter Circle

We inscribe a quarter of a unit circle inside this square:

- It's part of a circle of radius 1 centered at the origin (0,0).
- The full area of a circle is:
 Acircle=πr2=π · 12=πA {\text{circle}} = \pi r^2 = \pi \cdot 1^2 = \pi
- Since we're only using a **quarter** of the circle (from x = 0 to 1 and y = 0 to 1), its area is: Aquarter-circle= $14 \cdot \pi = \pi 4A_{\text{uarter-circle}} = \frac{1}{4} \cdot \pi = \frac{1}{4} \cdot \pi = \frac{1}{4}$

Monte Carlo Estimation

Now we generate **random points** (x, y) inside the square, where x and y are random numbers between 0 and 1.

We check if a point lies inside the quarter circle using:

x2+y2≤1x^2 + y^2 \leq 1

Let:

• N = total number of random points

M = number of points inside the quarter circle

Because the points are uniformly distributed, the **ratio** of points inside the quarter circle to the total points should approach the ratio of their areas:

 $MN \approx Area of quarter-circleArea of square= \pi 4 \frac{M}{N} \approx \frac{\text{Area of quarter-circle}}{\text{Area of square}} = \frac{\pi}{4}$

So,

 $\pi \approx 4 \cdot MN\setminus \{n\}$

That's where the formula comes from!

Summary

Concept	Value
Area of full circle	πr2=π\pi r^2 = \pi
Area of quarter circle	π4\frac{\pi}{4}
Area of square	1
Ratio (quarter circle to square)	π4\frac{\pi}{4}
Estimate π	π≈4 · Points in circleTotal points\pi \approx 4 \cdot \frac{\text{Points} in circle}}{\text{Total points}}

Would you like a visual diagram for this?