mp_mosaics

Monstrous Mosaics

Extra credit: Mar 25, 23:59 PM
Due: Apr 01, 23:59 PM

Doxygen

Partner MP mp_mosaics is a **partner MP**!

- Part 1 and Part 2 of this MP can be completed with a partner!
- The creative "Part 3" must be completed by yourself and must be unique (and different from your partner's work).

You should denote who you work with in the PARTNERS.txt file in mp_mosaics. If you worked alone, include only your NetID in PARTNERS.txt.

Goals and Overview

In this MP, you will:

- learn about k-d trees
- implement and use a nearest neighbor search (NNS) algorithm
- practice using templates
- practice `const`-correctness
- use your knowledge to make a useful application

Videos

- k-d tree : 2-D example
- (partition based) Quick Select
- findNearestNeighbor - Part 1: Explanation
- findNearestNeighbor - Part 2: Walkthrough

Checking Out Your Code

From your CS 225 git directory, run the following on EWS:

```
git pull
git fetch release
git merge release/mp_mosaics -m "Merging initial mp_mosaics files"
```

If you're on your own machine, you may need to run:

```
git pull
git fetch release
git merge --allow-unrelated-histories release/mp_mosaics -m "Merging initial mp_mosaics
files"
```

Upon a successful merge, your mp_mosaics files are now in your `mp_mosaics` directory.

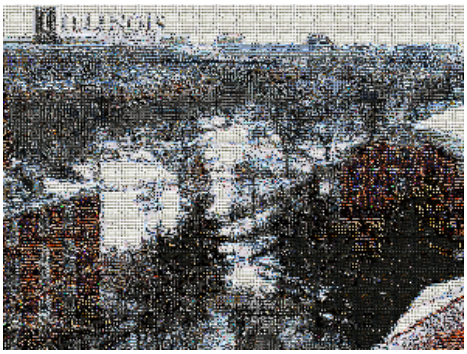
Doxygen

You can see all of the required functions on the TODO page on the Doxygen for this MP.

A list of relevant files is here.

Background: PhotoMosaics

A PhotoMosaic is a picture created by taking some source picture, dividing it up into rectangular sections, and replacing each section with a small thumbnail image whose color closely approximates the color of the section it replaces. Viewing the PhotoMosaic at low magnification, the individual pixels appear as the source image, while a closer examination reveals that the image is made up of many smaller tile images.



Click for the (rather large) full-size mosaic

For this project you will be implementing parts of a PhotoMosaic generator. Specifically your code will be responsible for deciding how to map tile images to the rectangular sections of pixels in the source image. Selecting the appropriate tile image is supported by a data structure called a k-d tree which we will describe in the next section. The pool of tile images are specified by a local directory of images. We provide the code to create the TileImage pool and the code to create the mosaic picture from a tiled source image.

A final thing to note is that the HSL color space does a poor job on finding the best tiled source image. Consider a nearly white pixel with `l=99%`: the pixel `(h=0, s=100%, l=99%)` will appear nearly just as white as the pixel `(h=180, s=0%, l=99%)` even though the pixels are very far apart. Instead, we have modified the `HSLAPixel` into a `LUVAPixel` using a perceptually uniform color space. You can read about the LUV color space on Wikipedia to find out more.

Background: K-d trees

Binary Search Trees are linear data structures that support the Dictionary ADT operations (`insert`, `find`, `remove`). They also support nearest neighbor search: If you have a binary search tree, given a key that may or may not be in the tree, you can find the closest key that is in the tree. To do so, you just recursively walk down the tree, as in `find`, keeping track of the closest node found:

```
K BST<K,V>::findNearestNeighbor(Node * croot, K target)
{
    // Look in the left or right subtree depending on whether target is smaller or larger
than our current root
    if (target < croot->key)
    {
        // if we have no child in the correct direction, our root must be the closest
        if (croot->left == NULL)
            return croot->key;
        childResult = findNearestNeighbor(croot->left);
    }
    else
    {
        if (croot->right == NULL)
            return croot->key;
        childResult = findNearestNeighbor(croot->right);
    }

    // Calculate closest descendent node's distance to the target
    childDistance = distance(childResult, target);

    // Find the distance of this node to the target
    currDistance = distance(croot->key, target);

    // If the root node is closer, return it, otherwise return the closer child
    if (currDistance < childDistance)
        return croot->key;
    else
        return childResult;
}
```

A k-d tree is a generalization of a Binary Search Tree that supports nearest neighbor search in higher numbers of dimensions — for example, with 2-D or 3-D points, instead of only 1-D keys. A 1-D-tree (a k-d tree with $k = 1$) is simply a binary search tree. For this MP, you will be creating a photomosaic, which requires that given a region on our original image, we can determine which of our available images best fills that region. If we use the average color of regions and tile-images, this can be determined by finding the nearest colored tile image to a given region. If we treat colors as (L, U, V) points in 3-D space, we can solve this problem with a 3-D tree.

More formally, a k-d tree is special purpose data structure used to organize elements that can be described by locations in k-dimensional space. It is considered a space-partitioning data structure because it recursively subdivides a space into two convex sets. These sets are rectangular regions of the space called hyperrectangles. k-d trees are particularly useful for implementing nearest neighbor search, which is an optimization problem for finding the closest element in k-dimensional space.

A k-d tree is a rooted binary tree. Each node in the tree represents a point in k-d-space, as well as a line (hyperplane) defined by one dimension of this point, which divides this space into two regions (hyperrectangles). At each level in the tree, a different dimension is used to decide the direction of the splitting line (hyperplane). An element is selected to define the splitting line by its coordinate value for the current dimension. This element should be the median of all the points in this part of the tree, taken over the current dimension. A node is then created for this element in the tree and its children are created recursively using the same process, which repeats until no elements remain in the region (hyperrectangle). The splitting dimension at any level of the tree can be selected to find the best partition of the data. For our purposes, we will change dimension cyclically, in order (for $k = 3$, we will use dimensions $0, 1, 2, 0, 1, 2, 0, \ldots$).

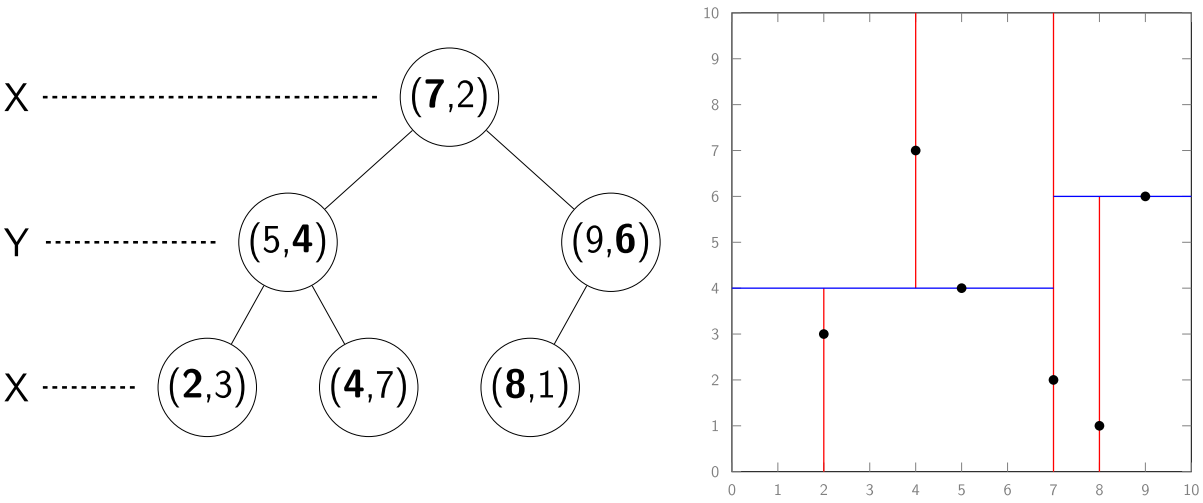


Figure 1: the tree on the left is an example 2-dimensional k-d tree and the diagram on the right shows how the space is partitioned by the splitting planes into hyperrectangles for that tree. (Note that our implementation will make a slightly different tree from this set of points because of the way we will define the median.)

k-d trees are particularly useful for searching points in Euclidean space. Perhaps the most common use of a k-d tree is to allow for fast search for the nearest neighbor of a query point, among the points in the tree. That is, given an arbitrary point in k-dimensional space, find the point in the tree which is nearest to this point. The search algorithm is defined in detail below.

For this MP, we will be using a 3-D tree (a 3-dimensional k-d tree) to find the closest average color of `TileImage`s to the average color of pixel sections in the source image. With the pool of average colors organized in a k-d tree, we can search for the best tile to match the average color of every region in the input image, and use it to create a PhotoMosaic!

Requirements

These are strict requirements that apply to **both** parts of the MP. Failure to follow these requirements may result in a failing grade on the MP.

- You must name all files, public functions, public member variables (if any exist), and executables **exactly** as we specify in this document.
- Your code must produce the **exact** output that we specify: nothing more, nothing less. Output includes standard and error output and files such as images.
- Your code must compile on the EWS machines using **clang++**. Being able to compile on a different machine is **not** sufficient.
- Your code must be submitted correctly by the **due date and time**. Late work is not accepted.
- Your code must not have any memory errors or leaks for full credit. Valgrind tests will be performed separately from the functionality tests.
- Your public function signatures must match ours **exactly** for full credit. If using different signatures prevents compilation, you will receive a zero. Tests for `const`-correctness may be performed separately from the other tests (if applicable).

Assignment Description

We have provided the bulk of the code to support the generation of PhotoMosaics. There is one critical component that is missing: the `KDTileMapper`. This class is responsible for deciding which `TileImage`s to use for each region of the original image. In order to make this decision it must be able to figure out which `TileImage` has the closest average color to the average color of that region. A data structure called a k-d tree is used to find the nearest neighbor of a point in k-dimensional space.

This assignment is broken up into the following two parts:

- Part 1 — the `KDTree` class.
- Part 2 — the `mapTiles` function.

As usual, we recommend implementing, compiling, and testing the functions in Part 1 before starting Part 2.

Part 1

For the first part of mp_mosaics, you will implement a generic `KDTree` class that can be used to organize points in k-dimensional space, for any integer $k > 0$.

The `KDTree` class

Although we will only be using a 3-D tree, we want you to create a more general data structure that will work with any positive non-zero number of dimensions. Therefore, you will be creating a templated class where the template parameter is an integer, specifying the number of dimensions. We have provided the skeleton of this class, but it is your assignment to implement the member functions and any helper functions you need.

A k-d tree is constructed with `Point`s in k-dimensional space. To support this, we have provided a templated `Point` class, which takes the same integer template parameter as the k-d tree.

In this part of assignment we ask you to implement all of the following member functions.

Implementing `smallerDimVal`

Please see the Doxygen for `smallerDimVal`.

This function should take in two templatized `Point`s and a dimension and return a boolean value representing whether or not the first `Point` has a smaller value than the second in the dimension specified. That is, if the dimension passed in is k, then this should be `true` if the coordinate of the first point at k is less than the coordinate of the second point at k. **If there is a tie, break it using `Point`'s `operator<`. For example:**

```
Point<3> a(1, 2, 3);
Point<3> b(3, 2, 1);
cout << smallerDimVal(a, b, 0) << endl; // should print true,
                                        //    since 1 < 3
cout << smallerDimVal(a, b, 2) << endl; // should print false,
                                        //    since 3 > 1
cout << smallerDimVal(a, b, 1) << endl; // should print true,
                                        //    since a < b according to operator<,
```

Implementing `shouldReplace`

Please see the Doxygen for `shouldReplace`.

This function should take three templated `Point`s: `target`, `currentBest`, and `potential`. This should return `true` if `potential` is closer (i.e., has a smaller distance) to `target` than `currentBest` (with a tie being broken by the `operator<` in the `Point` class: `potential < currentBest`). The Euclidean distance between two k-dimensional points, $P(p_1, p_2, \ldots, p_k)$ and $Q(q_1, q_2, \ldots, q_k)$, is the square root of the sum of squares of the differences in each dimension:

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_k - q_k)^2} = \sqrt{\sum_{i=1}^{k} (p_i - q_i)^2}$$

Note that minimizing the distance is the same as minimizing squared-distance, so you can avoid invoking the square root, and just compare squared distances throughout your code:

```
Point<3> target        (1, 3, 5);
Point<3> currentBest1  (1, 3, 2);
Point<3> possibleBest1 (2, 4, 4);
Point<3> currentBest2  (1, 3, 6);
Point<3> possibleBest2 (2, 4, 4);
Point<3> currentBest3  (0, 2, 4);
Point<3> possibleBest3 (2, 4, 6);
cout << shouldReplace(target, currentBest1, possibleBest1) << endl; // should print true
cout << shouldReplace(target, currentBest2, possibleBest2) << endl; // should print false
cout << shouldReplace(target, currentBest3, possibleBest3) << endl; // based on operator<,
this should be false!!!
```

Implementing the `KDTree` Constructor

Please see the Doxygen for the `KDTree` constructor.

This takes a single parameter, a reference to a constant `std::vector` of `Point<Dim>`s. The constructor should build the tree using recursive helper function(s).

Just like there is a way to represent a balanced binary search tree using a specially sorted vector of numbers (how?), we can specially sort a vector of points in such a way that it represents a k-d tree. More specifically, in the `KDTree` constructor, we are interested in first copying the input list of points into a points vector, sorting this vector so it represents a k-d tree, and building the actual k-d tree along while we sort.

> **Definition** A rooted binary tree T is a k-d tree if:
>
> - T is empty, OR
> - T consists of
>   - A k-dimensional point r that represents the root of the tree.
>   - A splitting dimension d
>   - Two k-d tree subtrees T_L and T_R of splitting dimension $(d+1) \bmod k$ such that
>   - if v is an element in T_L, then $v_d \leq r_d$
>   - if v is an element in T_R, then $v_d \geq r_d$
>
>   where v_d and r_d are the dth components of the points v and r. This property of k-d trees is called its **recursive property** because, similar to binary search trees, k-d trees are recursive data structures.
>
>   Furthermore, in our implementation, r is the **median** of all the points (defined below) in T in dimension d.
>
> We define the **median** of the points across a splitting dimension d to be the $\lceil \frac{n}{2} \rceil$ smallest element in a sorted list using d; in other words, it is the **middle-most element** of a (odd length) sorted list containing n elements. For the general case of the median of a vector between zero-based indices a and b, the median would be the element located at $\lfloor \frac{a+b}{2} \rfloor$.

The **median index** of n nodes is calculated as the cell $\lfloor \frac{n-1}{2} \rfloor$. That is, the middle index is selected if there are an odd number of items, and the item before the middle if there are an even number of items. **If there are ties (two points have equal value along a dimension), they must be decided using the `Point` class's `operator<`.** Although this is arbitrary and doesn't affect the functionality of the k-d tree, it is required to be able to grade your code.

The k-d tree construction algorithm is defined recursively as follows for a vector of points between indices a and b at splitting dimension d:

1. Find the median of points with respect to dimension d.
2. Place the median point r at index $m = \left\lfloor \frac{a+b}{2} \right\rfloor$ such that
   - if point v is between indices a and $m-1$, then $v_d \leq r_d$
   - if point v is between indices $m+1$ and b, then $v_d \geq r_d$
3. Create a subroot based on the median and then recurse on the indices between a though $m-1$ for its left subtree, and $m+1$ through b for its right subtree, using splitting dimension $(d+1) \bmod k$.

To satisfy steps 1 and 2 of the k-d tree construction algorithm, we recommend finding the median of the vector of points using **quickselect**. The quickselect algorithm allows you to find the median of the vector while achieving the constraints mentioned in step 2. We recommend that you first understand the algorithm and then write your own code from scratch to implement it. This will make debugging far, far easier.

☢ Note that you are **not** allowed to use any standard library functions to sort the data or find the median of the `vector`. This includes functions in `<algorithm>` like `std::sort` and `std::nth_element`. For a complete list see the functions in `mp_mosaics_provided/no_sort.h`.

ℹ Here's an example of how the algorithm works on the array below.

0	1	2	3	4	5	6	7
(3, 2)	(5, 8)	(6, 1)	(4, 4)	(9, 0)	(1, 1)	(2, 2)	(8, 7)

With respect to splitting dimension 0, we would now find the median of these points, and place it in index $\left\lfloor \frac{0+7}{2} \right\rfloor = 3$. (This is step 1 and 2 of the algorithm.) We could achieve this using quickselect. This yields the following array.

0	1	2	3	4	5	6	7
			(4, 4)				

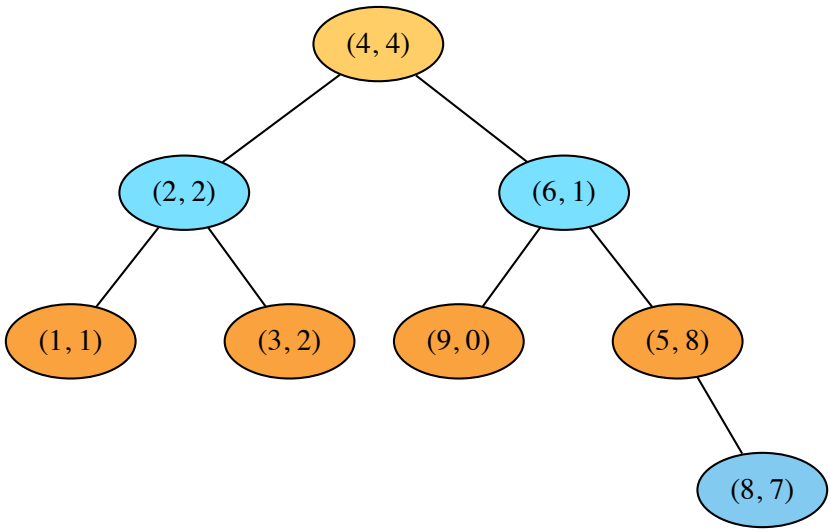
What's important to note is that the two sublists contained in indices 0–2 and 4–7, L_1 and L_2 respectively, achieve the constraint mentioned in step 2 of the k-d tree construction algorithm. (See above.) Hence, the full list may appear like this:

0	1	2	3	4	5	6	7
(1, 1)	(3, 2)	(2, 2)	**(4, 4)**	(6, 1)	(5, 8)	(9, 0)	(8, 7)

When we recursively call the algorithm on L_1 and L_2 using splitting dimension 1 (step 3), we achieve the following ordering. (Follow along this example using pen and paper.)

0	1	2	3	4	5	6	7
(1, 1)	**(2, 2)**	**(3, 2)**	**(4, 4)**	**(9, 0)**	**(6, 1)**	**(5, 8)**	**(8, 7)**

This, likewise, represents the following k-d tree:



The orange colors represent nodes that were split across the 0th dimension, while the blue colors represent nodes that were split across the 1st dimension. (Why is $(2, 2) < (3, 2)$ with respect to the 1st dimension?)

Implementing `findNearestNeighbor`

Please see the Doxygen for `findNearestNeighbor`.

This function takes a reference to a template parameter `Point` and returns the `Point` closest to it in the tree. We are defining closest here to be the minimum Euclidean distance between elements. Again, **if there are ties (this time in distance), they must be decided using the `Point` class's `operator<`**.

The `findNearestNeighbor` search is done in two steps: a search to find the smallest hyperrectangle that contains the target element, and then a back traversal to see if any other hyperrectangle could contain a closer point, which may be a point with smaller distance or a point with equal distance, but a "smaller" point (as defined by `operator<` in the `Point` class).

In the first step, you must recursively traverse down the tree, at each level choosing the subtree which represents the region containing the search element. (Remember that the criteria for which you choose to recurse left or recurse right depends on the splitting dimension of the current level.) When you reach the lowest bounding hyperrectangle, then the corresponding node is effectively the "current best" neighbor. Note that this search is similar to a binary search algorithm, except with the possibility of a tie across a level's splitting dimension.

At then end of first step of the search, we start traversing back up the k-d tree to the parent node. We now want to find better matches that exist outside of the containing hyperrectangle. The current best distance defines a radius which contains the nearest neighbor. During the back-traversal (i.e., stepping out of the recursive calls), you must first check if the distance to the parent node is less than the current radius. If so, then that distance now defines the radius, and we replace the "current best" match.

Next, it is necessary to check to see if the current splitting plane's distance from search node is within the current radius. If so, then the opposite subtree could contain a closer node, and must also be searched recursively.

During the back-traversal, it is important to only check the subtrees that are within the current radius, or else the efficiency of the k-d tree is lost. If the distance from the search node to the splitting plane is greater than the current radius, then there cannot possibly be a better nearest neighbor in the subtree, so the subtree can be skipped entirely.

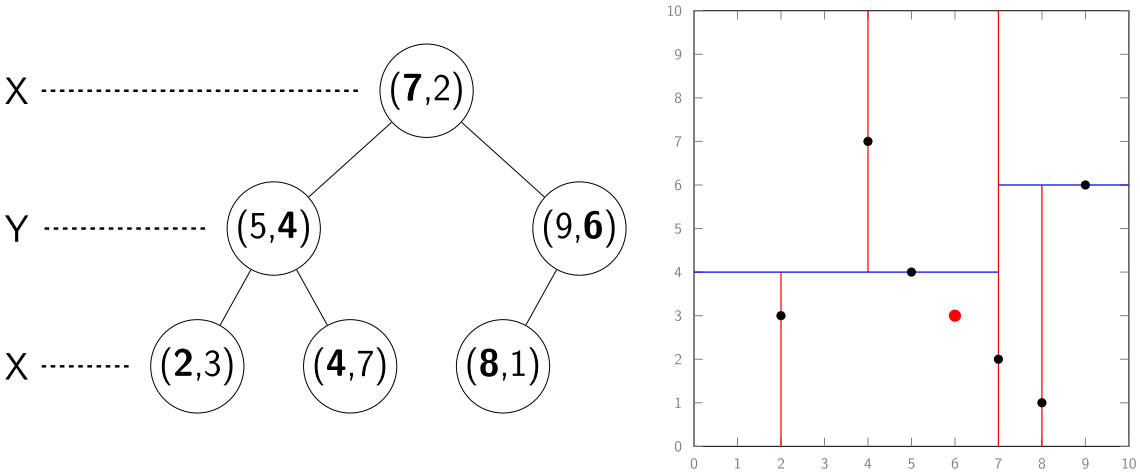
Here is a reference we found quite useful in writing our k-d tree: Andrew Moore's Kd-tree Tutorial.

You can assume that `findNearestNeighbor` will only be called on a valid k-d tree.

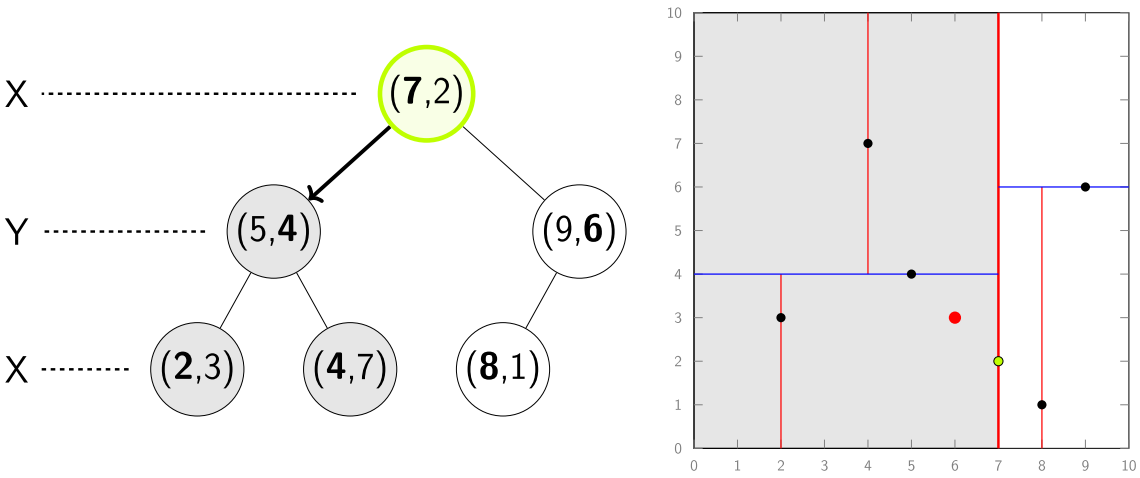
Here is an example:

Example

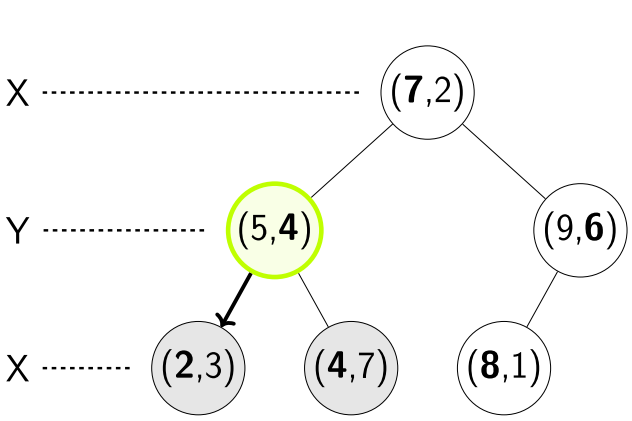
Suppose we have the same k-d tree as in Figure 1 and that the target point (in red) is $(6, 3)$, as shown in the figure below. We wish to find the point in the k-d that is closest to the target; i.e., to determine which of the black points is closest to the red point.

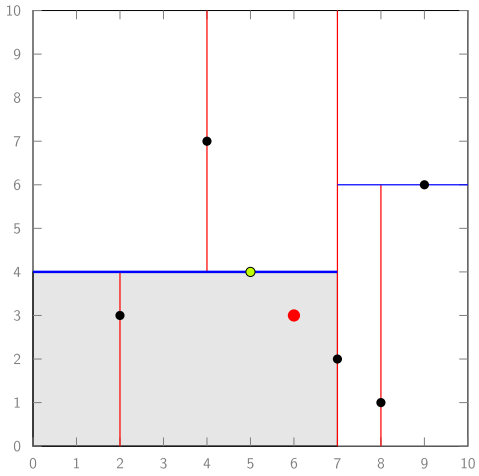


To start the search, we begin a depth-first search to find the leaf node within the same splitting plane as the target node. At the root of the tree, the node is defined by the point $(7, 2)$, with the splitting plane based on the first coordinate. Since $6 < 7$ (using the target coordinate's first dimension) we search the left subtree (the grey region in the figure below).

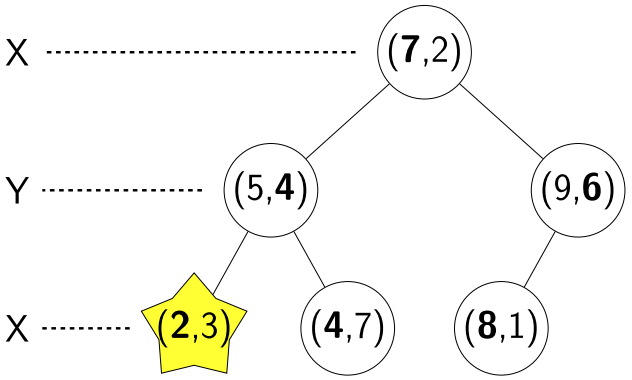


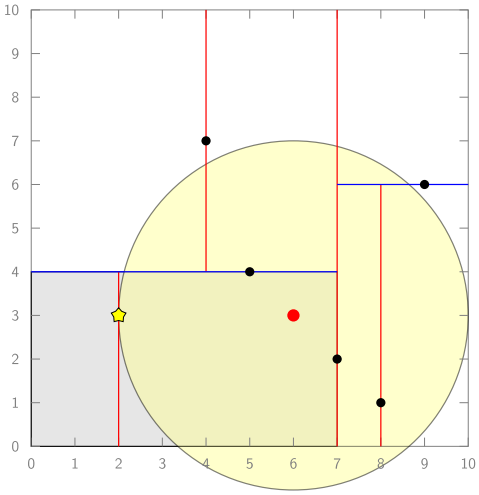
The child node is defined by $(5, 4)$, and the splitting plane is based on the second coordinate. Again, the target node $(6, 3)$ is in the left subtree, so we split left.



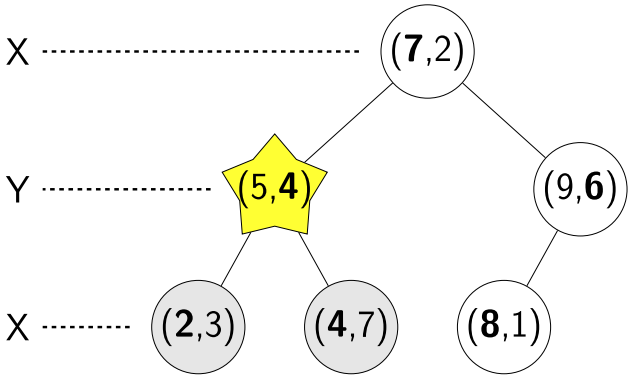


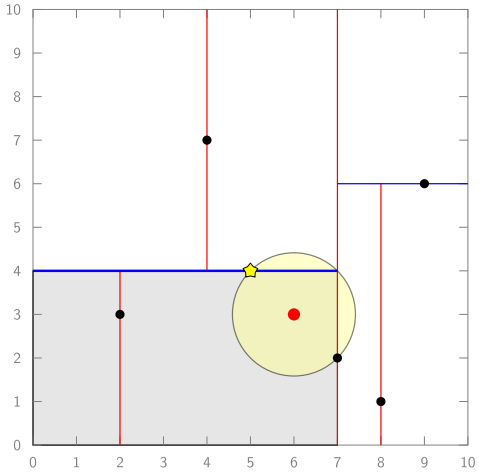
At the next step, we hit a leaf node, $(2, 3)$. At this point, $(2, 3)$ becomes our current best node, and the distance from the target node to $(2, 3)$ defines a "current best" radius, as indicated by the circle below. That is, any point outside of this radius cannot be the closest point to the target, since $(2, 3)$ will always be closer; however, there may be a point within the radius that is closer. We now start the back-traversal to check for other nodes within this radius.



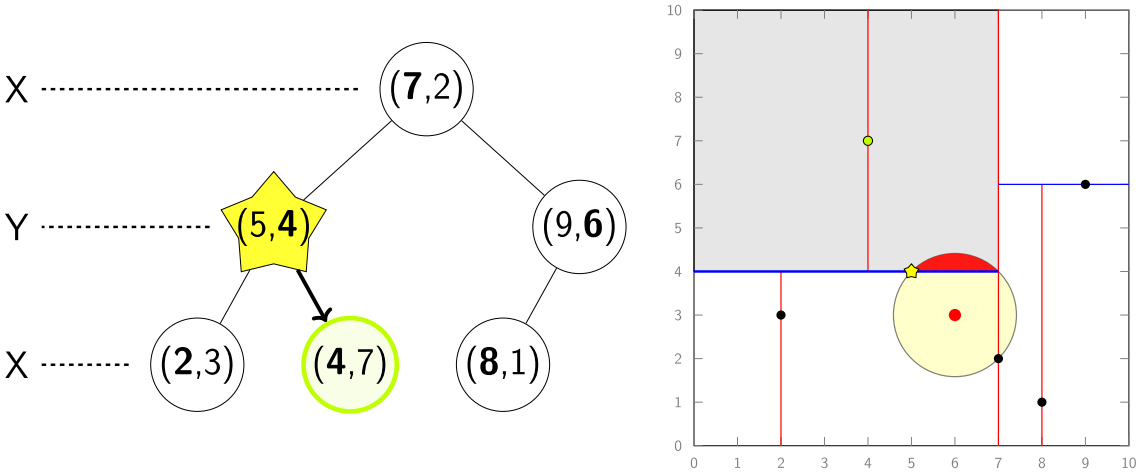


Back at the parent node, $(5, 4)$, we see that it is closer to our target point than the current best of $(2, 3)$. So, $(5, 4)$ is stored as the current best, and we update the radius.

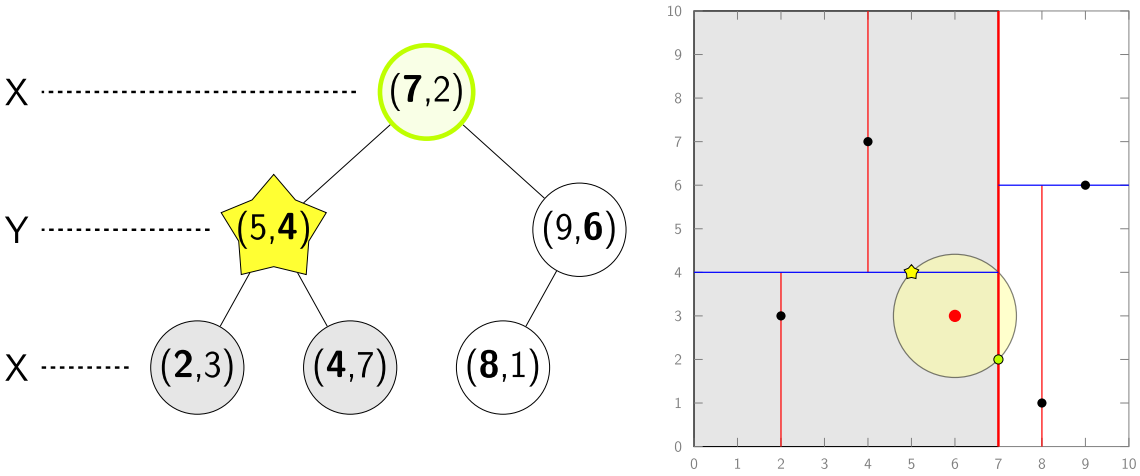




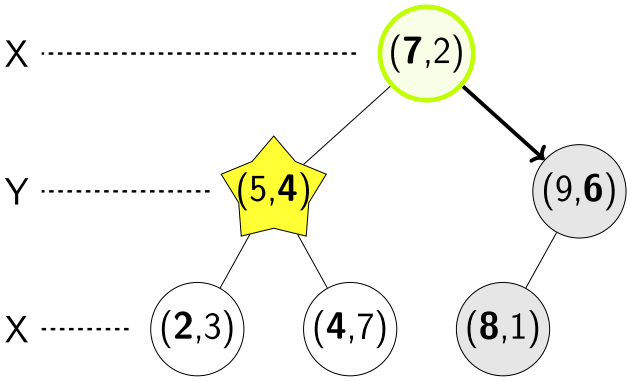
The distance from the target point to the splitting plane for the node $(5, 4)$ is within the current radius, so we must search the other subtree, indicated by the grey region below. This can be visualized as the hypersphere (in 2-d, a circle) intersecting the region opposite the splitting plane, as shown by the red region in the figure below. We descend into the subtree and find a leaf node $(4, 7)$, which is farther away than our current best.

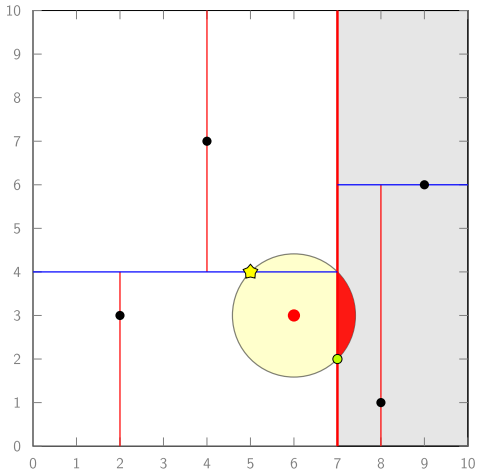


We return all the way to the root node, defined by $(7, 2)$. The distance between this node and the target is exactly equal to the current radius. In this case, we check `Point<2>::operator<`, which says our current best of $(5, 4)$ is less than $(7, 2)$, so we don't replace the current best node.

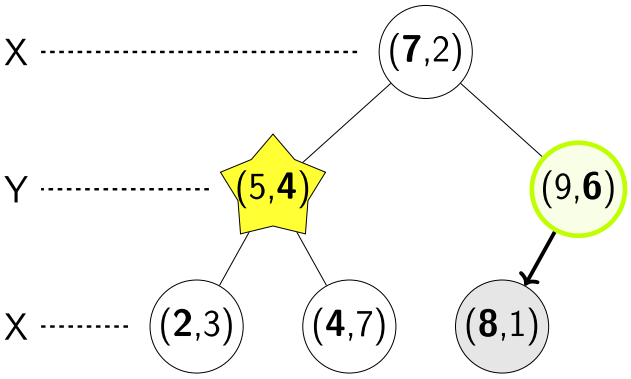


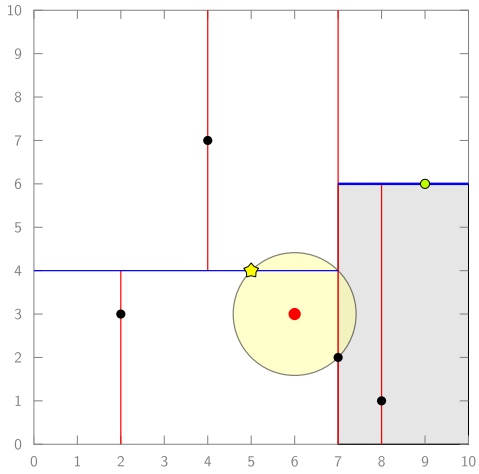
Once again, the distance between the splitting plane defined by $(7, 2)$ and the target point is within the current radius (i.e., the red region exists), so we must search the other subtree.



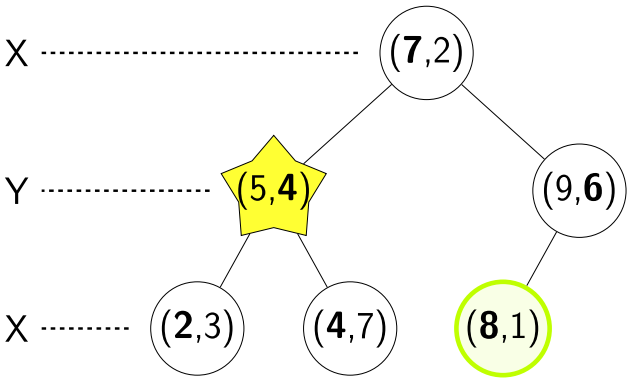


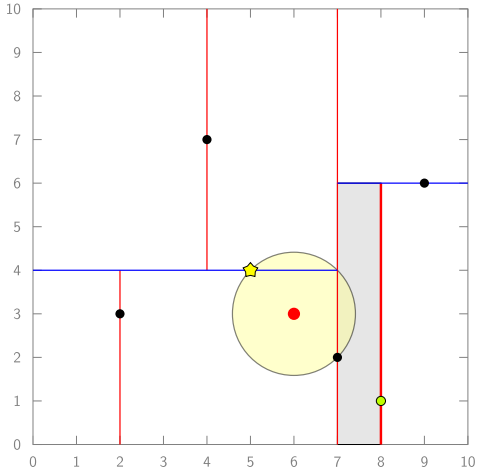
The target point is less than the splitting plane defined by the node at $(9, 6)$, so we first descend into the left subtree.



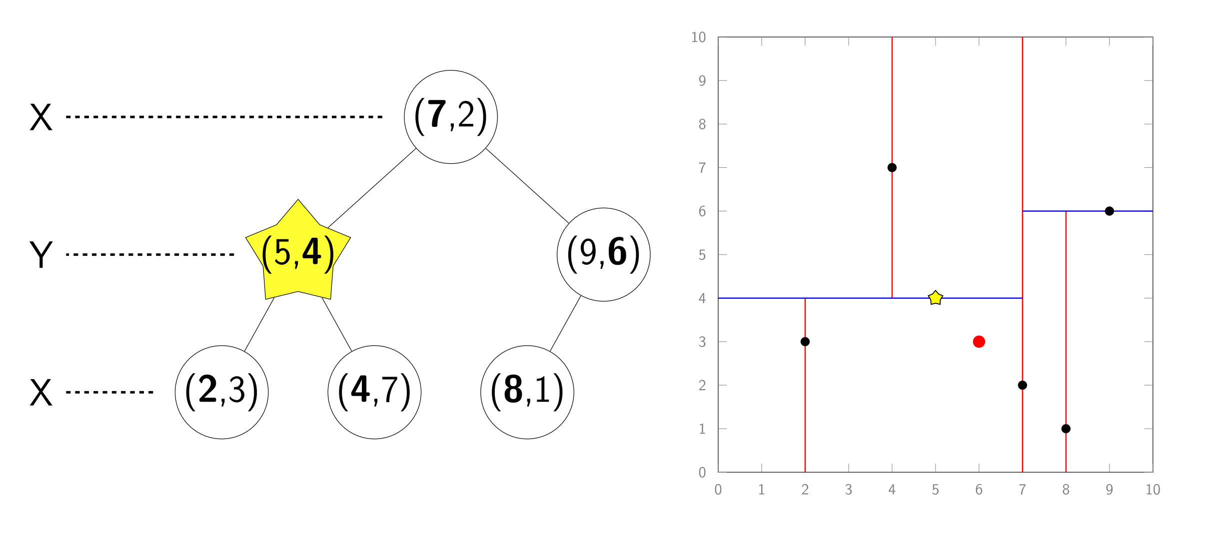


We encounter a leaf node, $(8, 1)$, but the distance is greater than the current best, so we don't do anything.





We finally step back up the tree, and find there are no more regions that intersect the hypersphere (i.e., no other rectangles intersect the circle). Therefore, $(5, 4)$ is the nearest neighbor, and our search is complete.



Function `printTree`

We've provided this function for you! It allows easy printing of the tree, with code like this:

```
KDTree<3> tree(v);
tree.printTree(cout);
```

Note that the tree is printed as such:

```
                             (51,
                       ______ 35)_____
                ______/               \______
             (44,                            {84,
           __ 43)_                         __ 44}_
        __/       \__                   __/       \__
     {28,            (43,            {60,            {88,
      10}             65)             30}             72}
    /   \           /   \           /   \           /   \
 {14,    {48,    (42,    (44,    {59,    {74,    {54,    {95,
  15}     0}      63)     79)     0}      0}      62}     50}
           \               \               \       \       \
           {34,            (49,            {82,    {75,    {96,
            15}             83)             20}     68}     56}
```

The bold dimensions are the pivot dimensions at each node. The green indicate that the tree matched the solution tree. The `{ }` curly braces indicate that a node is a land mine - a point that should not be traversed in the given nearest neighbor search, and will "explode" if you look at it. As these functions are implemented in `kdtree_extras.hpp`, which will not be used for grading, please do not modify them. All of your k-d tree code should be in `kdtree.h` and `kdtree.hpp`.

Implementation Notes

- This is a template class with one integer template parameter (i.e. `int Dim`). You might be curious why we don't just let the client specify the dimension of the tree via the constructor. Since we specify the dimension through a template, the compiler will assure that the dimension of the `Point` class matches the dimension of our k-d tree.
- You should follow the rules of `const` correctness and design the class to encapsulate the implementation. That is, any helper functions or instance variables should be made private.

Testing

We have provided a small number of tests for the `KDTree` class. The test cases are defined in `tests/tests_part1.cpp`. Be aware that these are deliberately insufficient. You should add additional test cases to more thoroughly test your code. You can compile the unit tests with the following command:

```
make test
```

This will create an executable named `test` which you can execute with the following command to run tests for Part 1:

```
./test [part=1]
```

> **Warning** `KDTree` is a templated class. Recall that template functions are not compiled if they are never called. Make sure all of your code compiles or we will not be able to grade your work.

Extra Credit Submission

For extra credit, you can submit the code you have implemented and tested for part one of mp_mosaics. You must submit your work before the extra credit deadline as listed at the top of this page. See Handing in Your Code for instructions.

Part 2

For the second part of mp_mosaics, you will implement the `mapTiles()` function which maps `TileImages` to a `MosaicCanvas` based on which `TileImage` has an average color that is closest to the average color of that region in the original image.

> **`LUVAPixel` to `Point<3>` conversion.**
>
> Your points should be in L-U-V order. That is, L should be the x (0th dimension), U should be the y (1st dimension), and V should be the z (2nd dimension).

Classes Involved in Part 2

In implementing `mapTiles`, you will need to interact with a number of classes, including the `KDTree` class which you've built.

- `MosaicCanvas`: Doxygen
- `TileImage`: Doxygen
- `SourceImage`: Doxygen

The source code for all these classes is provided for you, meaning you can look at their implementation if you have questions about return types, parameters, or the way the functions work.

The `mapTiles()` function

Please see the Doxygen for `mapTiles`.

`mapTiles()` is a function that takes a `SourceImage` and a vector of `TileImage`s and returns a `MosaicCanvas` pointer. It maps the rectangular regions of the `SourceImage` to `TileImage`s.

- Its parameters are a `SourceImage` and a constant reference to a `std::vector` of `TileImage` objects in that order.

- It creates a new dynamically allocated `MosaicCanvas`, with the same number of rows and columns as the `SourceImage`, and returns a pointer to this object.
- For every region in the `SourceImage`, `mapTiles()` should take the `TileImage` with average color closest to the average color of that region and place that `TileImage` into the `MosaicCanvas` in the same tile position as the `SourceImage`'s region.
- `map_tiles` - The locations of the tiles in the mosaic are defined by a `MosaicCanvas`. This function should create a new `MosaicCanvas` which is appropriately sized based on the rows and columns of tiles in the `SourceImage`. Then, each tile in the `MosaicCanvas` should be set to an appropriate `TileImage`, using a `KDTree` to find the Nearest Neighbor for each region. Note that most of the real work here is done by building a k-d tree and using its nearest neighbor search function. Return a pointer to the created `MosaicCanvas`. You can assume that the caller of the function will free it after it has been used.

You may return `NULL` in the case of any errors, but we will not test your function on bad input (e.g., a `SourceImage` with 0 rows/columns, an empty vector of `TileImages`, etc.).

Implementation Notes

- There are two classes representing a color in this portion of the MP: `LUVAPixel` and `Point<3>`. You will need to convert between these different representations.
  - Note that your points should be in L-U-V order. That is, L should be the x (0th dimension), U should be the y (1st dimension), and V should be the z (2nd dimension).
- Use your `KDTree` class to find the nearest neighbor, which is the tile image that minimizes average color distances.
- You can easily convert from a `TileImage` to its average color using `TileImage::getAverageColor()`. You will also need to convert from an average color to the `TileImage` that would generate that color. You may want to use the `std::map` class to do this.

Compiling and Running A PhotoMosaic

After finishing both the `KDTree` class and the `mapTiles` function, you can compile the executable by linking your code with the provided code with the following command:

```
make
```

The executable created is called `mosaics`. You can run it as follows:

```
./mosaics background_image.png [tile_directory/] [number of tiles] [pixels per tile]
[output_image.png]
```

Parameters in `[square brackets]` are optional. Below are the defaults:

Parameter	Default	Notes
`background_image.png`		
`tile_directory/`	[EWS only]	See below (default only valid on EWS)
`number of tiles`	100	The number of tiles to be placed along the shorter dimension of the source image

`pixels_per_tile`	50	The width/height of a `TileImage` in the result mosaic. Don't make this larger than 75 for the provided set of `TileImages`
`output_image.png`	mosaic.png	`.png`, `.jpg`, `.gif`, and `.tiff` files also supported

Additional Resources

In addition to the given code, we have provided a directory of small thumbnail images which can be used as the `tile_directory` of the `mosaics` program. These images are every Instagram photo shared by @illinois1867, @illinoiscs, and @eceillinois.

If you are working on EWS, then you can use `/class/cs225/mp5_uiuc-ig/` as the `tile_directory` (default value). If you are working on your own machine, you can download them from here: `uiuc-ig.zip`. If you prefer, you can download them directly to your `mp_mosaics` directory by running

```
wget https://courses.engr.illinois.edu/cs225/sp2019/assets/assignments/mps/mp_mosaics/uiuc-ig.zip
```

Once downloaded, you need to extract it. Do so by running

```
zip -r uiuc-ig.zip uiuc-ig
```

You may also use your own directory of images to create your own PhotoMosaics. However, for the supplied tests, you should use our provided images.

Testing

We have provided a simple test case for `mapTiles()`, which can be run with:

```
make test
./test [part=2]
```

Be aware that these are deliberately insufficient. You should add additional test cases to more thoroughly test your code.

We have also provided you with a sample input `sourceimage` and output `mosaiccanvas`, which can be tested as follows:

```
make

# On EWS:
./mosaics tests/source.png

# On your own machine (after downloading and unzip uiuc-ig)
./mosaics tests/source.png uiuc-ig/

wget
https://courses.engr.illinois.edu/cs225/sp2019/assets/assignments/mps/mp_mosaics/mosaic-provided-solution.png
diff mosaic.png mosaic-provided-solution.png
```

Part 3 (Creative): Your Mosaic!

Solo Portion This creative part of the MP must be completed individually and must be significantly different from your partner's creative work.

You have two weeks making an mosaic – you should show off your work! You'll have to gather some pictures, convert them to PNGs, and generate a mosaic using your `mosaics` executable.

After generating your mosaic, make sure to commit it to git as `mymosaic.png`.

Making a great mosaic: Gathering Pictures

A good mosaic requires a lot of tile images. A baseline for a decent mosaic is ~100 tile images if the images are all different (eg: not all daylight pictures or selfies) and ~1000 for a great mosaic. You probably already have many images:

- If you have an Android, Google Photos usually backs up your photos to the cloud at photos.google.com. You can download them as a ZIP file.
- If you have an iPhone, Apple usually backs up your photos in iCloud. You can download them as a ZIP file.
- Using a computer and a bit of time, you can download a bunch of your photos frome Facebook, Instagram, Twitter, etc.

Making a great mosaic: Converting to PNG

The program you built requires PNG files as input. Often photos are JPEG files and must be converted.

Once you have converted all of the image into PNG, place all of the images into a single directory inside of your mp_mosaics folder. *This folder will likely be very large* – ***you should NOT commit it to git!***

Making a great mosaic: Sharing and explaining what you've made

A mosaic looks like a fun Instagram "block" transformation at first glance, but becomes even more amazing when someone understands what they're seeing – an image made entirely from other images.

If you share you image, it's best if you describe what you've done! If you want to share it with your peers, post it with `#cs225` so we can find it. :)

You just made something awesome that never existed before -- you should share your art (but do not have to)!

*If you share your art on Facebook, Twitter, or Instagram with **#cs225**, I will 👍 or ❤ the post as soon as I see it. I think many of your peers will too!* — Wade

Grading Information

The following files are used to grade mp_mosaics:

- `maptiles.cpp` (Part 2 only)
- `maptiles.h` (Part 2 only)
- `kdtree.hpp`
- `kdtree.h`
- `PARTNERS.txt`
- `mymosaic.png`

All other files will not be used for grading.

Guide: How to submit CS 225 work using git

Good Luck!