Group Name: Unfiltered Commentary

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```
import numpy as np
import imageio.v2 as imageio
from glob import glob
from skimage import img as float32
from natsort import natsorted
import matplotlib.pyplot as plt
import cv2
from typing import Tuple
import json
from collections import defaultdict
from sklearn.neighbors import NearestNeighbors
import networkx as nx
import random
import math
path pairs = list(zip(
natsorted(glob('./puzzle_corners_1024x768/images-1024x768/*.png')),
natsorted(glob('./puzzle corners 1024x768/masks-1024x768/*.png')),
imgs = np.array([img as float32(imageio.imread(ipath)) for ipath, in
path pairs1)
msks = np.array([img as float32(imageio.imread(mpath)) for , mpath in
path pairs])
```

Part 1 Finding Contours

1.1 get_puzzle_contour

1.2

```
def get_clockwise_contour(contours):
   if cv2.contourArea(contours,oriented=True)<0:
        return contours[::-1]
   return contours</pre>
```

```
def get_puzzle_contour(mask):
    mask_uint8 = cv2.convertScaleAbs(mask)
    contours, _ = cv2.findContours(mask_uint8, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE)
```

1.3 **how does cv2.findContours work and ow the oriented=True version

```
of cv2.contourArea detects orientation :**
```

1.4 plot of the any 3 contours

```
#Show Contours
for i in range(3):
    contour = get_puzzle_contour(msks[i])

fig, ax = plt.subplots()

# image
    ax.imshow(imgs[i], cmap='gray')

# contours
    x_coords, y_coords = zip(*contour)
    ax.plot(x_coords, y_coords, c='lime', linewidth=2)
    ax.axis('off')
    plt.show()
```







Shape models

2.1.1

```
with open("./puzzle_corners_1024x768/corners.json", mode="r") as f:
    names, corner_ratios = json.load(f)

#Convert Ratios to coordinates
for picture in range(len(corner_ratios)):
    for points in range(len(corner_ratios[picture])):
        corner_ratios[picture][points]=[corner_ratios[picture][points]
[0]*1024,corner_ratios[picture][points][1]*768]
```

2.1.2

NOTE: Using cv2.CHAIN_APPROX_SIMPLE is helpful since it only stores the endpoints of the lines that form the contour - this is what we need if we want to find the nearest point in the contour to the corner. makes finding the nearest contour easier.

```
def extract_sides(contour, corners):
    corner_indices=[]
    for corner in corners:
        #get distance
        corner_dists = np.linalg.norm(contour - corner, axis=-1)
        # using argmin to get the closest points since smaller
distance
```

```
nearest idx = np.argmin(corner dists)
        corner indices.append(nearest idx)
    corner indices = sorted(corner indices)
    side contours = []
    for \bar{i} in range(4):
        start idx = corner indices[i]
        end i\overline{d}x = corner\_indices[(i + 1) % 4]
        if start idx < end idx:</pre>
            side contour = contour[start idx:end idx + 1]
        else:
            side contour = np.concatenate([contour[start idx:],
contour[:end idx + 1])
        side contours.append(side contour)
    return side contours
### 2.1.3
### helper to plot the contours
def plot puzzle piece(img,contour, corners, sides):
    corners = np.array(corners)
    # colors of quad and sides
    quad color = (1.0, 1.0, 1.0)
    side colors = [(1.0, 0.75, 0.0),
                    (0.0, 0.25, 1.0),
                     (0.0, 1.0, 0.0),
                     (1.0, 0.0, 0.0), 1
    plt.figure(figsize=(6, 6))
    plt.imshow(img)
    # contour for each side with different colors
    for i, side in enumerate(sides):
        # ide contour in its color
        plt.plot(side[:, 0], side[:, 1], color=side colors[i],
linewidth=2)
        # colored dot at the start of each side
        plt.scatter(side[0, 0], side[0, 1], color=side colors[i],
zorder=6, s=100)
```

```
# white dots along the side
# num_points = 10
# sparse_indices = np.linspace(0, len(side) - 1, num_points,
dtype=int)

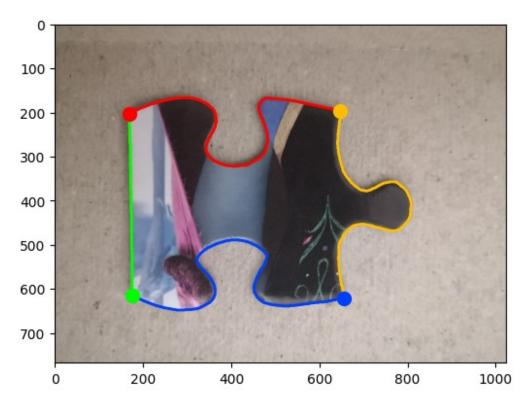
# plt.scatter(side[sparse_indices, 0], side[sparse_indices,
1], color='white', zorder=5, s=20)

plt.show()

def plot_side(img_index):
    contour = get_puzzle_contour(msks[img_index])
# print("contours\n",contours)

sides = extract_sides(contour,corner_ratios[img_index])

plot_puzzle_piece(imgs[img_index],contour,
corner_ratios[img_index], sides)
plot_side(1)
```



NOTE

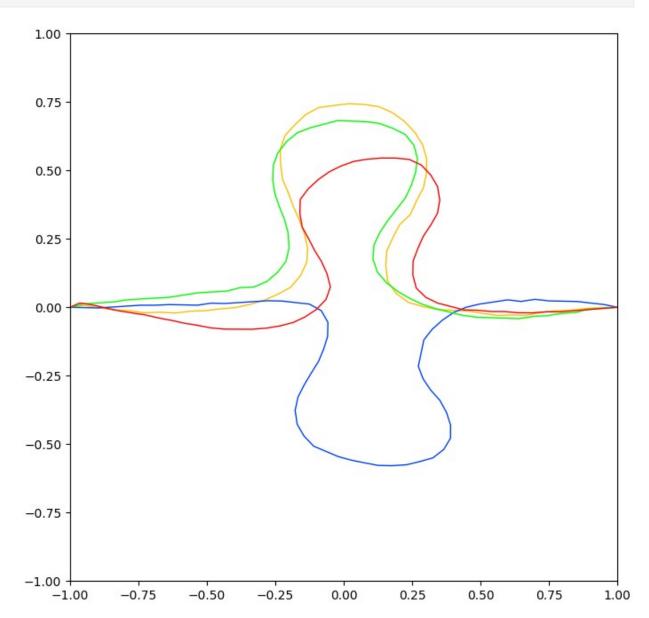
had to comment out the plot in this function because it was messing the the plot for the ijnterpolation!!!

2.2.1

```
def transform puzzle side(contour): # contour is a side
    point1 = np.array(contour[0])
    point2 = np.array(contour[-1])
    line = np.array([point1,point2])
    midpoint = (point1 + point2)/2
    #print(midpoint)
    #Do translation
    translated contour = contour - midpoint
    #scale
    length = np.linalg.norm(point2 - point1)
    scale factor = 2.0/length
    scaled contour = (translated contour)* scale factor
    #Do Rotation
    theta =np.arctan2(translated contour[0][1],translated contour[0]
[0]
    #print(theta)
    rotation matrix = np.array([[np.cos(-theta), -np.sin(-theta)],
                                [np.sin(-theta), np.cos(-theta)]])
    rotated contour = (rotation matrix @ scaled contour.T).T
    # x coords = rotated contour[:, 0]
    # y coords = rotated contour[:, 1]
    # # Create the scatter plot
    # plt.scatter(x coords, y coords)
    # # Optional: Add titles and labels
    # plt.title('Scatter Plot of Points')
    # plt.xlabel('X-axis')
    # plt.ylabel('Y-axis')
    # plt.show()
    return rotated contour
    # Show the plot
contour = get puzzle contour(msks[1])
sides = extract sides(contour,corner ratios[1])
side 0 = transform puzzle side(sides[0])
```

```
def even spaced contour(contour, num points=64):
    #distance between consecutive points
    diffs = np.diff(contour, axis=0)
    segment lengths = np.sgrt((diffs**2).sum(axis=1)) #just the
euclidean
    #cumultive len init to 0
    cumulative lengths = np.insert(np.cumsum(segment lengths), 0, 0)
    #normalisation of len
    total_length = cumulative_lengths[-1] #since cumulative las it
total
    cumulative_ratios = cumulative lengths/ total length
    #to space evenly
    spacing = np.linspace(0,1,num points)
    #interpolation
    x_{new} = np.interp(spacing, cumulative ratios, contour[:,0])
    y_new = np.interp(spacing, cumulative ratios, contour[:,1])
    new contour = np.vstack((x new, y new)).T
    return new contour
new side = even_spaced_contour(side_0)
def plot normalised(contour, corners, num sides=4):
    sides = extract sides(contour,corners)
    plt.figure(figsize=(8, 8))
    plt.xlim(-1, 1)
    plt.ylim(-1, 1)
    side colors = [(1.0, 0.75, 0.0),
                   (0.0, 0.25, 1.0),
                    (0.0, 1.0, 0.0),
                    (1.0, 0.0, 0.0),]
    for i in range(num sides):
        side = transform_puzzle_side(sides[i])
        simplified side = even spaced contour(side, 64) #said to use
10 points for a simplified plot
        plt.plot(simplified side[:, 0], simplified side[:, 1],
color=side_colors[i], linestyle='-', linewidth=1, marker=None)
    plt.gca().set aspect('equal', adjustable='box')
    plt.show()
```

```
contour = get_puzzle_contour(msks[2])
plot_normalised(contour, corner_ratios[2])
```



3 Match Shape Models

3.1 Before we can apply these rules, we need to know which sides of pieces are flat so we can determine if they should be matched or not, and so that we can determine if a piece is an interior piece (no flat sides), edge piece (1 flat side), corner piece (2 flat sides) or invalid piece (3 or 4 flat sides). Note that with side information, you could solve for possible the widths and heights of the puzzle in terms of pieces. Taking into account the number of pieces along the perimeter and the total area. Code is_flat_side(contour, min_ratio=0.9) that checks if the distance cont_dist between the two endpoints of a non-closed contour is approximately equal to the entire length

cont_len of the contour. If cont_dist/cont_len >= min_ratio then the side should be considered flat. Hint: np.linalg.norm and cv2.arcLength7 called with closed=False may come in handy.

```
def is flat side(contour, min ratio=0.9):
    contour = contour.reshape((-1, 1, 2))
    contour = contour.astype(np.float32)
    point to point = np.array([contour[0], contour[-1]])
    point to_point_length = cv2.arcLength(point_to_point,closed=False)
    total length = cv2.arcLength(contour,closed=False)
    #print("Straight:", point to point length)
    #print("Curve:",total length)
    if(point to point length/total length <min ratio):</pre>
        return False
    return True
def flat sides(contour, corners, num sides=4):
    sides = extract sides(contour,corners)
    for i in range(num sides):
        side = transform_puzzle_side(sides[i])
        simplified side = even spaced contour(side, 64) #said to use
10 points for a simplified plot
        is flat side(simplified side)
contour = get puzzle contour(msks[1])
flat sides(contour,corner ratios[1])
class Piece:
    A class for each piece
        Attributes:
        contour
        corners
        sides : extracted sides normalized and translated.
        sides_objects : list of objects of type Side
        num_flat (int) : the number of flat sides
        interior piece : if is interior piece
    0.00
    def __init__(self,mask,corners) -> None:
        self.contour = get puzzle_contour(mask)
        self.corners = corners
        self.sides = extract_sides(self.contour,corners)
        self.sides objects:Side = [Side]*4
```

```
# normalize, translate sides, determine flat and not flat sides
        for i in range(4):
            side = transform puzzle side(self.sides[i])
            self.sides[i] = even spaced contour(side, 64) #said to use
10 points for a simplified plot
            self.sides objects[i] = Side(self,self.sides[i])
        self.interior piece =
self.is_interior_piece(self.sides_objects)
        # set flags if the piece is anticlockwise or clockwise from an
flat edge
        for i in range(len(self.sides objects)):
            before_index = (i - 1) % len(self.sides_objects)
            after index = (i + 1) % len(self.sides objects)
            # is this piece after a flat edge
            if(self.sides objects[before index].is flat):
                self.sides objects[i].after flat = True
            elif(self.sides objects[after index].is flat):
                self.sides objects[i].before flat = True
    def is interior piece(self, side objects):
        interior:bool = True
        for x in (side objects):
            if(x.is flat == True):
                interior = False
                return interior
        return interior
class Side :
    A class for each side
        Attributes:
        Piece : A refrence to the parent piece class.
        Side : contour of the side.
        is flat (bool) : Boolean flag for if the side is flat.
        protruding (bool) :
        after flat : if the edge is clockwise after a flat edge.
        before flat : if the edge is anticlockwise from a flat edge.
    0.00
    def __init__(self,piece,contour):
        self.piece = piece
        self.contour = contour
        self.rotated side = self.rotate side(self.contour)
        self.is flat = is flat side(self.contour)
        self.protruding = self.determine protruding(self.contour,-
0.25)
```

```
self.after flat = False
        self.before flat = False
        pass
    def plot side(self):
        plt.figure(figsize=(3,3))
        plt.plot(self.contour[:, 0], self.contour[:, 1],
linestyle='-', linewidth=1, marker=None)
        plt.ylim(-1, 1)
        plt.show()
    def determine protruding(self,contour,threshold):
        if(np.min(contour[:,1])<threshold):</pre>
            return False
        else:
            return True
    def rotate side(self,contour):
        reversed side = (contour * -1)[::-1]
        return reversed side
    def str (self):
        return f"Side(is_flat={self.is flat},
protruding={self.protruding},
after flat={self.after flat}, before flat={self.before flat})"
def get nearest neighbour model(rotated sides):
    knn = NearestNeighbors(n neighbors=192,algorithm="brute")
    return knn.fit(rotated sides)
def plot graph(V, E, seed=42):
    random.seed(seed) # graphs are randomly plotted
    np.random.seed(seed) # graphs are randomly plotted
    G = nx.DiGraph()
    G.add nodes from(V)
    G.add edges from(E)
    nx.draw kamada kawai(G, with labels=True)
    plt.show()
def plot all connections(indeces, pieces array):
    V = [i for i in range(len(pieces_array))]
    E = []
    for side in range(len(indeces)):
        #Check if side is flat
        if not(pieces array[math.floor(side/4)].sides objects[side
%4].is flat):
            index = 0
            while(pieces array[math.floor(side/4)].sides objects[side
%4].after flat and not pieces array[math.floor(indeces[side]
```

```
[index]/4)].sides objects[indeces[side][index]%4].before flat) or
(pieces array[math.floor(side/4)].sides objects[side%4].before flat
and not pieces array[math.floor(indeces[side]
[index]/4)].sides objects[indeces[side][index]%4].after flat):
                index+=1
            E.append((math.floor(side/4), math.floor(indeces[side]
[index]/4))
    plot graph(V,E)
def plot double connections(indeces, pieces array):
    V = [i for i in range(len(pieces array))]
    double indicies = []
    for i in range(len(indeces)):
        index = 0
        while(pieces array[math.floor(i/4)].sides objects[i
%4].after flat and not pieces array[math.floor(indeces[i]
[index]/4)].sides objects[indeces[i][index]%4].before flat) or
(pieces array[math.floor(i/4)].sides objects[i%4].before flat and not
pieces array[math.floor(indeces[i][index]/4)].sides objects[indeces[i]
[index]%4].after flat):
            index+=1
        check = indeces[i][index]
        if(indeces[check][index]==i):
            double indicies.append([math.floor(i/4),i%4,indeces[i]
[index]])
    E = []
    for side in double indicies:
        #Check if side is flat
        if not(pieces array[side[0]].sides objects[side[1]].is flat):
            E.append((side[0], math.floor(side[2]/4)))
    plot graph(V,E)
def plot edge connections(indeces, pieces array):
    V = [1]
    for i in range(len(pieces array)):
        if not(pieces array[i].interior piece):
            V.append(i)
    double indicies = []
    for i in range(len(indeces)):
        index = 0
        while(pieces array[math.floor(i/4)].sides objects[i
```

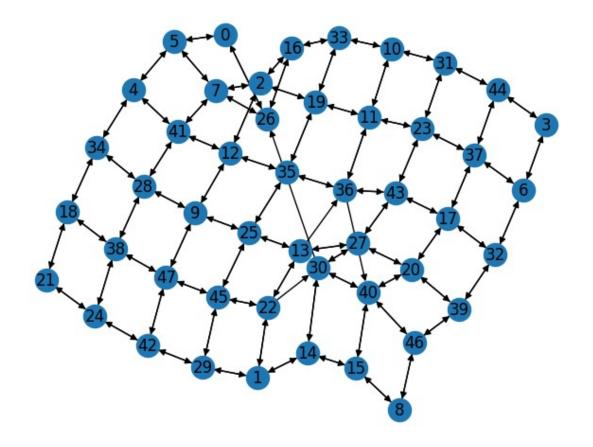
```
%4].after flat and not pieces array[math.floor(indeces[i]
[index]/4)].sides objects[indeces[i][index]%4].before flat) or
(pieces_array[math.floor(i/4)].sides_objects[i%4].before_flat and not
pieces array[math.floor(indeces[i][index]/4)].sides objects[indeces[i]
[index]%4].after flat):
            index+=1
        check = indeces[i][index]
        if(indeces[check][index]==i):
            double indicies.append([math.floor(i/4),i%4,indeces[i]
[index]])
    E = []
    for side in double indicies:
        if pieces array[side[0]].interior piece or
pieces_array[math.floor(side[2]/4)].interior_piece:
            continue
        #Check if side is flat
        if not(pieces array[side[0]].sides objects[side[1]].is flat):
            E.append((side[0], math.floor(side[2]/4)))
    plot graph(V,E)
```

3.2,3.3

```
pieces_array = []
rotated_sides = []
side_features = []
for image in range(len(imgs)):
    piece = Piece(msks[image],corner_ratios[image])
    pieces_array.append(piece)
    for i in piece.sides_objects:
        side_features.append(i.contour.flatten()) ##Flatten to give a

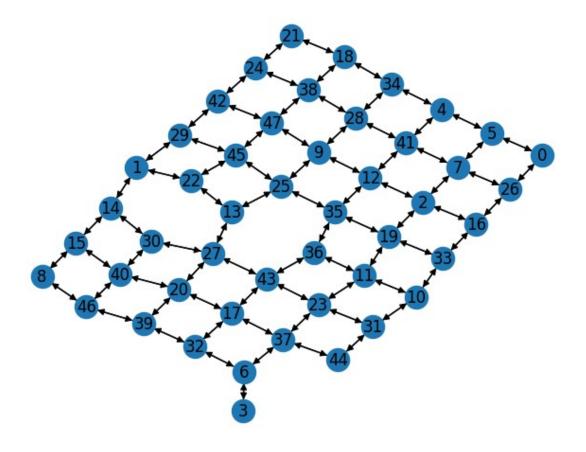
1D feature array
        rotated_sides.append(i.rotated_side.flatten()) ##Flatten to
give a 1D feature array
knn = get_nearest_neighbour_model(rotated_sides)
distances , indeces = knn.kneighbors(side_features)
```

```
plot_all_connections(indeces,pieces_array)
```



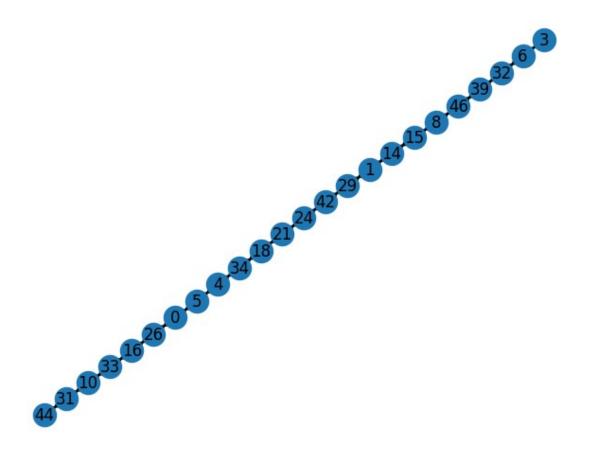
3.5

plot_double_connections(indeces,pieces_array)



3.6

plot_edge_connections(indeces,pieces_array)

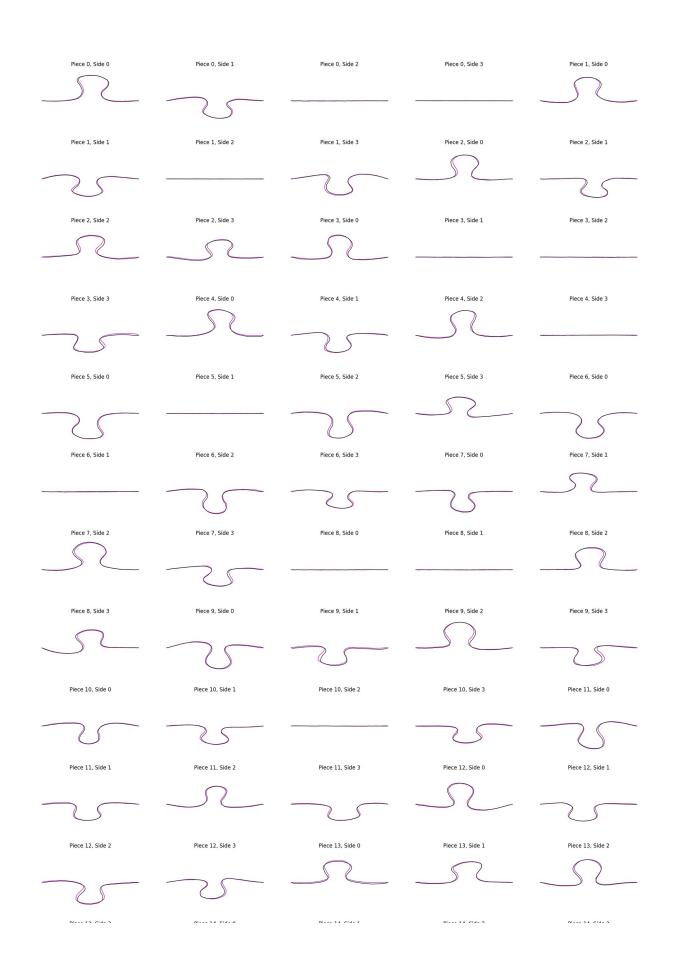


```
def plot_all_matches(indecies,pieces_array):
    rows = 40
    cols = 5
    # Create a figure with the specified rows and columns
    fig, axes = plt.subplots(rows, cols, figsize=(20, 100)) # Adjust
size as needed
    for i in range(len(indecies)):
        piece_idx = math.floor(i / 4) # Get the piece index
        side_idx = i % 4
        piece = pieces_array[piece_idx]
        side = piece.sides objects[side idx]
        row = i // cols
        col = i % cols
        axes[row, col].plot(side.contour[:, 0], side.contour[:, 1],
linestyle='-',color='m', linewidth=1, marker=None)
        axes[row, col].set title(f"Piece {piece idx}, Side
{side idx}")
```

```
axes[row, col].set_ylim(-1, 1)
    matched_sides = [indeces[i][0]]
    for x in matched_sides:
        piece_idx = math.floor(x / 4)  # Get the piece index
        side_idx = x % 4
        piece = pieces_array[piece_idx]
        side = piece.sides_objects[side_idx]
        axes[row, col].plot(side.rotated_side[:, 0],
side.rotated_side[:, 1], linestyle='-',color='black', linewidth=1,
marker=None)

axes[row, col].axis('off')
plt.tight_layout()
plt.show()

plot_all_matches(indeces,pieces_array)
```



3.7

Having plotted all of the pieces and their matches, we can see that the sunken sides are always smaller than the protruding sides. This shows a human bias to mark beyond the edge, inflating the object (which makes holes smaller and extremeties bigger).

How can this be remedied? Post matching we can find the average distance between the matched pieces and adjust all pieces using dilation on sunknen and erosion on protruding sides. And then rematch all of the pieces.

3.8

Computational Complexity:

As the number of puzzle pieces increases, the computational complexity of k-nearest neighbors matching will grow quadratically. For very large puzzles (e.g., 1000+ pieces), this could become a significant bottleneck.

Memory Usage:

Storing shape models and match data for each piece will require increasing amounts of memory as the puzzle size grows. With our current methods it will be quadratic, as we find 192 neighbors to each 192 sides. An improvement would be to find the relationsip between number of pieces and number of perimiter pieces. With more pieces, there's a higher chance of accumulating matching errors, potentially leading to incorrect solutions for larger puzzles.

A stable marriage matching algorithm would solve many of these problems.

How well it performs? Considering with what we were expected to do (example baseline). Even though not all of the pieces are matched to their exact neighbours, as long as there is 1 correct match, the puzzle will be solved. So the high but not perfect accuracy of the model will suffice.