```
In [2]: from __future__ import print_function
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import cv2
from IPython.display import HTML, YouTubeVideo
import matplotlib.patches as patches
from matplotlib.lines import Line2D
#import ganymede
#ganymede.configure('uav.beaver.works')
```

Enter your name below and run the cell:

Individual cells can be run with Ctrl + Enter

```
In [3]: # ganymede.name('Charlie Lai')
        def check(p):
             ganymede.update(p,True)
         check(0)
       NameError
                                                    Traceback (most recent call las
       t)
       Cell In[3], line 4
              2 def check(p):
                    ganymede.update(p,True)
        ---> 4 check(0)
       Cell In[3], line 3, in check(p)
              2 def check(p):
        ---> 3
                    ganymede.update(p,True)
       NameError: name 'ganymede' is not defined
        https://www.khanacademy.org/math/statistics-probability/describing-relationships-
         quantitative-data/more-on-regression/v/squared-error-of-regression-line
```

Note: All Khan Academy content is available for free at khanacademy.org

```
In [ ]: YouTubeVideo('60vhLPS7rj4', width=560, height=315)
In [ ]: YouTubeVideo('mIx20j5y9Q8', width=560, height=315)
In [ ]: YouTubeVideo('f60noxctvUk', width=560, height=315)
In [ ]: YouTubeVideo('u1HhUB3NP8g', width=560, height=315)
In [ ]: YouTubeVideo('8RSTQl0bQuw', width=560, height=315)
In [ ]: YouTubeVideo('GAmzwIkGFgE', width=560, height=315)
```

The last video is optional

```
In [ ]: YouTubeVideo('ww yT9ckPWw', width=560, height=315)
In [4]:
       lightningbolt = cv2.imread('shapes/lightningbolt.png', cv2.IMREAD GRAYSCA
        _, lightningbolt = cv2.threshold(lightningbolt,150,255,cv2.THRESH_BINARY)
        print(lightningbolt.shape)
        fig,ax = plt.subplots()
        ax.imshow(lightningbolt, cmap='gray');
        check(1)
       (215, 209)
       NameError
                                                   Traceback (most recent call las
       t)
       Cell In[4], line 6
             4 fig,ax = plt.subplots()
             5 ax.imshow(lightningbolt, cmap='gray');
       ----> 6 check(1)
       Cell In[3], line 3, in check(p)
             2 def check(p):
       ---> 3
                   ganymede.update(p,True)
       NameError: name 'ganymede' is not defined
          0 -
         25 -
         50 -
         75 -
        100 -
        125 -
        150 -
        175 -
       200 -
                      50
                                  100
                                             150
                                                        200
In [5]: np.argwhere?
```

Signature: np.argwhere(a)

```
Docstring:
       Find the indices of array elements that are non-zero, grouped by element.
       Parameters
       -----
       a : array like
           Input data.
       Returns
       index array : (N, a.ndim) ndarray
           Indices of elements that are non-zero. Indices are grouped by element.
           This array will have shape ``(N, a.ndim)`` where ``N`` is the number o
       f
           non-zero items.
       See Also
       -----
       where, nonzero
       Notes
       ``np.argwhere(a)`` is almost the same as ``np.transpose(np.nonzero(a))``,
       but produces a result of the correct shape for a OD array.
       The output of ``argwhere`` is not suitable for indexing arrays.
       For this purpose use ``nonzero(a)`` instead.
       Examples
       >>> x = np.arange(6).reshape(2,3)
       >>> X
       array([[0, 1, 2],
              [3, 4, 5]])
       >>> np.argwhere(x>1)
       array([[0, 2],
              [1, 0],
              [1, 1],
                  ~/.local/lib/python3.10/site-packages/numpy/core/numeric.py
       File:
                  function
       Type:
In [6]: bolt = np.argwhere(lightningbolt)
        bolt
Out[6]: array([[ 47, 88],
                [ 47, 89],
                [ 47, 90],
                [164, 166],
                [164, 167],
                [164, 168]])
```

Linear Regression

$$m=rac{ar xar y-ar xy}{(ar x)^2-ar x^2}$$

$$b = \bar{y} - m\bar{x}$$

Question: how can we extract the xs and ys separately from the result of argwhere?

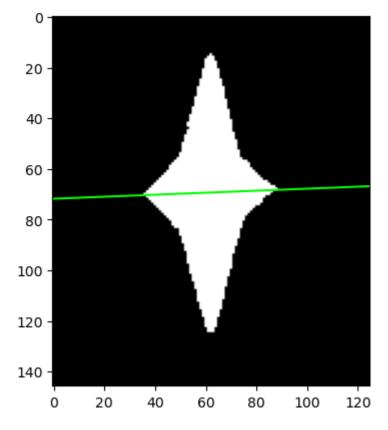
Hint: review numpy slicing by columns and rows

```
In [7]: # TODO
    # We can first run the argwhere function to find the coordinates where th
    # y_coords = coords[:, 0]
    bolt[:,0]
    bolt[:,1]
Out[7]: array([ 88, 89, 90, ..., 166, 167, 168])
```

Question: Why would we want to convert x and y points from int values to floats?

The intercept we calculated, b, may be outside of the pixel space of the image, so we must find two points inside of pixel space, (x_1,y_1) and (x_2,y_2) which will allow us to plot our regression line on the image. It may be best to choose points on the regression line which also occur on the boundaries/extrema of the image.

```
In [11]: | star = cv2.imread('shapes/squishedstar.png', cv2.IMREAD GRAYSCALE)
         print(star.shape)
          _, star = cv2.threshold(star,125,255,cv2.THRESH_BINARY)
         fig,ax = plt.subplots()
         ax.imshow(star, cmap='gray');
        (146, 125)
           0 -
          20 -
          40 -
          60 -
          80 -
         100 -
         120 -
         140
                   20
                          40
                                60
                                       80
             0
                                             100
                                                    120
In [12]: | m,b = calculate_regression(np.argwhere(star))
         x1, y1, x2, y2 = find inliers(m,b, star.shape)
In [13]: # below is an example of how to draw a random line from (10,25) to (10,55)
         # TODO: replace this with the result of find_inliers
         # -- pay attention to the directions of the x and y axes
         # in image space, row-column space, and cartesian space
         # Look at the help function for Line2D below
         fig,ax = plt.subplots()
         ax.imshow(star, cmap='gray');
         regression = Line2D([x1,x2],[y1,y2], color='lime')
         ax.add line(regression);
```



In [14]: Line2D?

```
Init signature:
Line2D(
    xdata,
    ydata,
    linewidth=None,
    linestyle=None,
    color=None,
    marker=None,
    markersize=None,
    markeredgewidth=None,
    markeredgecolor=None,
    markerfacecolor=None,
    markerfacecoloralt='none',
    fillstyle=None,
    antialiased=None,
    dash capstyle=None,
    solid capstyle=None,
    dash joinstyle=None,
    solid joinstyle=None,
    pickradius=5,
    drawstyle=None,
    markevery=None,
    **kwargs,
)
Docstring:
A line - the line can have both a solid linestyle connecting all
the vertices, and a marker at each vertex. Additionally, the
drawing of the solid line is influenced by the drawstyle, e.g., one
can create "stepped" lines in various styles.
Init docstring:
Create a `.Line2D` instance with *x* and *y* data in sequences of
*xdata*, *ydata*.
Additional keyword arguments are `.Line2D` properties:
Properties:
    agg filter: a filter function, which takes a (m, n, 3) float array and
a dpi value, and returns a (m, n, 3) array
    alpha: scalar or None
    animated: bool
    antialiased or aa: bool
    clip box: `.Bbox`
    clip on: bool
    clip path: Patch or (Path, Transform) or None
    color or c: color
    dash_capstyle: `.CapStyle` or {'butt', 'projecting', 'round'}
dash_joinstyle: `.JoinStyle` or {'miter', 'round', 'bevel'}
    dashes: sequence of floats (on/off ink in points) or (None, None)
    data: (2, N) array or two 1D arrays
    drawstyle or ds: {'default', 'steps', 'steps-pre', 'steps-mid', 'step
s-post'}, default: 'default'
    figure: `.Figure`
    fillstyle: {'full', 'left', 'right', 'bottom', 'top', 'none'}
    qid: str
    in layout: bool
    label: object
    linestyle or ls: {'-', '--', '-.', ':', '', (offset, on-off-seq), ...}
    linewidth or lw: float
    marker: marker style string, `~.path.Path` or `~.markers.MarkerStyle`
    markeredgecolor or mec: color
```

```
markeredgewidth or mew: float
    markerfacecolor or mfc: color
    markerfacecoloralt or mfcalt: color
    markersize or ms: float
    markevery: None or int or (int, int) or slice or list[int] or float or
(float, float) or list[bool]
    path effects: `.AbstractPathEffect`
    picker: float or callable[[Artist, Event], tuple[bool, dict]]
    pickradius: float
    rasterized: bool
    sketch params: (scale: float, length: float, randomness: float)
    snap: bool or None
    solid_capstyle: `.CapStyle` or {'butt', 'projecting', 'round'}
    solid joinstyle: `.JoinStyle` or {'miter', 'round', 'bevel'}
    transform: unknown
    url: str
    visible: bool
    xdata: 1D array
    ydata: 1D array
    zorder: float
See :meth:`set linestyle` for a description of the line styles,
:meth:`set marker` for a description of the markers, and
:meth:`set drawstyle` for a description of the draw styles.
File:
               /usr/lib/python3/dist-packages/matplotlib/lines.py
Type:
                type
Subclasses:
               AxLine, Line3D
```

TODO

- 1. Run your linear regression algorithm on the following images.
- 2. Plot each of the results.
- 3. Include each result in your submitted PDF.

When you are done:

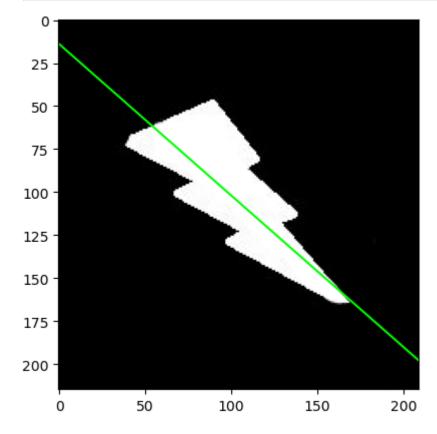
You should have six images with regression lines plotted on top of them.

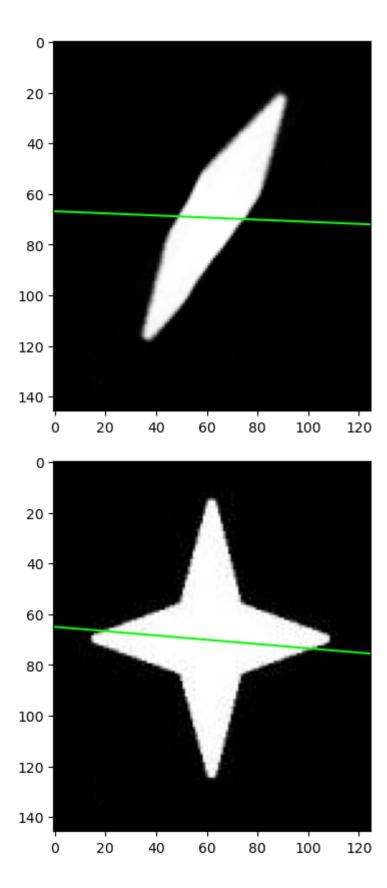
- 1. Double-check that you filled in your name at the top of the notebook!
- 2. Click File -> Export Notebook As -> PDF
- 3. Email the PDF to YOURTEAMNAME@beaver.works

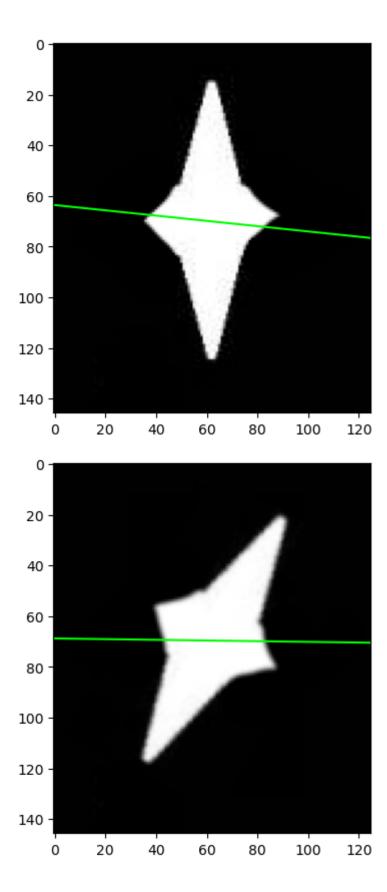
```
squishedturnedstar = cv2.imread('shapes/squishedturnedstar.png', cv2.IMRE
letterj = cv2.imread('shapes/letterj.png', cv2.IMREAD_GRAYSCAL

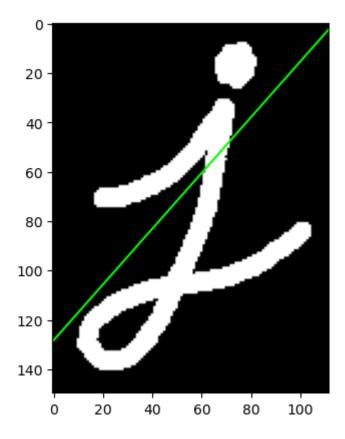
images = [lightningbolt, blob, star, squishedstar, squishedturnedstar, le
for img in images:
    fig,ax = plt.subplots()
    ax.imshow(img, cmap='gray');

m,b = calculate_regression(np.argwhere(img))
    x1, y1, x2, y2 = find_inliers(m, b, img.shape)
    regression = Line2D([x1,x2],[y1,y2], color='lime')
    ax.add_line(regression);
```









Stretch goal

Implement a machine learning algorithm!

Random **Sa**mple **C**onsensus, commonly referred to as *RANSAC*, is one of the most widely used machine learning algorithms. In essence, it is a 'guess and check' algorithm. Take a small random sample of your data - two points in this case. Next, define a line through those two points. After doing so, count the number of *inliers*, or points closest to that line (euclidean distance is one way to do this).

https://en.wikipedia.org/wiki/Random_sample_consensus

Implement RANSAC for linear regression, and run it on all of your images.