```
In [70]: 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

https://www.khanacademy.org/math/statistics-probability/describing-relationships-quantitative-data/more-on-regression/v/squared-error-of-regression-line

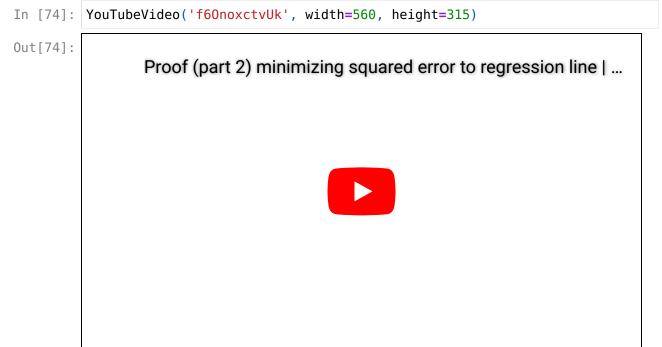
Note: All Khan Academy content is available for free at khanacademy.org

```
In [72]: YouTubeVideo('60vhLPS7rj4', width=560, height=315)

Out[72]: Squared error of regression line | Regression | Probability a...
```

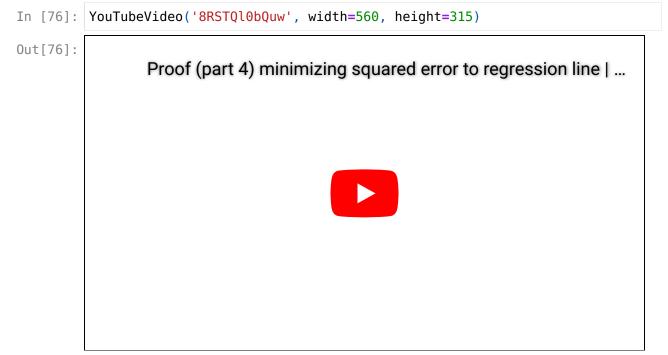
In [73]: YouTubeVideo('mIx20j5y9Q8', width=560, height=315)





In [75]: YouTubeVideo('u1HhUB3NP8g', width=560, height=315)





In [77]: YouTubeVideo('GAmzwIkGFgE', width=560, height=315)

Out [77]:

Regression line example | Regression | Probability and Stati...

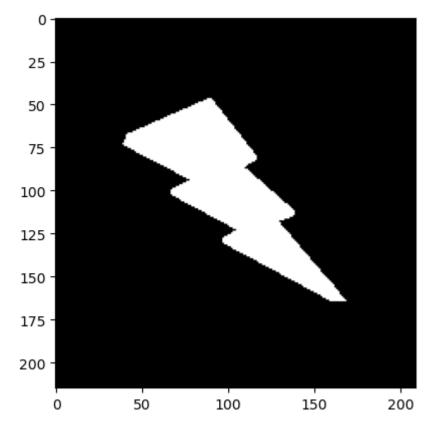
#### The last video is optional

```
In [78]: YouTubeVideo('ww_yT9ckPWw', width=560, height=315)

Out[78]: Second regression example | Regression | Probability and S...
```

```
In [79]: 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)
```



In [80]: 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 [81]: | bolt = np.argwhere(lightningbolt)
         bolt
Out[81]: 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 [82]: # TODO
# Your answer here
# Use a loop to pull out each row of lists, then indexing by using list[0]
```

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

```
In [83]: # TODO
         # Your answer here
         # to make the line more accurate when graphed and to avoid any "type" err
In [84]: def calculate_regression(points): # input is the result of np.argwhere
             # convert points to float
             points = points.astype(float) #TODO (see astype, https://docs.scipy.o
             xs = []
             ys = []
             for lists in points:
                 xs.append(lists[0])
                 ys.append(lists[1])
             \# xs = points[:][0]
             # ys = points[:][1]
             x_mean = np.mean(xs)
             y mean = np.mean(ys)
             xys=np.multiply(xs,ys)
             xy mean = np.mean(xys)
             x squared mean = np.mean(np.multiply(xs,xs))
             m = ((x mean*y mean)-xy mean)/(((x mean)**2)-x squared mean)
             b = (y mean) - m*x mean
             return (m,b)
```

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.

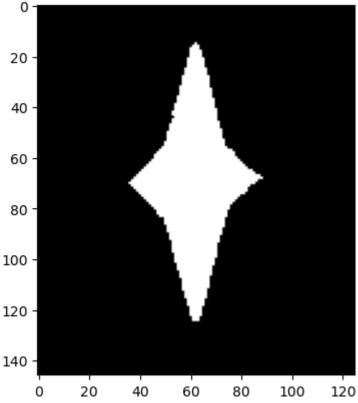
```
In [85]: def find_inliers(m, b, shape):
```

```
xs=[0, shape[0], -b/m, (shape[1] - b) / m] #todo
xs.sort()
x1=xs[1]
x2=xs[2]
y1=m*x1+b
y2=m*x2+b
return x1,y1,x2,y2
```

```
In [86]: | 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');
```

0

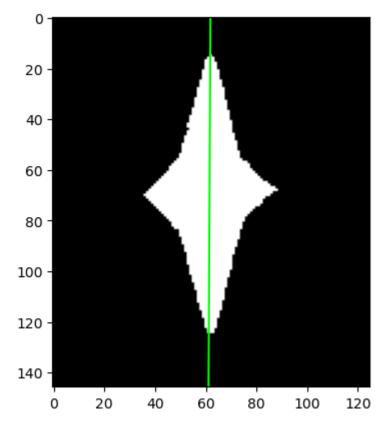
(146, 125)



```
In [87]: | m,b = calculate regression(np.argwhere(star))
         = find inliers(m,b, star.shape)
```

```
In [88]: # 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([_[1], _[3]],[_[0],_[2]], color='lime')
         ax.add line(regression);
```

7/12/24, 10:20 8 of 13



In [89]: 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
```

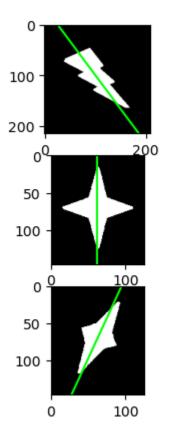
```
markeredgewidth or mew: float
    markerfacecolor or mfc: color
    markerfacecoloralt or mfcalt: color
    markersize or ms: float
    markevery: None or int or (int, int) or slice or list[int] or float or
(float, float) or list[bool]
    path effects: `.AbstractPathEffect`
    picker: float or 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
```

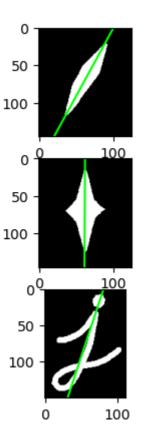
#### TODO

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

```
In [90]: lightningbolt
                            = cv2.imread('shapes/lightningbolt.png', cv2.IMREAD GR
         blob
                            = cv2.imread('shapes/blob.png', cv2.IMREAD GRAYSCALE)
                            = cv2.imread('shapes/star.png', cv2.IMREAD GRAYSCALE)
         star
         squishedstar
                            = cv2.imread('shapes/squishedstar.png', cv2.IMREAD GRA
         squishedturnedstar = cv2.imread('shapes/squishedturnedstar.png', cv2.IMRE
         letterj = cv2.imread('shapes/letterj.png', cv2.IMREAD GRAYSCALE)
         # 11, lightningbolt = cv2.threshold(lightningbolt,125,255,cv2.THRESH BIN
         # ax.imshow(lightningbolt, cmap='gray');
         # m1,b1 = calculate regression(np.argwhere(lightningbolt))
         # 1 = find inliers(m1,b1, lightningbolt.shape)
         # fig1,ax1 = plt.subplots()
         # ax.imshow(lightningbolt, cmap='gray');
         # regression1 = Line2D([ 1[1], 1[3]],[ 1[0], 1[2]], color='lime')
         # ax.add line(regression1);
         # ############################
         # m2,b2 = calculate regression(np.argwhere(blob))
         \# 2 = find inliers(m2,b2, blob.shape)
         # fig2,ax2 = plt.subplots()
```

```
# ax.imshow(blob, cmap='gray');
# regression2 = Line2D([_2[1], _2[3]],[_2[0],_2[2]], color='lime')
# ax.add line(regression2);
# ###########################
# m3,b3 = calculate regression(np.argwhere(star))
# 3 = find inliers(m3,b3, star.shape)
# fig3,ax3 = plt.subplots()
# ax.imshow(star, cmap='gray');
# regression3 = Line2D([_3[1], _3[3]],[_3[0],_3[2]], color='lime')
# ax.add line(regression3);
# ###########################
# m4,b4 = calculate regression(np.argwhere(squishedstar))
# 4 = find inliers(m4,b4, squishedstar.shape)
# fig4,ax4 = plt.subplots()
# ax.imshow(squishedstar, cmap='gray');
# regression4 = Line2D([ 4[1], 4[3]],[ 4[0], 4[2]], color='lime')
# ax.add line(regression4);
# #########################
# m5,b5 = calculate regression(np.argwhere(squishedturnedstar))
# 5 = find inliers(m5,b5, squishedturnedstar.shape)
# fig5,ax5 = plt.subplots()
# ax.imshow(squishedturnedstar, cmap='gray');
# regression5 = Line2D([_5[1], _5[3]],[_5[0],_5[2]], color='lime')
# ax.add line(regression5);
# ###########################
# m6,b6 = calculate regression(np.argwhere(letterj))
# 6 = find inliers(m6,b6, letterj.shape)
# fig6,ax6 = plt.subplots()
# ax.imshow(letterj, cmap='gray');
# regression6 = Line2D([ 6[1], 6[3]],[ 6[0], 6[2]], color='lime')
# ax.add line(regression6);
fig,ax = plt.subplots(nrows=3, ncols=2)
images = [lightningbolt, blob, star, squishedstar, squishedturnedstar, le
for a,i in zip(ax.flatten(), images):
    , i = cv2.threshold(i,125,255,cv2.THRESH BINARY)
    m,b = calculate regression(np.argwhere(i))
    _ = find_inliers(m,b, i.shape)
    a.imshow(i, cmap='gray');
    regression = Line2D([_[1], _[3]],[_[0],_[2]], color='lime')
    a.add line(regression);
```





### 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

## Stretch goal

Implement a machine learning algorithm!

**Ran**dom **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.