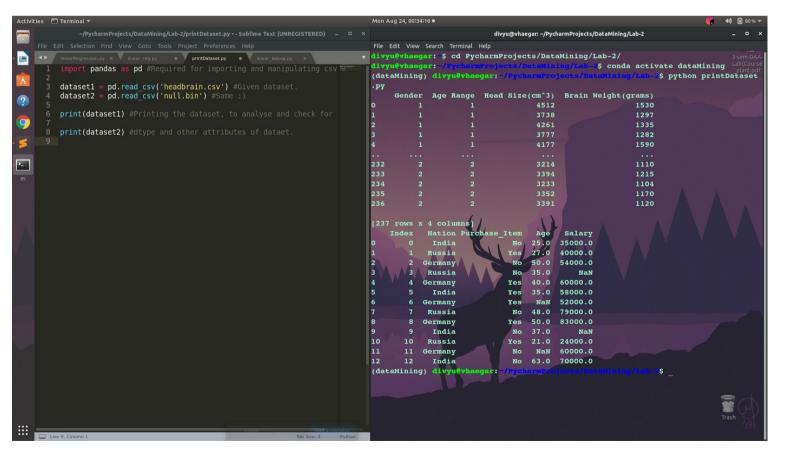
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Data-Mining and predictions by machine~

~Given datasets

- > headbrain -> Datasets of shape (237 x 4), the columns of significant usecase being `head size` and `brain wieght`. Provides information about brain wieght(in g) w.r.t head size(in cm^3).
- > age_salary -> Dataset of size (13 X 4), the columns of significant usecase being `head size` and `brain wieght`. Provides information about salary of an individual w.r.t his/her age.

Glance of the given datasets



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Which ML-model is best applicable?

Since, data-points seem to have linear-dependance i.e can be represented as linear-algebraic combination of the known-variable, Single variable linear regression model will be best applicable.

I will be calculating Linear Regression using Least Square method, the required parameters for the same are,

- > x (known variable ~ headsize / age.
- > y (uknown variable ~ brain weight / salary.
- > x-mean(x)
- > y-mean(y)
- > [x-mean(x)]^2 {Taking the square is necessary because, x-mena(x) can be negative at instances, since it's deviation from mean, sum of all data-points would be 0, hence squaring the term is necessary}
- > [y-mean(y) * x-mean(x)]

The goal is to find the equation of the best-fit line that describes the relation from known to unknown variables with least error.

```
Coefficient (or slope of line):  \Sigma\{x-\text{mean}(x)\}^2 / \Sigma\{(y-\text{mean}(y) * (x-\text{mean}(x))\}  Intercept (or y-intercept of line):  \text{mean}(y) - \text{slop} * \text{mean}(x)
```

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Code for the Single Variable Linear Regression model

```
self, X test = np.array(self.dataset[self.Xcoloumn][200:])

def newMatrix noNan(self): #Mimics the dataset but with no missing data.

data = self.dataset.dropna()

self.Y = np.array(data('salary'))

self.X = np.array(data('salary'))

self.X = np.array(data('salary'))

self.X = np.array(data('salary'))

def apply_linear regression(self): #Aapplies linear regression and fetches the best-fit eq parameters in dictionary.

x mean, y mean = np.mean(self.X), np.mean(self.Y)

x mean, y mean = np.mean(self.X), np.mean(self.Y)

self.X = self.Xx = np.array(np.quaret(x.X))

yolff xolff = np.array(np.multiply(x.x, y,y))

coefficient = np.sum(yolff xolff) / np.sum(x.ssl)

yolff xolff = np.array(np.multiply(x.x, y,y))

coefficient = np.sum(yolff xolff) / np.sum(x.ssl)

self.bestFit = ('coefficient': coefficient, 'intercept': intercept)

self.pestFit = ('self.bestFit['coefficient']*x=self.bestFit['intercept']) for x in self.X test]

self.yPred all = [(self.bestFit['coefficient']*x=self.bestFit['intercept']) for x in self.X test]

def calculate accuracy(self): #Calculates accuracy of prediction of the model.
 y error = [abs(y test y pred)y test for y test,y pred in zip(self.y-test, self.yPred)]

self.split()

self.apply_linear regression()

self.apply_linear regression()
```

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```
def visualize(packer): #Visualizes the linear model, with regression line, predicted data-points, given data-points, and noise cloud.

fig, axs = plt.subplots(2)

for plot id, self in enumerate(packet):

keyContent = 'Accuracy: (:.27)*'.format(self.acc)-self.title

fig.patch.set facecolor('xkcd:aint green')

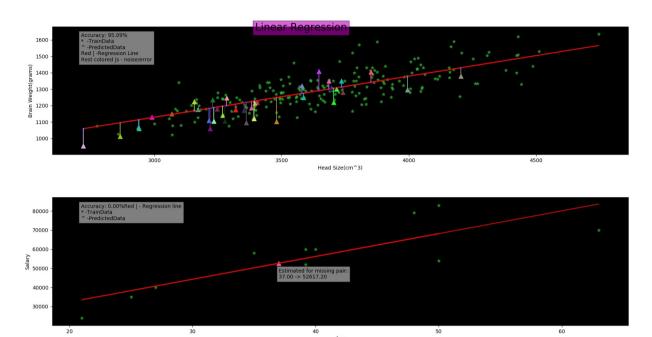
axs[plot_id].text(0.80, 0.95, keyContent, transform=axs[plot_id].transAxes, fontsize=10, bbox-dict(facecolor='w', alpha=0.5), verticalaligne

axs[plot_id].set(1.08, 0.95, keyContent, verticalaligne

axs[
```

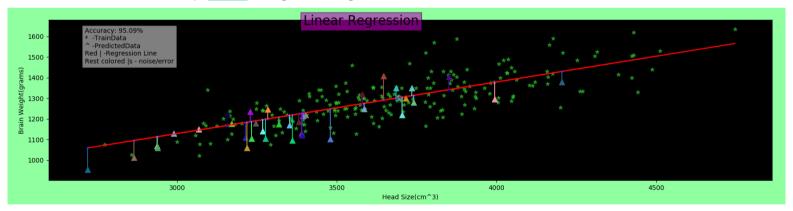
Output of the model with visualization, in next page >>

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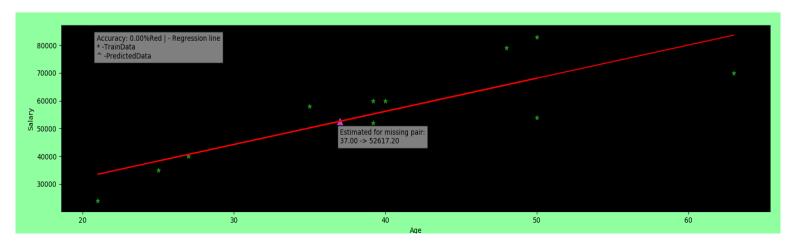


Zooming in | Predicts Brain-Weight on the basis of Head-Size.

| COLORFUL data-points are predicted data.
| Lines connecting them represent the error.
| Green data points are plots of data in data-set.



Zooming into age-salary



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