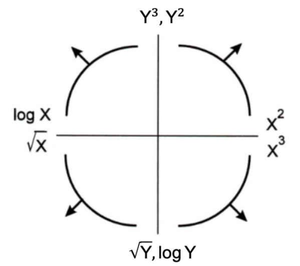
Visualization

Matplotlib: x and y are sequences of values. `import matplotlib.pyplot as plt`

Function	Description
`plt.plot(x, y)`	Creates a line plot of x against y
`plt.scatter(x, y)`	Creates a scatter plot of x against y
`plt.hist(x, bins=None)`	Creates a histogram of x; `bins` can be an integer or a sequence
`plt.bar(x, height)`	Creates a bar plot of categories x and corresponding heights `height`

Tukey-Mosteller Bulge Diagram.



Seaborn: x and y are keyword arguments assigned to string column names in a DataFrame `data`. `import seaborn as sns`

Function	Description
`sns.countplot(data=None, x=None)`	Create a barplot of value counts of variable x from `data`
`sns.histplot(data=None, x=None, stat='count', kde=False)` `sns.displot(data=None, x=None, stat='count', rug=False, kde=True)`	Creates a histogram of x from `data`, where bin statistics `stat` is one of `'count'`, `'frequency'`, `'probability'`, `'percent'`, and `'density'`; optionally overlay a kernel density estimator.
`sns.boxplot(data=None, x=None, y=None)` `sns.violinplot(data=None, x=None, y=None)`	Create a boxplot of a numeric feature (e.g., y), optionally factoring by a category (e.g., x), from `data`. `violinplot` is similar but also draws a kernel density estimator of the numeric feature
`sns.scatterplot(data=None, x=None, y=None)`	Create a scatterplot of x versus y from `data`
`sns.lmplot(data=None, x=None, y=None, fit_reg=True)`	Create a scatterplot of x versus y from `data`, and by default overlay a least-squares regression line
`sns.jointplot(data=None, x=None, y=None, kind)`	Combine a bivariate scatterplot of x versus y from `data`, with univariate density plots of each variable overlaid on the axes; `kind` determines the visualization type for the distribution plot, can be `scatter`, `kde` or `hist`
`sns.kdeplot(data=None, x=None)`	Create a kernel density estimate (KDE) of the distribution of x from `data`

Modeling

Concept	Formula	Concept	Formula
Variance, σ_x^2	$\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$	Correlation r	$r = \frac{1}{n}\sum_{i=1}^{n}\frac{x_i - \bar{x}}{\sigma_x}\frac{y_i - \bar{y}}{\sigma_y}$
L_1 loss	$L_1(y, \hat{y}) = \mid y - \hat{y} \mid$	Linear regression estimate of y	$\hat{y} = \theta_0 + \theta_1 x$
L_2 loss	$L_2(y, \hat{y}) = (y - \hat{y})^2$	Least squares linear regression	$\hat{\theta}_0 = \bar{y} - \hat{\theta}_1\bar{x} \qquad \hat{\theta}_1 = r\frac{\sigma_y}{\sigma_x}$
Empirical risk with loss L	$R(\theta) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, \hat{y}_i)$		