

1. Using the example code we reviewed in class or by creating your own implementation, write a Python function to generate a random dataset in two dimensions, e.g. a collection of points $\{(x_i, y_i)\}$ for $i = 1, \dots, n$. Specifically, use the `numpy.random.rand()` function to generate random x_i values and corresponding y_i values then use the `matplotlib` library to plot a scatterplot of your dataset.

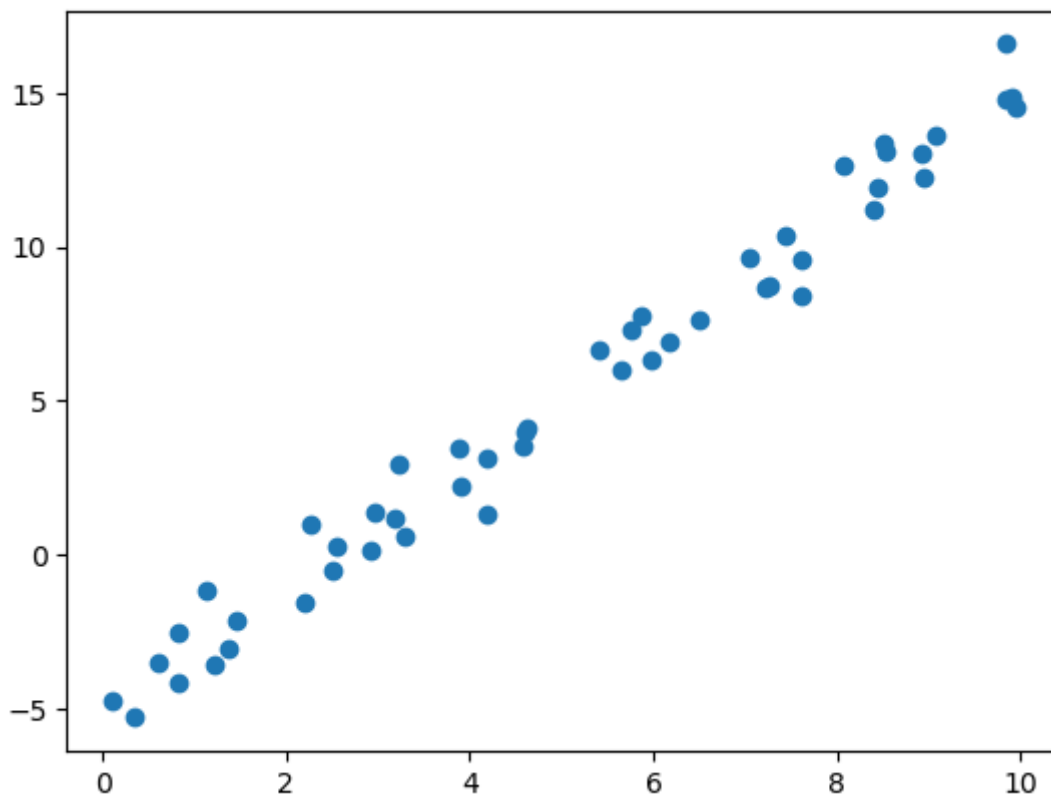
```
In [12]: import pandas as pd
import numpy as np
```

```
In [13]: %matplotlib inline
import matplotlib.pyplot as plt
```

```
In [14]: import seaborn as sns; sns.set
```

```
In [19]: # y=numpy.random.rand(y0, y1, ..., yn);
# x=numpy.random.rand(x0, x1, ..., xn);
rng = np.random.RandomState(1)
x=10*np.random.rand(50)
y=2*x-5+0.9*rng.randn(50)
plt.scatter(x,y)
```

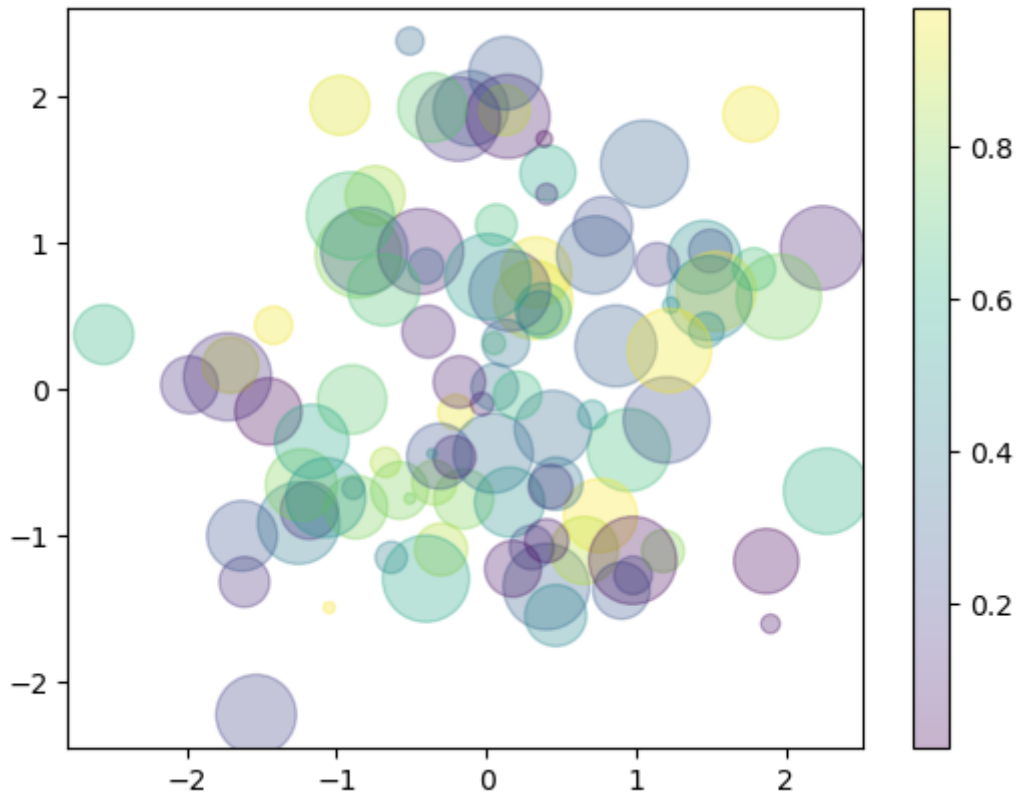
```
Out[19]: <matplotlib.collections.PathCollection at 0x7fe963f50130>
```



It appears that in this example, x and y values have a positive relationship. Positive relationships have points that incline upwards to the right. As x values increase, y values increase. As x values decrease, y values decrease.

```
In [16]: rng = np.random.RandomState(0)
x = rng.randn(100)
y = rng.randn(100)
colors = rng.rand(100)
sizes = 1000 * rng.rand(100)
```

```
plt.scatter(x, y, c=colors, s=sizes, alpha=0.3,
            cmap='viridis')
plt.colorbar(); # show color scale
```



2. Next fit the one dimensional linear model $f(x) = \beta_0 + \beta_1 x + \epsilon$ and then plot your line $f(x) = \hat{\beta}_0 + \hat{\beta}_1 x$ overlaid upon the previous scatter plot of data.

```
In [4]: # from sklearn.linear_model import LinearRegression
# model = LinearRegression(fit_intercept=True)
# model.fit(x[:, np.newaxis], y)
# xfit = np.linspace(0, 10, 1000)
# yfit = model.predict(xfit[:, np.newaxis])
# plt.scatter(x, y)
# plt.plot(xfit, yfit)
```

```
In [5]: import numpy as np
from sklearn.linear_model
import LinearRegression
x = np.array([5, 15, 25, 35, 45, 55]).reshape((-1, 1))
x
y = np.array([5, 20, 14, 32, 22, 38])
y
```

```
Out[5]: array([ 5, 20, 14, 32, 22, 38])
```

```
In [6]: model = LinearRegression()
model.fit(x, y)
```

```
Out[6]: ▼ LinearRegression
LinearRegression()
```

```
In [7]: model = LinearRegression().fit(x, y)
```

```
In [10]: r_sq = model.score(x, y)
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"slope: {model.coef_}")
```

```
coefficient of determination: 0.715875613747954
intercept: 5.633333333333329
slope: [0.54]
```

```
In [11]: new_model = LinearRegression().fit(x, y.reshape((-1, 1)))
print(f"intercept: {new_model.intercept_}")
y_pred = model.predict(x)
print(f"predicted response:\n{y_pred}")
y_pred = model.intercept_ + model.coef_ * x
print(f"predicted response:\n{y_pred}")
x_new = np.arange(5).reshape((-1, 1))
x_new
y_new = model.predict(x_new)
y_new
```

```
intercept: [5.63333333]
predicted response:
[ 8.33333333 13.73333333 19.13333333 24.53333333 29.93333333 35.33333333]
predicted response:
[[ 8.33333333]
 [13.73333333]
 [19.13333333]
 [24.53333333]
 [29.93333333]
 [35.33333333]]
```

```
Out[11]: array([5.63333333, 6.17333333, 6.71333333, 7.25333333, 7.79333333])
```

```
In [ ]:
```