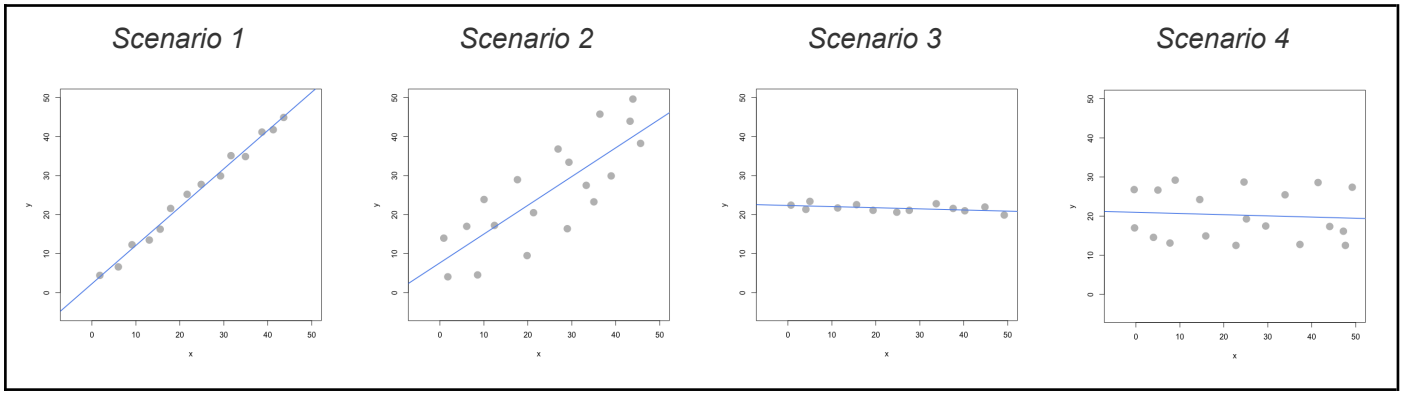
# BACS HW (Week 10)

**Question 1)** We will use the `interactive_regression()` function from CompStatsLib again – Windows users please make sure your desktop scaling is set to 100% and RStudio zoom is 100%; alternatively, run `R` from the Windows Command Prompt.

To answer the questions below, understand each of these four scenarios by simulating them:
Scenario 1: Consider a very narrowly dispersed set of points that have a negative or positive steep slope
Scenario 2: Consider a widely dispersed set of points that have a negative or positive steep slope
Scenario 3: Consider a very narrowly dispersed set of points that have a negative or positive shallow slope
Scenario 4: Consider a widely dispersed set of points that have a negative or positive shallow slope




a. Comparing scenarios 1 and 2, which do we expect to have a stronger $R^2$ ?
b. Comparing scenarios 3 and 4, which do we expect to have a stronger $R^2$ ?
c. Comparing scenarios 1 and 2, which do we expect has bigger/smaller SSE, SSR, and SST? (intuitively)
d. Comparing scenarios 3 and 4, which do we expect has bigger/smaller SSE, SSR, and SST? (intuitively)

**Question 2)** Let's analzye the `programmer_salaries.txt` dataset we saw in class. Read the file using `read.csv("programmer_salaries.txt", sep="\t")` because the columns are separated by tabs (`\t`).

a. Use the `lm()` function to estimate the regression model `Salary ~ Experience + Score + Degree`
Show the beta coefficients, $R^2$, and the first 5 values of $\hat{y}$ (`$fitted.values`) and $\varepsilon$ (`$residuals`)
b. Use only linear algebra and the geometric view of regression to estimate the regression yourself:
   *i.* Create an `X` matrix that has a first column of 1s followed by columns of the independent variables *(only show the code)*
   *ii.* Create a `y` vector with the Salary values *(only show the code)*
   *iii.* Compute the `beta_hat` vector of estimated regression coefficients *(show the code and values)*
   *iv.* Compute a `y_hat` vector of estimated $\hat{y}$ values, and a `res` vector of residuals *(show the code and the first 5 values of `y_hat` and `res`)*
   v. Using only the results from (i) – (iv), compute SSR, SSE and SST *(show the code and values)*
c. Compute $R^2$ for in two ways, and confirm you get the same results *(show code and values)*:
   i. Use any combination of SSR, SSE, and SST
   ii. Use the squared correlation of vectors $y$ and $\hat{y}$

*(see question 3 on next page)*

**Question 3)** We're going to look back at the early, heady days of global car manufacturing, when American, Japanese, and European cars competed to rule the world. Take a look at the data set in file `auto-data.txt`. We are interested in explaining what kind of cars have higher fuel efficiency (`mpg`).

1. mpg: miles-per-gallon (dependent variable)
2. cylinders: cylinders in engine
3. displacement: size of engine
4. horsepower: power of engine
5. weight: weight of car
6. acceleration: acceleration ability of car
7. model_year: year model was released
8. origin: place car was designed (1: USA, 2: Europe, 3: Japan)
9. car_name: make and model names

Note that the data has missing values ('?' in data set), and lacks a header row with variable names:

```
auto <- read.table("auto-data.txt", header=FALSE, na.strings = "?")
names(auto) <- c("mpg", "cylinders", "displacement", "horsepower", "weight",
                 "acceleration", "model_year", "origin", "car_name")
```

a. Let's first try exploring this data and problem:
    i. Visualize the data as you wish (report only relevant/interesting plots)
    ii. Report a correlation table of all variables, rounding to two decimal places
    (in the `cor()` function, set `use="pairwise.complete.obs"` to handle missing values)
    iii. From the visualizations and correlations, which variables appear to relate to `mpg`?
    iv. Which relationships might not be linear? *(don't worry about linearity for rest of this HW)*
    v. Are there any pairs of independent variables that are highly correlated ($r > 0.7$)?
b. Let's create a linear regression model where `mpg` is dependent upon all other suitable variables
*(Note: `origin` is categorical with three levels, so use `factor(origin)` in `lm(...)` to split it into two dummy variables)*
    i. Which independent variables have a 'significant' relationship with mpg at 1% significance?
    ii. Looking at the coefficients, is it possible to determine which independent variables are the *most effective* at increasing mpg? If so, which ones, and if not, why not? (hint: units!)
c. Let's try to resolve some of the issues with our regression model above.
    i. Create *fully standardized* regression results: are these slopes easier to compare?
    (note: consider if you should standardize `origin`)
    ii. Regress mpg over each *nonsignificant* independent variable, individually.
    Which ones become significant when we regress `mpg` over them individually?
    iii. Plot the distribution of the *residuals*: are they normally distributed and centered around zero?
    (get the residuals of a fitted linear model, e.g. `regr <- lm(...)`, using `regr$residuals`