Klion Lab2

October 26, 2022

```
[1]: import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = (14,8)
```

1 E1: Generate N = 5000 points from this bivariate distribution and visualize them using a scatter plot. Plot histograms to show the marginal distributions of x_1 and x_2 .

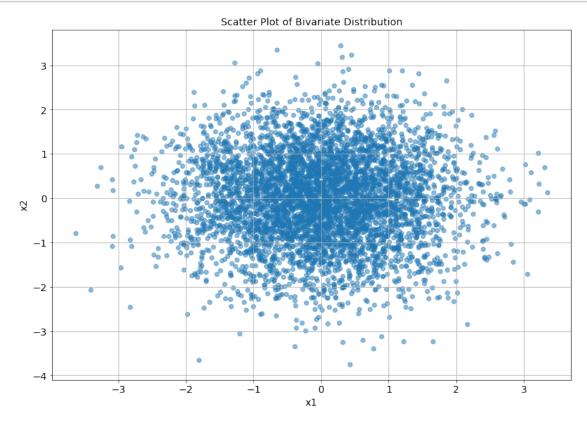
```
[22]: def bivariateDist(npts: int, mean: np.ndarray = [0, 0], cov: np.ndarray = [[1, __
       \hookrightarrow 0], [0, 1]], isPlot: bool = False):
          Create a bivariate normal distribution with given mean and variance
          Params:
              npts: number of points to sample from distribution
              mean: 1-D array of the mean of each variable (default: [0, 0])
              cov: 2-D array analogous to variance of 1d normal dist (default: [[1,\sqcup
       (0, 1]
              isPlot: bool
          Returns:
              out: The samples drawn of shape (npts, )
          rng = np.random.default_rng()
          pts = rng.multivariate_normal(mean, cov, npts)
          x1, x2 = pts[:, 0], pts[:, 1]
          if isPlot:
              plt.figure(figsize=(13,9))
              plt.tick_params(labelsize=14)
              plt.scatter(x1, x2, alpha = 0.5)
              plt.title("Scatter Plot of Bivariate Distribution", fontsize = 14)
              plt.xlabel("x1", fontsize = 14)
              plt.ylabel("x2", fontsize = 14)
```

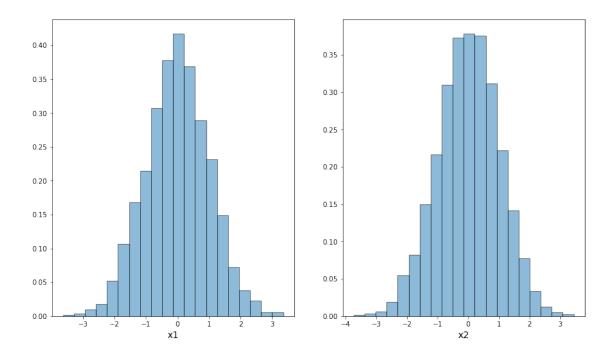
```
plt.grid()
  plt.show()
return x1, x2
```

```
[3]: #draw 5000 samples from the bivariate distribution
x1, x2 = bivariateDist(5000, isPlot=True)

#histogram of x1
plt.subplot(121)
plt.hist(x1, 20, alpha = 0.5, density = True, label = 'x1', edgecolor = 'k')
plt.xlabel('x1', fontsize = 14)

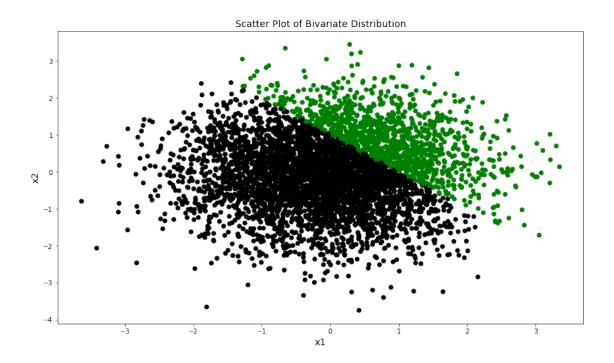
#histogram of x2
plt.subplot(122)
plt.hist(x2, 20, alpha = 0.5, density = True, label = 'x2', edgecolor = 'k')
plt.xlabel('x2', fontsize = 14)
plt.show()
#plt.hist([x1, x2], 20, density = True, label = ['x1', 'x2'])
```





2 E2: For the samples generated in E1, show/highlight only the points $x_1 + x_2 \ge 1$.

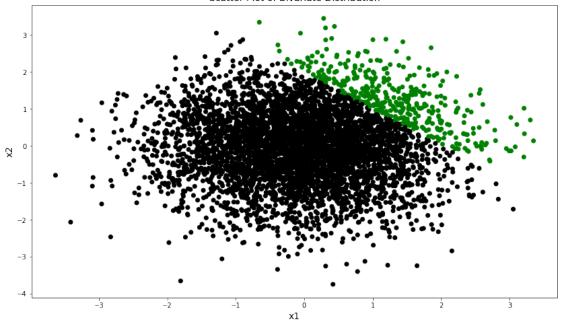
```
[4]: import matplotlib as mpl
cond1 = (x1 + x2 >= 1) #highlighting condition
my_cmap = mpl.colors.ListedColormap(['k', 'green']) #green if cond met,
otherwise black
plt.scatter(x1, x2, c = cond1, cmap = my_cmap)
plt.title("Scatter Plot of Bivariate Distribution", fontsize = 14)
plt.xlabel("x1", fontsize = 14)
plt.ylabel("x2", fontsize = 14)
plt.show()
```



3 E3: Repeat E2 for a more stringent selection criteria: $x_1 + x_2 \ge 2$.

```
[7]: cond2 = (x1 + x2 >= 2) #highlighting condition
plt.scatter(x1, x2, c = cond2, cmap = my_cmap)
plt.title("Scatter Plot of Bivariate Distribution", fontsize = 14)
plt.xlabel("x1", fontsize = 14)
plt.ylabel("x2", fontsize = 14)
plt.show()
```





Var[x1[cond]] 0.5516015311448879

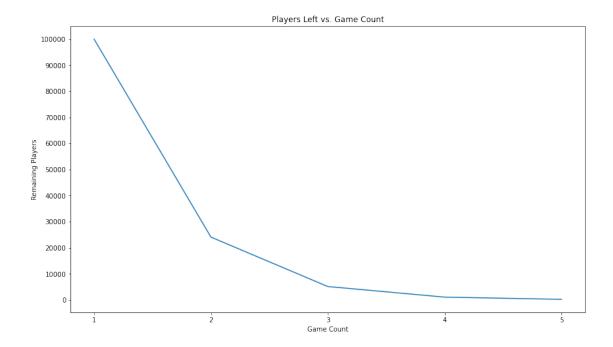
The more stringent condition makes the correlation between skill and luck that much more negative while also lowering the variance slightly.

4 E4: Write a program to model a dynamic game that shows the paradox of skill

```
[13]: def gameModel(numPlayers: int, cutoff: float, mean: float, std: float):
    #create an instance of the default RNG generator
    rng = np.random.default_rng()
    #fix skill level at game start
    skillLvls = rng.normal(mean, std, numPlayers) #x1

#start current player skills equal to starting number of player skills
```

```
#currSkills = skillLvls
          #create an array to store surviving players and their skills per game number
          survivors, survSkillMean, survSkillVar = [], [], []
          #game ends when less than cutoff of original players left
          ''' while len(currSkills) > (cutoff * numPlayers):
              survivors.append(len(currSkills))
              #draw fresh luck for each player each game
              luckLvls = rng.normal(mean, std, len(currSkills))
              #calculate the mean skill level for threshold
              mu = np.mean(currSkills)
              threshold = currSkills + luckLvls >= 1 + mu
              currSkills = currSkills[threshold]'''
          while len(skillLvls) > (cutoff * numPlayers):
              survivors.append(len(skillLvls))
              #draw fresh luck for each player each game
              luckLvls = rng.normal(mean, std, len(skillLvls))
              #calculate the mean skill level for threshold
              mu = np.mean(skillLvls)
              #calculate the variance of the skill level
              var = np.std(skillLvls)
              #append post values to an array for future plotting
              survSkillMean.append(mu)
              survSkillVar.append(var)
              #threshold of success for continuation in game
              threshold = skillLvls + luckLvls >= 1 + mu
              #apply threshold
              skillLvls = skillLvls[threshold]
          return survivors, survSkillMean, survSkillVar
      totPlayers = 100000
      playerCts, meanSkill, varSkill = gameModel(totPlayers, 0.001, 0, 1)
[18]: gameCount = range(1, len(playerCts) + 1)
      ystep = totPlayers / 10 #get 10 yticks for better idea on number players
       →remaining
      plt.plot(gameCount, playerCts)
      plt.xticks(gameCount)
      plt.yticks(np.arange(0, totPlayers + ystep, ystep))
      plt.xlabel('Game Count')
      plt.ylabel('Remaining Players')
      plt.title("Players Left vs. Game Count")
      plt.show()
```



```
[21]: plt.plot(gameCount, meanSkill, label = 'skill level mean')
   plt.plot(gameCount, varSkill, label = 'skill level variance')
   plt.xticks(gameCount)
   plt.xlabel('Game Count')
   plt.ylabel('Skill of Remaining Players')
   plt.title("Mean and Variance of Skill vs. Game Count")
   plt.legend(loc = 'upper left')
   plt.show()
```

