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import numpy as np
#Theoretical notes and considerations
#X is my conditional distribution
#Y is the probability of each Gaussian
#X | Y is one of the Gaussians
#Class to model the conditional Gaussian in our example
class Conditional Gaussian .
       #List of means and variances, the parameters of our Gaussians
       #List of probabilities of the random variables
                 _init__(self, means, variances, probabilities):
               if (sum (probabilities) != 1):
                     raise ValueError ("Probabilities do not respect probabilities axioms")
              if(len(probabilities) != len(means) & len(means) != len(variances) & len(probabilities) != len(variances)):
                      raise ValueError ("Not ok data")
              self.means = means
              self.variances = variances
               self.probabilities = probabilities
       \#E[X] = mean\_1 * probability\_1 + mean\_2 * probability\_2 + ... + mean\_n * probability\_n
       def get_conditional_mean(self):
              return np.dot(self.means, self.probabilities)
       \#Var(X) = E[Var(X|Y)] + Var(E[X|Y])
       def get_conditional_variance(self):
              #E[Var(X|Y)] = variance_1 * probability_1 + variance_2 * probability_2 + ... + variance_n * probability_n
              expected_variance = np.dot(self.variances, self.probabilities)
              #Let's call it mu
              computed_mean = self.get_conditional_mean()
               \#Var(E[X|Y]) = (mean\_1 - mu) \land 2 * probability\_1 + (mean\_2 - mu) \land 2 * probability\_2 + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + \ldots + (mean\_n - mu) \land 2 * probability\_n + (mean\_n - mu)
              variance_of_expectation = np.dot(list(map(lambda x: (x-computed_mean)**2, self.means)), self.probabilities)
              return expected_variance + variance_of_expectation
       def sample(self):
               #We use random.choices to choose from which Gaussian to sample.
               #We extract one specific Gaussian basing on the probability.
              index = random.choices(range(len(self.probabilities)), weights=self.probabilities)[0]
              From the documentation:
                      The period is 2**19937-1.
                      It is one of the most extensively tested generators in existence.
                      The random() method is implemented in C, executes in a single Python step,
                      and is, therefore, threadsafe.
              mean = self.means[index]
              variance = self.variances[index]
              return random.gauss(mean, np.sqrt(variance))
myvar = ConditionalGaussian([-2, 4, 10, 15], [2, 1, 3, 2], [0.15, 0.25, 0.35, 0.25])
print("Theoretical mean: " + str(myvar.get_conditional_mean()))
print("Theoretical variance: " + str(myvar.get_conditional_variance()))
#number of samples to draw
N = 1 000 000
samples = []
for i in range(N):
      samples.append(myvar.sample())
empirical_mean_dataset, empirical_var_dataset = np.mean(samples), np.var(samples)
print("Dataset mean: " + str(empirical_mean_dataset), "\nDataset variance: " + str(empirical_var_dataset), "\n")
#Conclusions: both mean and variances computed on the dataset of the samples meet with theoretical evidences
print(f"Absolute error in mean {abs(empirical_mean_dataset-myvar.get_conditional_mean())}")
print(f"Absolute error in variance {abs(empirical_var_dataset-myvar.get_conditional_variance())}")
print(f"Relative error in mean {abs(empirical_mean_dataset-myvar.get_conditional_mean()) / abs(myvar.get_conditional_mean())) ")
print(f"Relative error in variance {abs(empirical_var_dataset-myvar.get_conditional_variance()) / abs(myvar.get_conditional_variance())}")
```