

accent. Alexa always confuses it with 2:59 when I ask her, with my French accent, to set an alarm at 2:39 to go pick up my son at school. A simple fix in this case would be for Alexa to learn directly from me, recognize her error as I train her, and then get it fixed for good. This has the benefit to let Alexa adapt to each customer, offering customized chats rather than relying only on a central training set. Finding counter-examples to your system, to make it fail, in essence to crack it, is referred to as **adversarial learning** [Wiki]. It helps you better understand how your black-box works, and by integrating these tricky cases, it helps you improve your system.

Finally, **generative adversarial networks** (GANs) [Wiki] are popular in computer vision. Given a training set, this technique learns to generate new data with the same statistics as the training set. For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics. To identify a fake GAN-generated picture from a real one of the same person based on iris parameters, see [52].

16.7.1 Sensitivity analysis, bias reduction and other uses of synthetic data

Synthetic data was originally developed as a method to replace missing values with synthetic ones: this is known as **imputation** [Wiki]. It did not work well as the missing values typically don't follow the underlying statistical model. A potential solution is as follows. Use real or synthetic data (ideally, both) and remove some values to emulate a data set with missing values. Then replace the missing values by synthetic ones. Try with a large number of parameter-driven simulations to see which parameter values are best at producing meaningful missing values. Another benefit of synthetic data is its ability to test model resilience: replace some real observations in your **validation set** with synthetic ones, and see how your predictions are sensitive to this change. Eliminate models that show lack of resilience. This is an easy way to reduce **overfitting**.

Another use of synthetic data is for **bootstrapping** [Wiki] or to compute **confidence regions** based on **parametric bootstrap**. Numerous examples are included in this book: see the keywords in question in the index. This simulation-heavy technique requires a large amount of data generated with the same parameter values as those estimated on your original data set. Also, synthetic data is used to benchmark and test algorithms. Again, this book features numerous examples. It is also used to correct for imbalanced data or to reduce algorithm biases, by over-sampling from groups or segments with few observations or representing minorities. The example in section 16.7.2 shows how to generate synthetic data at the group level, rather than globally. It allows you to choose how many observations you want to generate, for each group.

The technique must be properly implemented to reduce **algorithmic bias** [Wiki] that penalizes minorities. When using copulas, see the issues in section 16.7.2.1. A solution is to add extra features (say, education level) to your real data to better capture the nuances of a population segment that is consistently penalized as a whole (high crime area), to detect sub-segments that do well. Then you can compute a separate copula for sub-segments such as college-educated in high crime area.

Finally, for authors and publishers, synthetic images can mimic and replace copyrighted ones, eliminating licensing fees and authorization issues. Synthesized art is called **AI art**. The question is: who owns it? Can you own randomly generated patterns or numbers?

16.7.2 Using copulas to generate synthetic data

One method to generate data with the exact same correlation structure and same marginal distributions as in your real dataset is to use **copulas** [Wiki]. The algorithm to produce n synthesized observations is as follows:

- Step 1: Compute the correlation matrix W associated to your real data.
- Step 2: Generate n deviates from a multivariate Gaussian distribution with zero mean and covariance matrix W . Each deviate is a vector Z_i ($i = 1, \dots, n$), with the components matching the features in the real data set.
- Step 3: For each generated Z_{ij} (the j -th feature in your i -th vector) compute $U_{ij} = \Phi(Z_{ij})$, where Φ is the CDF (cumulative distribution function) of a univariate standard normal distribution. Thus $0 \leq U_{ij} \leq 1$.
- Step 4: Compute $S_{ij} = Q_j(U_{ij})$ where Q_j is the univariate **empirical quantile distribution** (the inverse of the **empirical distribution**) attached to the j -th feature, and computed on the real data.

Assuming W is non singular, your set of feature vectors S_i ($i = 1, \dots, n$) is your synthesized data, mimicking your real data set. I implicitly used the Gaussian copula here, but other options exist. This method is a direct application of **Sklar's theorem** [Wiki]. There are various ways to measure the similarity or distance between the synthetic and real version of the data. In this context, the **Hellinger distance** [Wiki] is popular. See also section 6.4 on comparing two datasets. However these metrics lead to **overfitting**: the best synthetic data being an exact replica of the real data. Having statistical summaries matching those in the real data as in Table 16.4, combined with the worst Hellinger score, leads to richer synthetic data. In the end, the quality

Statistic	Real data	Synthetic 1	Synthetic 2
Mean age	39.21	39.21	38.61
Min age	18	18	18
Max age	64	64	64
Mean bmi	30.66	30.97	30.79
Min bmi	15.96	17.29	16.11
Max bmi	53.13	47.74	52.98
Mean charges	13,270	13,516	13,253
Min charges	1122	1137	1126
Max charges	63,770	49,993	59,588
Stdev charges	12,110	12,330	12,132
Correl age, bmi	0.11	0.06	0.09
Correl age, children	0.04	0.02	0.03
Correl age, charges	0.30	0.29	0.30
Correl bmi, charges	0.20	0.14	0.18
Stdev children	1.21	1.19	1.20

Table 16.4: Comparing real data with two different synthetic copies

should be measured by the improvement obtained when making predictions for the **validation set**, after adding your synthetic data to the training set.

In Python, the four steps of the algorithm are performed respectively with the functions `np.corrcoef`, `np.random.multivariate_normal`, `norm.cdf` and `np.quantile`. Except for `norm.cdf` (CDF of standard Gaussian distribution) which comes from the Scipy library, the other ones are implemented in Numpy. To generate the exact same synthetic data each time you run the program, use `np.random.seed` with the same **seed**.

Finally, a few Python libraries deal with copulas, for instance **Copulalib** and **Copulas**. See also **SDV** (the Synthetic Data Vault, in Python) for more options including deep learning. The Python program `copula.py` on my GitHub repository (main folder) shows how it works. It is also possible to avoid copulas and deal directly with the correlation matrix, as in section 7.2.1. Or ignore correlations altogether, and simply add uncorrelated white noise to each feature: this may be the easiest way to generate synthetic data. This approach is significantly superior to copulas to generate synthetic values outside the range observed in the real data. It also preserves the correlation structure, and in some sense, generates richer data. Another popular method is **rejection sampling** [Wiki].

16.7.2.1 The insurance dataset: Python code and results

I used the algorithm in section 16.7.2 to synthesize the insurance dataset shared on Kaggle, [here](#). The spreadsheet [insurance.xlsx](#) on GitHub (main folder) summarizes all the findings, and contains three datasets: the real data, synthetic data that I produced with `insurance.py` (same folder), and synthetic data generated by Mostly.ai. The dataset has the following fields: age, sex, bmi (body mass index), number of children covered by plan, smoker (yes or no), region (Northeast and so on), and charges incurred by the insurer for the customer in question.

I don't know what algorithm Mostly.ai uses, but their synthetic copy of the real data is strikingly similar to mine. Both have all the hallmarks (quality and defects) of being copula-generated. My version is slightly better because I generated a different copula (and thus, a different correlation matrix) for each group of observations. I grouped the observations by sex, smoker status and region while Mostly.ai applied the same copula across all these groups. Automatically detecting the groups as large homogeneous **nodes** in a decision tree, combined with using a separate copula for each node, would lead to an **ensemble method** not unlike the **boosted trees** described in chapter 2. By large node, I mean a node with many observations (enough to compute a meaningful correlation matrix and empirical quantiles) but little depth to avoid overfitting. The nodes are detected on the real data.

Table 16.4 provides some high-level summary statistics: Synthetic 1 is produced by Mostly.ai, and Synthetic 2 using the methodology described here. The correlation structure is well reconstituted. Synthetic 2 is better than Synthetic 1 for “Max charges” (the maximum computed over all observations) because it generates separate copulas for each group. Also, this feature has a bimodal distribution.

The sore point is that copulas are unable to generate values outside the range observed in the real dataset:

this is evident when looking at the maxima and minima. All data sets have the same number of observations. Even when I increase the number of synthesized observations by a factor 100, I am still stuck with a maximum charge less than \$63,770, even though this ceiling is not an outlier in the real data. The same is true with “age”, although this is compounded by the fact that ages 18 and 64 are cut-off points. The issue is that the quantile functions Q_j in section 16.7.2 generate values between the minimum and maximum observed in the real data, for each feature j . A workaround is to introduce uncorrelated white noise either in the real or synthetic data.

The Python code in this section can be optimized for speed as follows: pre-compute the empirical quantiles functions associated to each feature in the real dataset, as well as the CDF of the standard Gaussian distribution. In other words, use a table of pre-computed values. Note that the empirical quantiles in my method need to be computed separately for each group. Except for “bmi”, the features in the insurance dataset are highly non-Gaussian: “charges” is bimodal, “number of children” has a geometric (discrete) distribution, and “age” is uniform except for the extremes.

```
import csv
from scipy.stats import norm
import numpy as np

filename = 'insurance.csv' # make sure fields don't contain commas
# source: https://www.kaggle.com/datasets/teertha/ushealthinsurance dataset
# Fields: age, sex, bmi, children, smoker, region, charges

with open(filename, 'r') as csvfile:
    reader = csv.reader(csvfile)
    fields = next(reader) # Reads header row as a list
    rows = list(reader) # Reads all subsequent rows as a list of lists

#-- group by (sex, smoker, region)

groupCount = {}
groupList = {}
for obs in rows:
    group = obs[1] + "\t" + obs[4] + "\t" + obs[5]
    if group in groupCount:
        cnt = groupCount[group]
        groupList[(group, cnt)] = (obs[0], obs[2], obs[3], obs[6])
        groupCount[group] += 1
    else:
        groupList[(group, 0)] = (obs[0], obs[2], obs[3], obs[6])
        groupCount[group] = 1

#-- generate synthetic data customized to each group (Gaussian copula)

seed = 453
np.random.seed(seed)
OUT=open("insurance_synth.txt", "w")
for group in groupCount:
    nobs = groupCount[group]
    age = []
    bmi = []
    children = []
    charges = []
    for cnt in range(nobs):
        features = groupList[(group, cnt)]
        age.append(float(features[0])) # uniform outside very young or very old
        bmi.append(float(features[1])) # Gaussian distribution?
        children.append(float(features[2])) # geometric distribution?
        charges.append(float(features[3])) # bimodal, not gaussian
    mu = [np.mean(age), np.mean(bmi), np.mean(children), np.mean(charges)]
    zero = [0, 0, 0, 0]
    z = np.stack((age, bmi, children, charges), axis = 0)
    corr = np.corrcoef(z) # correlation matrix for Gaussian copula for this group

    print("-----")
    print("\n\nGroup: ", group, "[", cnt, ", obs ]\n")
    print("mean age: %2d\nmean bmi: %2d\nmean children: %1.2f\nmean charges: %2d\n"
```

```

    % (mu[0],mu[1],mu[2],mu[3]))
print("correlation matrix:\n")
print(np.corrcoef(z), "\n")
nobs_synth = nobs # number of synthetic obs to create for this group
gfg = np.random.multivariate_normal(zero, corr, nobs_synth)
g_age = gfg[:,0]
g_bmi = gfg[:,1]
g_children = gfg[:,2]
g_charges = gfg[:,3]

# generate nobs_synth observations for this group
print("synthetic observations:\n")
for k in range(nobs_synth):
    u_age = norm.cdf(g_age[k])
    u_bmi = norm.cdf(g_bmi[k])
    u_children = norm.cdf(g_children[k])
    u_charges = norm.cdf(g_charges[k])
    s_age = np.quantile(age, u_age) # synthesized age
    s_bmi = np.quantile(bmi, u_bmi) # synthesized bmi
    s_children = np.quantile(children, u_children) # synthesized children
    s_charges = np.quantile(charges, u_charges) # synthesized charges
    line =
        group+"\t"+str(s_age)+"\t"+str(s_bmi)+"\t"+str(s_children)+"\t"+str(s_charges)+"\n"
    OUT.write(line)
    print("%3d. %d %d %d %d" % (k, s_age, s_bmi, s_children, s_charges))
OUT.close()

```

16.8 Advice to beginners

In this section, I provide guidance to machine learning beginners. After finishing the reading and the accompanying classes (including successfully completing the student projects), you should have a strong exposure to the most important topics, many covered in detail in this book. At this point, you should be able to pursue the learning on your own – a never ending process even for top experts – in particular with the advice provided in section 16.8.1.

16.8.1 Getting started and learning how to learn

The first step is to install Python on your laptop. While it is possible to use Jupyter notebooks instead [Wiki], this option is limited and won't give you the full experience of writing and testing serious code as in a professional, business environment. Installing Python depends on your system. See the official Python.org website [here](#) to get started and download Python. On my Windows laptop, I first installed the Cygwin environment (see [here](#) how to install it) to emulate a Unix environment. That way, I can use Cygwin windows instead of the Windows command prompt [Wiki]. The benefit is that it recognizes Unix commands. An alternative to Cygwin is [Ubuntu](#). You could also use the [Anaconda](#) environment.

Either way, you want to save your first Python program as a text file, say `test.py`. To run it, type in Python `test.py` in the command window. You need to be familiar with basic file management systems, to create folders and sub-folders as needed. Shortly, you will need to install Python libraries on your machine. Some of the most common ones are `pandas`, `scipy`, `seaborn`, `numpy`, `random` and `matplotlib`. You can create your own too, as illustrated in section 5.4.3. In your Python script, only use the needed libraries. Typically, they are listed at the beginning of your code, as in the following example:

```

import numpy as np
import matplotlib.pyplot as plt
import moviepy.video.io.ImageSequenceClip # to produce mp4 video
from PIL import Image # for some basic image processing

```

To install (say) the `numpy` library, type in `pip install numpy` in the Windows command prompt.

16.8.1.1 Getting help

One of the easiest ways to learn more and solve new problems using Python or any programming language is to use the Internet. For instance, when I designed my sound generation algorithm in Python (see section 16.1), I