Find the relative frequency for the b grade

Twenty students were asked how many hours they worked a day. Their responses in hours are as follows: 5, 6, 3, 3, 2, 4, 7, 5, 2, 3, 5, 6, 5, 4, 3, 5, 2, 5, 3. The following table shows the different values of the data in ascending order and their frequencies. Frequency table of student working hours FREQUENCY VALUE 2 3 3 5 4 3 5 6 2 7 1 In this research, 3 students studied for 2 hours. 5 students study for 3 hours. Frequency is the number of occurrences of a data value. According to the table, there are three students who work two hours, five students who work three hours, and so on. The sum of the values in the frequency column of 20 represents the total number of students included in the sample. A relative frequency is the ratio (fraction or proportion) of the number of occurrences of a data value in me of all results to the total number of results. To find relative frequencies, separate each frequency by the total number of students in the sample -in this case, 20. Relative frequencies can be written as fractions, percentages, or decimal places. Relative frequency = [latex]\frac{\text{class}}}{\text{total}}[/latex] Cumulative relative frequency is the accumulation of previous relative frequencies. To find cumulative relative frequencies, add all previous relative frequencies to the relative frequency for the current row, as shown in the following table. Kumulativní relativní frekvence = součet předchozích relativních frekvencí + frekvence aktuální třídy Příklad 1 Frekvenční tabulka studentských pracovních hodin s relativními a kumulativními relativními frekvencemi FREKVENCE DAT RELATIVNÍ FREKVENCE RELATIVNÍ FREKVENCE KUMULATIVNÍ RELATIVNÍ FREKVENCE 2 3 [latex]\frac{3}{20}[/latex] nebo 0,15 0,15 3 5 [latex]\frac{5}{20}/latex] nebo 0,25 0,15 + 0,25 = 0,40 4 3 [latex]\frac{3}{20}[/latex] nebo 0,15 0,40 + 0,15 = 0,55 0,55 0, 5 [latex]\frac{6}{20}[/latex] nebo 0,30 0,55 + 0,30 = 0,85 6 2 [latex]\frac{2}{20}[/latex] nebo 0,10 0,85 + 0.0.10 = 0,95 7 1 [latex]\frac{1}{20}[/latex] nebo 0,05 0,95 + 0,05 = 1,00 Poslední položka kumulativního sloupce relativní frekvence je jedna, což znamená, že bylo nashromážděno sto procent dat. Example 2 We will taste the height of 100 footballers. The result is given below. Height (inches) Frequency 59.95 - 61.95 5 61.95 - 63.95 3 63.95 - 65.95 15 65.95 - 67.95 40 67.95 - - 69.95 17 69.95 – 71.95 12 71.95 – 73.95 7 73.95 – 75.95 1 Total = 100 Find: a. relative frequency for each class.b. percentage for a height that is less than 63.95 inches. c. percentage for height that is between 69.95 inches and 73.95 inches. In this sample, five players whose heights fall to an interval of 59.95-61.95 inches, three players whose heights fall to an interval of 61.95-63.95 inches, 15 players whose heights fall within an interval of 63.95-65.95 inches, 40 players whose heights fall an interval of 65.95-67.95 inches, 17 players whose heights fall within the 67.95-69.95-69.95-inch interval. 12 players whose heights fall within an interval of 69.95-71.95, seven players whose height falls within the interval of 71.95–73.95, and one player whose heights fall within the interval of 73.95-75.95, All heights fall between the end points of the interval and not the end points. Example 3 The table shows the amount of annual rainfall in inches in a sample of cities. Precipitation (inches) Frequency 2.95 - 4.97 6 4.97 - 6.99 7 6.99 - 9.01 15 9.01 - 11.03 8 11.03 - 13.05 9 13.05 - 15.07 5 Find the relative frequency and cumulative relative frequency for each class. percentage of heights that fall between 61.95 and 65.95 inches. The table shows the total number of earthquake deaths worldwide between 2000 and 2012. Year Total deaths 2000 231 2001 21 357 2002 11 685 2003 33 819 2004 228 802 2005 88 003 2006 6 605 2007 712 2008 88 011 2009 1 790 2010 320 120 2011 21 953 2012 768 Total 823 356 What is the frequency of deaths measured from 2006 to 2009? What percentage of deaths occurred after 2009? What is the relative frequency of deaths that occurred in 2003 or earlier? What is the percentage of deaths that occurred in 2004? What kind of data is the number of deaths? Richter scales are used to quantify the energy produced by earthquakes. Examples of Richter scale numbers are 2.3, 4.0, 6.1, and 7.0. What kind of data are these numbers? Example 4 The table shows the total number of motor vehicle fatalities in the United States between 1994 and 2011. Year Total number of accidents Year Total number of accidents 1994 36 254 2004 38 444 1995 37 241 2005 39 252 1996 1999 637 494 2006 38 648 1997 37 324 2007 37 435 1998 37 107 2008 34,0 0 72 1999 37 140 2009 30 862 2000 37 526 2010 30 296 2001 37 862 2 2011 29 757 2002 38 491 Total 653 782 2003 38 477 What is the frequency of deaths measured between 2000 and 2004? What percentage of deaths occurred after 2006? What is the relative frequency of deaths that occurred in 2000 or earlier? What is the percentage of deaths that occurred in 2011? What is the cumulative relative frequency for 2006? Explain what this number will tell you about the data. In order to continue to enjoy our site, we ask you to confirm your identity as a person. Thank you very much for your cooperation. The Alan Anderson Frequency Distribution shows the number of elements in the data set that belong to each class. In a relative frequency distribution, the value assigned to each class is a proportion of the total data set that belongs to the class. For example, suppose the frequency distribution is based on a sample of 200 supermarkets. It turns out that 50 of these supermarkets charge a price between and $8.99 a pound of coffee. In a relative frequency distribution, the number assigned to this class would be 0.25 (50/200). In other words, that's 25 percent of the total. Here is a useful formula for calculating the relative frequency of a class: The frequency of a class refers to the number of observations in each class; n represents the total number of observations in the entire dataset. For example, the supermarket has a total number of observations of 200. The relative frequency can be expressed as a percentage (fraction) of the total or as a percentage of the total. For example, the following table shows the distribution of gas price frequencies at 20 different stations. Frequency Distribution of prices for 20 gas stations ($/Gallon) Number of gas stations $3.50-$3.74 6 $3.75-$3.99 4 $4.00-$4.24 5 $4.25-$4.49 5 Based on this information, you can use the relative frequency formula to create another table that displays the relative frequency of prices in each class, both as a fraction and as a percentage. Relative frequency for gas station prices Gas prices ($/Gallon) Number of pumping stations Relative frequency (fraction) Relative frequency (percentage) $3.50-$3.74 6 6/20 = 0.30 30% $3.75-$3.99 4 4/20 = 0.20 20% $20 4.00-$4.24 5 5/20 = 0.25 25% $4.25-$4.49 5 5/20 = 0.25 25% With a sample size of 20 petrol stations, the relative frequency of each class is equal to the actual number of service stations divided by 20. The result is then expressed as a fraction or percentage. For example, you calculate a relative price frequency between $3.50 and $3.74 as 6/20 to get 0.30 (30 percent). Similarly, the relative price frequency between $3.75 and $3.99 is equal to 4/20 = 0.20 = 20 percent. One of the advantages of using relative frequency distribution is that you can compare data sets that do not necessarily contain the same number of observations. For example, suppose a researcher is interested in comparing the distribution of gas prices in New York and Connecticut. Since New York has a much larger population, it also has many more gas stations. The researcher decides to select 1 percent of gas stations in New York and 1 percent of gas stations in Connecticut for a sample. Turns out it's 800 in New York and 200 in Connecticut. The researcher compiles the frequency distribution as shown in the following table. Frequency Distribution of gas prices in New York and Connecticut Price New York Gas Station Connecticut Gas Station $ 3.00- $3.49 210 48 $3.50-$3.99 420 96 $4.00-$4.49 170 56 Based on this frequency distribution, it's embarrassing compared to distribution prices in two states. Converting this data to a relative frequency distribution greatly simplifies the comparison, as shown in the final table. Relative Frequency Of Gas Price Distribution in New York and Connecticut Price New Gas Station Relative Frequency Connecticut Gas Station Relative Frequency $3.00-$3.49 210 210/800 = 0.2625 48 48/200 = 5 0.2400 $3.50-$3.99 420 420/800 = 0.2400 $3.50-$3.9 9,420,420/800 = 0.0.05250 96 96/200 = 0.4800 $4.00-$4.4.00 49 170/800 = 0.2125 56 56/200 = 0.2800 Results show that the distribution of gas prices in both states is almost identical. Roughly 25 percent of gas stations in each state charge a price between $3.00 and $3.49; about 50 percent charge a price between $3.50 and $3.99; and about 25 percent charge a price between $4.00 and $4.49. The relative frequency distribution shows the proportion of the total number of observations associated with each value or class of values and is related to the probability distribution, which is widely used in statistics. From: Statistical Methods (third edition), 2010Rudolf J. Freund, ... Donna L. Mohr, in statistical methods (third edition), 2010Very little information about the properties of recently sold houses can be obtained by random glance into table 1.2. We might be able to conclude that most homes have brick exteriors, or that the sale price of a home ranges from $30,000 to $395,000, but much more information about this dataset can be obtained using some fairly simple organizational tools. To provide more information, we create a frequency breakdown by grouping data into categories and counting the number of observations that fall within each of them. Because we want to count each house only once, these categories (called classes) are designed so that they do not overlap. Because we count each observation only once, if we add up the number (called frequencies) of houses in all classes, we get the total number of houses in the dataset. Nominally scaled variables naturally have these classes or categories. For example, the exter variable has three values, Brick, Frame, and Next. Processing sequence, interval, and ratio measurements can be a little more complicated, but as the subsequent discussion shows, we can easily process this data simply by defining classes correctly. Once the frequency distribution is created, it is usually presented in tabular form. For the exter variable from table 1.2, we get the frequency distribution shown in Table 1.4. Note that one of our first impressions is evidenced by the fact that 48 of the 69 houses are brick, while only 8 have frame exteriors. This simple summary shows how the frequency of exteriors is divided into exter values. Table 1.4. ExterexterFrequencyBrick48Frame8Other13Definition 1.10A frequency distribution is a list of frequencies of all categories of observed variable values. We can create frequency distributions for any variable. For example, Table 1.5 shows the layout of the zip variable, which, despite the numerical values, is in fact Variables. This frequency distribution is produced by Proc Freq from the SAS system, where the frequency distribution is displayed in the frequency column. Apparently the area represented by zip code 4 has the most homes for sale. Table 1.5. Distribution zipzipFrekvencyTHE FREQ PROCEDURECumulative percentageCentpercentCumulative Frequency168.7068.7021318.841927.5431623.1935 50.7243449.2869100.00Alcent 1.11A relative frequency distribution consists of relative frequencies or proportions (percentages) of observations belonging to each category. Relative frequencies expressed as percentages are listed in Table 1.5 under the heading Percentage and are useful for comparing frequencies between categories. These relative frequencies have a useful interpretation: They give a chance or probability of getting observations from each category in a blind or random draw. Therefore, if we randomly infer observations from the data in Table 1.2, there is an 18.84% chance that it will be from zip area 2. For this reason, the relative frequency distribution is often referred to as the observed or empirical probability distribution (Chapter 2). Creating a frequency distribution of a numeric variable is a little more complicated. Defining individual variable values as categories usually creates only a list of original observations, because very few, if any, individual observations will usually have the same values. Therefore, it is common to define categories as intervals of values called class intervals. These intervals must be unsteered and usually each class interval is the same size with respect to the measurement scale. The frequency distribution of the variable price is given in Table 1.6. Obviously, the predominance of houses is in the range of 50- to 150-thousand dollars. Table 1.6. House price distribution at intervals of $50,000RangeFrequencyTHE FREQ PROCEDURECumulative PercentPercentCumulative Frequencyless than 50k45.8045.8050k to 100k2231.882637.68100k to 150k23333.334971.101150k to 200k1014.495985.51200k up to 250k22.906188.41250k up to 300k11.456289.86300k up to 350k45.806695.300k11.456289.86300k up to 350k45.806695.300k11.456289.86300k up to 350k45.806695.300k11.456289.86300k to 3 50k45.806695.306695.30 65350k to 400k34.3569100.00A cumulative frequency group in Table 1.6 is a cumulative frequency distribution that indicates the frequency of observed values less than or equal to the upper limit of this class interval. So, for example, 59 homes are priced at less than $200,000. The Cumulative Percentage column is a cumulative relative frequency distribution that indicates the percentage (percentage) of observed values less than the upper limit of this class interval. So 59 homes priced at less than $200,000 account for 85.51% of the number of homes offered. Later, we will see that cumulative relative frequencies - especially those approaching 0 and 100% - can be of considerable importance. Using the principle that an image is thousands of words (or numbers), the information in the frequency distribution is easier to grasp when presented in graphic form. The most common graphical presentation of frequency distribution for numeric data is a histogram, while the most common presentation of nominal, categorical, or discrete data is a bar chart. Both of these charts are constructed in the same way. The heights of vertical rectangles represent a frequency or relative frequency. In the histogram, the width of each rectangle represents the size of the class, and the rectangles are usually contiguous and the same width so that the rectangles areas reflect the relative frequency. In a bar chart, the width of the rectangle has no meaning; however, all rectangles should be the same width to avoid distortion. Figure 1.1 shows the frequency bar graph for the exter from Table 1.2, which clearly shows a large proportion of brick houses. Figure 1.2 shows a frequency histogram at a price that clearly shows the predominance of homes selling from 50 to 150 thousand dollars. FIGURE 1.1. Bar chart for exter. FIGURE 1.2. Histogram of the price. The next distribution presentation is provided by a pie chart, which is simply a pie divided into a number of slices whose sizes correspond to the frequency or relative frequency of each class. We've created these charts with different programs and options that show that while there may be slight differences in appearance, the basic information remains the same. FIGURE 1.3. Pie chart for relative zip frequency distribution The use of graphs and graphs is ubiquitous in news media, business and economic news, and government news and publications, mainly due to the ease of storing, searching, manipulating, and summaring large data sets using modern computers. For this reason, it is extremely important to be able to critically evaluate the information contained in a chart or chart. After all, a graphic presentation is simply a visual impression that is quite easily distorted. In fact, bias is so easy and commonplace that in 1992 the Canadian Institute of Chartered Accountants deemed it necessary to begin setting guidelines for financial graphics, after a study of hundreds of annual reports by large corporations reported nearly 10% of reports contained at least one misleading chart that masked adverse data. Whether intentional or honest errors, it is very easy to mislead with an incorrectly presented chart or chart. In a book called How to Lie with Statistics (1982), Darrell Huff illustrates many such charts and charts and discusses various questions about misleading charts. In general, a properly assembled chart or chart should have 1.all the wass marked correctly, with clearly identifiable scales, 2.be with subtitles correctly, 3.have bars rectangles of the same width to avoid distortion,4.have digit sizes correctly proportional, a5.contain only relevant information. Histograms of numerical variables provide information about the shape of the distribution, a characteristic that we will later see as important in carrying out statistical analyses. The shape is roughly defined by drawing a reasonably smooth line over the tops of the bars. In such a distribution representation, the region of the highest frequency is known as the vertex and end as tails. If the tails are approximately the same length, the distribution is said to be symmetrical. If the split on the right side has an elongated tail, the split is bemended to the right and vice versa. Other properties can consist of a sharp peak and long thick tails or a wide peak and short tails. We see that the price distribution is slightly sly to the right, which in this case is due to several unusually high prices. Later, we will see that recognizing the shape of the distribution can be very important. We continue to study the shapes of distributions with another example. Example 1.3Discipline of forest science is a frequent user of statistics. An important activity is the collection of data on the physical properties of a random sample of trees in the forest. The resulting data may be used to estimate the potential yield of the forest, to obtain information on the genetic composition of a particular species or to investigate the impact of environmental conditions. Table 1.7 is a list of these data. This set consists of measuring three characteristics of 64 sample trees of a particular species. The researcher would like to summarize this set of data in graphic form to help its interpretation. Table 1.7. Data on Tree MeasurementsOBSDFOOTHCRNHT14.11.524.523.44.725.034.42.829.043.65.127.054.41.626.563.91.927.073.65.327.084.37.628.094.81.128.5103.51.226.0114.32.328.0124.81.728.5134.52.030.0144.82.028.0152.91.120.5165.62.231.5174.28.029.3183.76.327.2194.63.027.0204.22.4254.424.0254.4254.32.0254.6242.73.0204.5242.73.0206.31.820.6275.01.724.6285.21.826.9294.71.526.7303.83.226.3313.82.627.3282.926.2364.11.325.8373.53.224.0384.81.726.5394.60.5405.11.627.0413.71.425.9425.03.029.5433.32.425.8444.33.025.2454.7 we z Table 1.7, the data set consists of 64 observations of three ratio variables. The three variables are measurements that characterize each tree and are identified by short mnemonic identifiers in the column headings as follows:1.DFOOT, the diameter of the tree on one leg above level, measured in inches,2.HCRN, height to the base of the crown measured in feet, a3. HT, total tree height measured in feet. The histogram for height (HT) of 64 trees is shown in Fig. Due to spatial constraints, not all class interval boundaries are displayed, but we can throw away that the default PROC INSIGHT option brought a class width of 1.5 feet, with the first interval being from 8.25pm to 9.75pm and the last from 30.75 to 32.25. In this program, the user can adjust the size of class intervals by clicking on the arrow at the bottom left (not shown in Fig. 1.4), which causes a menu to appear allowing such changes. For example, by changing the first tick to 20, the last to 32, and the tick interval to 2, the histogram will have 6 classes instead of 8 displayed. Many graphics programs allow this type of interactive editing. Of course, the basic shape of distribution does not change with these adjustments. Also note that in these histograms the legend gives boundaries of intervals; other graphics programs can give center points. FIGURE 1.4. Histogram of tree height. The histogram of the variable HCRN is shown in Fig. Now we can see that the distribution of HT is slightly squandered to the left, while the distribution of HCRN is quite heavily squandered on right.R.H. Riffenburgh, in statistics in medicine (Third edition), 2012Number 3.4 shows the relative frequency of distribution of tumor sizes of 115 liver cancers. Overlap with the same diameter (2.77 cm) and standard deviation (1.01 cm). Let's μ, for example, the standard σ shorthand. We ask what percentage of tumors is more than 5 cm. If we are willing to accept a normal curve as a probabate distribution of liver tumor sizes, the probability of a tumor greater than 5 cm is the proportion of the curve greater than 5. The value of 5 cm lies 5−2.77=2.23 cm to the right of μ. How σ is that? 2.23/1.01=2.21σ to the right of μ. Table 6.1 shows the area in the right tail to the right of 2.20 is 0.014. About 1.4% of tumors are larger than 5 cm.As further illustrations of what percentage of tumors is less than 1 cm? 1 cm lies 2.77−1=1.77 cm or 1.77/1.01=1.75 σ to the left of μ. Because the normal curve is symmetrical, the area below the curve to the left of μ-1.75σ is the same as the area to the right of μ+1.75σ. (This provides the information in the half table for so long.) From table 6.1, 1.75σ gives an area in the middle between 0.045 and 0.036, or about 4% of tumors are less than 1 cm.Figure 6.2 shows figure 3.4 with a 4% area to the left of 1 cm shaded black. Similarly, we could calculate that 1.4% of tumors exceed 5 cm.Figure 6.2. Figure 3.4 reproduced with a 4 % area to the left of the 1 cm shaded black.R.H. Riffenburgh, in statistics in medicine (Third edition), 2012So look for Figure 3.2, the relative frequency of distribution of the tumor size sample, we see that it is not far from symmetrical and bell-shaped. Does this result from a normal probability distribution? Figure 3.4 repeats the frequency distribution with an overlapping normal probability distribution. Although it is clearly not exactly in line with the normal shape, the frequency distribution is not far away. Later chapters will look at ways to test whether the frequency distribution is normal and slightly switched off as a result of a change in randomness in sampling or is unlikely to result from a normal distribution. Figure 3.4. Relative frequency of tumor size in 115 patients with liver cancer with a normal probate curve (symmetrical bell-shaped) with the same diameter and standard deviation. Chapter 4 will examine the properties of probability distribution and present the most frequently seen types that are abundantly used in the statistical method. Michel Jambu, in exploratory and multivariate data analysis, 1991This types of graphics are commonly used to represent frequency distributions: pie chart; a part bar chart and a bar chart (or a bar chart or bar chart). A pie chart is formed as follows:(a)base is a circle that represents 100% of the relative frequency distribution;(b)the angle is associated with each form i, which is proportional to the relative frequency fi = ni /N.Figure 3.8 shows an example of a pie chart based on table 3.5.Figure 3.8. Pie chart for answering a question: How many times a week do you use the Minitel phone service? Advantages: the percentage of each response is clearly represented. Cons: Graphics are not very accurate when the percentage is too small. It cannot be used to compare chronological variables. The component bar chart is formed as follows:(a)the basis is a rectangle that represents 100% of the relative frequency distribution;(b)the subrectangle is associated with each z form; the lengths of the temporary folds are proportional to the relative frequencies fi = ni / N.Figure 3.9 shows an example of a bar chart of a component based on table 3.5.Figure 3.9. Part bar chart for answering a question: How many times a week do you use Minitel phone service? A bar chart consists of as follows:(a)the rectangle is associated with each form i; the lengths of the rectangles are proportional to the relative frequencies fi = ni / N;(b)rectangles have the same width (the common width has no meaning), but are unrelated (do not overlap);(c)when the forms are also sorted by mathematical relationship, a cumulative bar chart can be drawn. Figure 3.10 shows an example of a bar chart based on Table 3.5.Figure 3.10. Bar chart of answers to the question: How many times a week do you use your Minitel phone H. RIFFENBURGH, in statistics in medicine (second edition), 20062.1.Pro range of body resection in DB12, a) select intervals to record, (b) sort data, (c) find median and (d) convert sum to relative frequency distribution. (e) They shall comment on whether the division appears to be almost normal. If not, in what characteristics do they differ? f) Give a visual estimate (without calculation) of the mean diameter and mode. How these conditions are compared with the median observed in (c)?2.For the age of the patient in DB12, select the intervals for the sum and (b) calculate the data. Compared to c) record the median when data were added up for 25 patients, then 50, 75, 100 and all patients. The mean shall be plotted according to the number of data taken similar to plot 2.2. Do the median converge to the final median? (d) Convert the sum to relative frequency distribution. (e) They shall comment on whether the division appears to be almost normal. If not, in what characteristics do they differ? f) Give a visual estimate (without calculation) of the mean diameter and mode. How are these values compared with the final median found in (c)?2.3.For the international normalized ratio (INR) values from the clinic in DB13, (a) select intervals for the sum, (b) match the data, (c) find the median, and (d) convert the sum to relative frequency distribution. e What does the median say compared to the average = 2.40 α symmetry?2.4.For the INR values from the laboratory in DB13, a) select the intervals for the sum, b) add up the data, c) find the median and d) convert the sum to relative frequency distribution. e) What does the median say compared to the average = 2.28 α symmetry?2.5.For computational ease, use glycosaminoglycan levels (GAG) for the type 1 test in DB8 rounded to 1 decimal place: 0,7,0.4, 0,3,0,2. Calculate (a) dispersion and (b) authoritable odchylka.2.6.Pro and computational ease use glycosaminoglycan levels (GAG) for a type 2 test in DB8 rounded to 1 decimal place: 0.5, 0.5, 0.4, 0.3. Calculate (a) dispersion and (b) the investigator's standard deviation.2.7.As, you want to make a conclusion from DB3 on whether the drug affects serum theophyline levels (5 days). From section 2.7, what steps would you go through?2.8.As an investigator, you want to draw a conclusion from DB14 about whether there is a difference in exhaled nitric oxide before exercise for 20 minutes after zero. From section 2.7, what steps would you go through?2.9.Squares of 60 plasma silicone levels in DB5 are (×104): 225, 169, 1521 400 1521 1764 576 324 144 676, 100, 121 225 361 729 784, 121 121 324 324 576 2304 484 729 361 324 1024 961 361 441 441 576 100 144,784,625,484,441,529,484,484, 576,1444,2025,529,484,324 , 225, 16, 196, 576, 400, 324, 576, 225, 361, 676, 900, 484, 576. Plot the relative distribution of the frequency of these squares intervals: 0-0.02, 0.02−0.04, ..., 0.22−0.24. Does it look more like a normal or chi-square probability in section 2.8? Why?2.10.For inr data from the clinic in DBI3, plot the frequency distribution at intervals of 0.25 in width. (This can be done in Exercise 2.3.) Is it more similar to normal or chi-square probability distribution?2.11.If we were to conclude on the average differences between preoperative and postoperative plasma levels of silicon in DB5, what would be df ? In order to mean into t statistics, we subtract what value, and then we separate what statistics? To decide whether t is significantly larger than zero, we choose a cut point greater than which t is significant and less than which t is not significant. As we say this cut point?2.12.If we were to conclude on the average differences between clinical and laboratory INR data in DB13, what would be df?2.13.Assign ranks (small to large) to platelet count in DB9.2.14.Assign ranks (small to large) to bone density values in DB? Patient 18 has a bone density reading much less than the others. How does this affect the distribution of readings? This also applies to the evaluation of values?2.15.If we would like to draw a conclusion about the proportion of patients suffering from nausea in DB2, what distribution would we use in this conclusion?2.16.If we wanted to draw a conclusion about the proportion of patients in DB12 who died after 2 cm or less of carious resection , what distribution would we use?2.17.Calculation of the SEM sample of rounded GAG levels (0.7, 0,4,0.3,0,2) for the type 1 test in DB8.2.18.In DB10 , the time difference between the legs has an average = 0.16 and a standard deviation = 0.2868. Calculate SEM.2.19.In DB3, the two related default variables, and the 5-day theophyline levels differ together. If we counted the degree of difference between one and the other, what would his name be? ROBERT H. RIFFENBURGH, in medicine statistics (second edition), 2006Tally. A collection of markers, one for each base marked at the appropriate interval, within the range of possible occurrences of variable values. The shape of the completed sum is close to the frequency distribution shape. Frequency distribution. A pattern in which data is distributed along the scale (or line) of a variable of interest. The pattern frequency distribution appears as a sequence of bars of different heights, with match intervals being wide. Relative frequency distribution. The frequency distribution in which the height of the rod at each interval represents the proportion of the sample falling within that interval. Probability. The relative frequency at which an event occurs when all events in the population are given equal opportunities As the sample size increases and moves toward the population size, the relative frequency distribution tends to divide the probability of the population. Means. Average; the centre of gravity of the μ in the distribution of the probability of the population and m in the relative frequency distribution of the sample. Median. Average; the value of the variable for which half of the sample or population is smaller and half larger. Mode. Average; the value of the variable with the highest relative frequency. Midrange. Average; the midpoint between the smallest and largest values of the variable that occur. (The probability distribution with one or both tails that extend without binding, e.g. normal distribution, is not middle class.) Derogation. Degree of variability; average (medium) quadrarous deviations from the sample or the mean value population. Deviation. Degree of variability; square root of the dispersion. The purpose is to place the degree of variability in the same units as observation and diameter. Skewness. The rate of distribution asymmetry. If one tail is stretched more than the other, the distribution is bemmed (e.g. right tail stretched: right beaken). Derive. The final characteristics of the sample-based file. (This is a simplification, but it's the core of what is a complex concept.) Robustness. Characteristics of the statistic (summarising the calculation from the sample), in which the statistics are little influenced by a slight violation of the assumptions under which the statistics were created. Normal distribution. Family distribution of probability in the form of a bell. Standard distribution. Probability distribution or relative frequency distribution that has been transformed to have a diameter of 0 and a standard deviation of 1. This transformation is achieved by subtracting the mean value from each data element and dividing it by the standard deviation. Most often it is used in the standard normal distribution. Central limit phrase (CLT). Data from any distribution (regardless of its form) has an average, the distribution of which is approximately normal.t Distribution. A bell-shaped distribution, slightly wider than normal, occurs when the standardization divisor is the standard deviation of the sample, not the standard deviation of the population. (Student: nom de plume W. S. Gossetta, who derived the division.) Degrees of freedom (df). An integer related to the sample size that determines which member of the probability distribution family is appropriate in a particular case. Standard normal has only one member and does not use df, but t has many members and uses df. Chi-square (ꭓ2) Distribution. Correct the family of probability curves resulting from the deviation. Statistics: dispersion of the × dispersion ÷ the population indicator is distributed ꭓ2. F Distribution. Properly bemmed family křivky vyplývající z poměru dvou rozptylů vzorku. Závisí na dvou hodnotách df, jedné pro každou odchylku vzorku. Binomické rozdělení. Diskrétní rozdělení pravděpodobnosti relativní pravděpodobnosti výsledků události dvou kategorií, například hlavy nebo orel hodu mincí, přežití nebo smrt pacienta nebo úspěch nebo neúspěch léčby. Poissonova distribuce. Diskrétní rozdělení pravděpodobnosti relativní pravděpodobnosti výsledků dvoukapitálové události, když je jedna z události vzácná, například počet otců rozrušit vzácnou nemocí z národa. Standardní chyba střední (SEM). Směrodatná odchylka střední hodnoty vzorku. Ve většině případů se jedná o směrodatnou odchylku pozorování vzorku dělenou druhou odmocninou velikosti vzorku. Distribuce společné frekvence. Vzor, ve kterém jsou data distribuována ve dvourozměrné rovině dvou simultánních měřítek (nebo os), které představují dvě proměnné zájmu. Každá proměnná má střední a směrodatnou odchylku, jak to bylo samo, ale existuje také kovariance (nebo korelace: kovariance dělená dvěma směrodatnými odchylkami) mezi dvěma proměnnými představujícími sílu jejich vztahu. Laurent Hodges, v metodách experimentální fyziky, 1994Mnoho rozdělení pravděpodobnosti, které se vyskytují ve vědě, mají tvar známé křivky ve tvaru zvonu znázorněné na obrázku 6. Toto je standardní normální (nebo Gaussovo) rozdělení pravděpodobnosti:Obr. Standardní funkce normální hustoty f(x; 0, 1). (2.7)f(z;0,1)=12πe−z22(definovaný pro -∞ <z<∞This continuous= distribution= is= most= easily= recognized= as= the= limiting= shape= of= the= discrete= binomial= distributions= as= the= number= of= trials= n→∞= as= may= be= seen= by= comparing= figure= 6= with= figure= 2(a).the= standard= normal= distribution= shown= in= figure= 6= has= mean= μ=0 and= variance= σ2=1. however,= it= can= be= generalized= to= the= probability= density= function= for= an= normal= random= variable= x= with= parameters= μ= and= σ,= where=></∞This> <> and= σ=>0), který má <>=The constant in front of the exponential function, known as the normalization constant, is chosen to ensure that the integral of f(x;μ,σ) from -∞ to +∞ is exactly 1. The mean of the normal distribution is E(X)=μ and its variance is V(X)=σ2, which is why the two parameters are given the symbols μ and σ.Tables for the normal distribution are given in terms of the standard normal random variable Z with mean 0 and variance 1, whose probability density function is the standard normal density function given in Eq. (2.7). Any normal random variable X can be converted to a standard normal random variable by the substitutionIt is then possible to make calculations of functions of, and integrals involving, X by making the substitutionsThe cumulative distribution function for the standard normal distribution is an important constant= in= front= of= the= function,= known= as= the= normalization= constant,= is= chosen= to= ensure= that= the= integral= of= f(x;μ,σ)= from= -∞= to= +∞= is= exactly= 1.= the= mean= of= the= normal= distribution= is= e(x)=μ and= its= variance= is= v(x)=σ2,= which= is= why= the= two= parameters= are= given= the= symbols= μ= and= σ.tables= for= the= normal= distribution= are= given= in= terms= of= the= standard= normal= random= variable= z= with= mean= 0= and= variance= 1,= whose= probability= density= function= is= the= standard= normal= density= function= given= in= eq.= (2.7).= any= normal= random= variable= x= can= be= converted= to= a= standard= normal= random= variable= by= the= substitutionit= is= then= possible= to= make= calculations= of= functions= of,= and= integrals= involving,= x= by= making= the= substitutionsthe= cumulative= distribution= function= for= the= standard= normal= distribution= is= an= important></∞The constant in front of the exponential function , known as the normalization constant, is chosen to ensure that the integral of f(x;μ,σ) from -∞ to +∞ is exactly 1. The mean of the normal distribution is E(X)=μ and its variance is V(X)=σ2, which is why the two parameters are given the symbols μ and σ.Tables for the normal distribution are given in terms of the standard normal random variable Z with mean 0 and variance 1, whose probability density function is the standard normal density function given in Eq. (2.7). Any normal random variable X can be converted to a standard normal random variable by the substitutionIt is then possible to make calculations of functions of, and integrals involving, X by making the substitutionsThe cumulative distribution function for the standard normal distribution is an important > tvar(2.8)f(x;μ,σ)=12πσe−(x−μ)22σ2Where—≪<x<∞> tvar(2.8)f(x;μ,σ)=12πσe−(x−μ)22σ2Where—≪<>, is an important(2.9)P(Z≤z)=Φ(z)=∫−∞zf(y;0,1)dy=12π∫−∞ze−y22dyΦ(z)Cumulative The distribution of the function for normal distribution with an average μ and a variance of σ2 is then found (using previous substitutions), which is after the normal density of the function is symmetrical in x-μ,Φ(0)=0.5.Table II shows some important special cases of this cumulative standard normal distribution. Přibližně 68 % hodnot v běžném souboru obyvatelstva leží v rámci jedné směrodatné odchylky (σ) střední μ, přibližně 95 % leží se dvěma směrodatnými odchylkami μ a přibližně 99,7 % leží ve třech směrodatných odchylkách μ. Tabulka II. Special Values of the Normal and Standard Normal Cumulative Distribution Functionsx − μzΦ(z)−3.08σ−3.080.0010−3Cσ−30.0013−2.58σ−2.580.0050−2.33σ−2.330.0100−2σ−20.0227−1.96σ−1.960.0250−1.645σ−1.6450.0500−1.28σ−1.280.1000−σ− 10.1587000.5000+ σ+ 10.8413+ 1.28σ+ 1.280.9000+ 1.645σ+ 1.6450.9500+ 1.96σ+ 1.960.9750+ 2σ+ 20.9773+ 2.33σ+ 2.330.9900+ 3σ+ 30.9987+ 3.08σ+ 3.080.9990The term percentile, as in 50th percentile or 95th percentile, is often used with normal distributions: it denotes the value of the random variable such that the cumulative distribution function at that value is 0.50, or 0.95. Percentile 100(1-α)th, for 0<α<1, therefore, the value zα (or its corresponding xα) for which Φ(zα)=1-α. From Table II it can be seen that 90 percentile corresponds z = 1.28 (orx = μ + 1.28σ), percentile99th to z = 2.33 and so on. Figure 7(a) shows two normal density functions for the same diameter (μ=0), but different variances (σ=0.8 and 0.4), while Figure 7(b) shows the corresponding normal cumulative distribution functions. (a) Normal probability density function for μ = 0 and σ = 0,4 and 0,8.b) Normal cumulative distribution functions for μ = 0 and σ = 0,4 and 0,8. Normal approximation to binomial distribution. It is often advisable to approximate discrete binomial distribution by continuous normal distribution. Let X be a binomial random variable based on n studies with a probability of success p. If the binomial probability histogram is not very snare, x has an approximate normal distribution with μ=np and σ=npq. Specifically, x is possible x, the cumulative binomial probability is (2.10)P(X≤x)=B(x;n,p)≈Φ(x+0.5−npnpq)which is the area below the normal curve to the left of x+0.5. In practice, this approximation is appropriate provided that both np≥5 and nq≥5. Figure 8 shows the binomial distribution for n = 20, p = 0.4, q = 1 − p = 0.6 to ether with normal approximation, using μ = np = 8 and σ=npq=2.19.Fig. Housing curve: normal probability density function for μ = 8, σ2 = np(1 − q) = 4.8. Histogram: binomial distribution for n = 20, p = 0.4. Experiments. Some examples are as follows:1.Repeated physical measurements, such as measuring the length of an object, are typically distributed. If there are no systematic errors in the measurements, the average of the measurement should be the actual value of the physical amount, and the dispersion is an indicator of the accuracy of the measurement method (the more accurate the method, the smaller the dispersion).2.The results of random samples from many large populations, such as adult heights in the general population, weights of children of first class, student grades in the test and so on, are usually distributed. (The key is that often these populations have relative distributions that are approximately Gaussus's.) 3.Any binomial distribution with n large enough to n is in a way that the distribution has continued for one of the other tasks and so on, are usually distributed the distribution that is very slicing is approximately normal as previously described. Example 2.5:A typical example of an experimental distribution that closely resembles a normal distribution is shown in Figure 9. Energy records for the three-month period were obtained for 368 single-family homes in a large metropolitan area, total energy consumption was determined by converting all fuels into the same energy units, and this energy consumption was then broken down by the number of heating grade days for the period covered by the energy records. The resulting amount, called final use heating consumption (EHC), has btus units (British heat units) per grade day. Related to the energy efficiency of households, homes with smaller EHC are more energy efficient.Fig. Histogram of final heat consumption values (units: 1000 Btd / degreeday) for 368 households in central Iowa.Normal distribution is very often found in science. Obviously, if a random X variable is normally distributed, the functions of this random variable (such as X2, X3, logX, and 1-X) will usually not be distributed normally. Sometimes it happens that a random variable emerging most naturally in a scientific situation is not normally distributed in itself, but a certain function of it is. For example, it is often found that while concentrations of air or water pollutants (such as sulphur dioxide in the air or phenol in river water samples) are not distributed in any way, their logarithms are. If the logarithm of random variable X is usually distributed, then X is said to be lognormally distributed. We had ln(x) represent the natural (basic e=2.71828...) logarithm x. The probability density function of this lognormal distributed random variable X is (2.11)P(X≤x)=F(x;μ,σ)=Φ(lnx−μ)σ forx >0=0σ forx ≤0Where μ and σ2 are mean E(ln(X)) and variance V(ln(X)) are commonly distributed random variables ln(X). It should be noted that μ and σ2 are not mean and the dispersion of lognormal distributed variable X. Variable X will have an E(X)=eμ+σ2/2 diameter and V(X)=e2μ+σ2(eσ2-1). The diameter of variable X is called its arithmetic mean. Quantity eμ is an important quantity, known as geometric diameter X; geometric diameter X is clearly always smaller than the arithmetic mean.X Cumulative distribution function of logarily random variables can easily be expressed as cumulative distribution function Φ(z) standard normal random variables. For xi0, the cumulative distribution function(2.12)P(X≤x)=F(x;μ,σ)=Φ(lnx−μ)σforx >0=0forx≤0Octeture 10 displays logarithmic-probability functions for cases (μ,σ)=(1.1) and (2, 1). Compared to a normal variable, a logarithmic variable is more likely in the right tail: very large values of logarithmial variables are much more common than for normal variables.Fig. a) Logarithmic probability density function for (μ, σ) = (1), 1) and (2, 1). (b) Loganormal cumulative distribution functions for the same two sets of parameters. Example 2.6Figure 11(a) shows the distribution of nearly 7,000 measurements of radon concentrations in the air in the basements of homes in Iowa. From the obliqueness of distribution, it is clear that radon concentrations are not normally distributed. However, Figure 11 b shows the distribution of logarithms by radon concentrations; this distribution is similar to normal distribution.Fig. and Histogram of radon concentrations in 6926 basements in Iowa. (b) Histogram of logarithms of the same radon concentrations. As a result of the fact that radon concentrations are approximately lognormally distributed, the geometric diameter of radon concentrations is a more meaningful distributional sum than the arithmetic mean. For example, one extra large concentration of radon found in one house can have a drastic effect on the arithmetic diameter, but will have little effect on the geometric diameter. Another commonly observed continuous probability distribution is exponential distribution. It is defined by the exponential density function(2.13)f(x;λ)=λe−λxforx≥0=0forx<0The mean= of= this= distribution= is= e(x)=1/λ and= the= variance= is= v(x)=1/λ2. The= cumulative= distribution= function= for= the= exponential= distribution= is= easy= to= calculate= by= direct= integration:= the= probability= that= the= random= variable= has= a= value= s≤x is(2.14)p(x≤x)=f(x;λ)=1−e−λxforx≥0=0forx<0Depositions 12(a) show two exponential density functions corresponding to λ=1 and 2, while figure 12 shows the corresponding cumulative distribution functions.Fig. Function of exponential probability density for λ = 1 and λ = 2. (b) Exponential cumulative distribution function for λ = 1 and λ = 2.One of the most common applications of this distribution include time as a random variable, in which case the random variable is generally marked T instead of </0The>X. One such application is radioactive decay, which we first described in connection with the Poisson division. When radioactive decay was introduced there, we considered a large number of nuclei and were interested in the number of decays observed at finite time intervals, such as 1 sec or 1 min. Now let's look instead at the probability that each kernel at t=0 will disintegrate within a certain time interval t1<t<t2, for example, within the first second. Radioactive decay was found to be a purely stochastic process, not a deterministic process. There is no way to accurately predict when a given core will disintegrate. However, there is a certain probability p that the core will disintegrate within the first second, so the probability of surviving the first second is 1-p. If he survives the first second, then he has exactly the same probability of p tightening during the next second, so the probability of surviving two seconds is (1-p)2. In general, the probability of survival of N seconds is (1-p)N. Survival function that has this shape is exponential: S(t)=e-λt. If we focus not on the survival function S(t), but on the function 1-S(t), this function takes the form of 1-e-λt. This is the probability that the core will have disintegrated over time t. This function takes the exact form of the exponential cumulative distribution function Eq. (2.14). The exponential density of the λe-λt function thus represents the function of probability density for the period of decay of individual nuclei. Note that this function is proportional to the S(t) survival function introduced earlier. Parameter λ that governs exponential decay is related to the half-life of radioactive material, which is defined as the time when individual nuclei will have a 50% chance of decay. With regard to the half-life of t1/2 we must have, which implies that t1/2=(ln2)λ=0.693/λ.To the extent that radioactive decay can be considered as a Poisson process, exponential distribution occurs in another way: in a large sample with many nuclei. the distribution of elapsed time between the occurrence of two consecutive decays is exponential with the same λ parameter. Poisson'3.An processes are further discussed in Chapter 3.An an important feature of exponential distribution is its memoryless function: the shape of the probability density function is the same beginning at any x value, which means that the distribution has no memory of where (or when) it began. Mathematically, this can be expressed by stating that the conditional probabilityThis condition leads directly to an exponential distribution, which is therefore a single distribution with a property that is memory-free. In the case of radioactive decay, the memory-free property corresponds to the fact that the rate of decay (probability of decay per unit time interval) is Cores. If the component failure rate is modeled by an exponential distribution, the memoryless property corresponds to a failure that is age-independent, i.e. a failure that is independent of age. Failure rates that do not have a memory-free property are described in the Section on Weibull distribution. Example 2.7Virtually all naturally occurring uranium atoms on earth are isotopes uranium-235 and uranium-238. The isotope uranium-235 has × half-life of 7.1 and 108 years and a quantity of 0.711%, while the isotope uranium-238 has × half-life of 4.51 and 109 years and a quantity of 99,283%. Both isotopes have been decomposing since the Earth formed about 4.6 million years ago 109 ×. How many of each isotope originally present fell apart, and what was the relative amount of both isotopes when the earth was young? When converting known half-lifes to λ speed parameters, we find that λ=9.76×10−10/year for uranium-235 and λ=1.54×10−10/year for uranium238. The e-λt values for t=4,6x109 years are 0,0112 and 0,493. Thus, only 1.12% of the original uranium-235 is still present on the ground, but 49.3% of the original uranium-238 is. As a result, when the current ratio of uranium-235 to uranium-238 is 0.711 to 99.283, or 1 to 140, the ratio when the country was young must be 0.711/0.0112 to 99,283/0.493 or 1 to 3.2.Sometimes the experiment is characterized by a continuous random variable, the probability distribution of which best corresponds to a function involving two or more parameters, which allows greater freedom in experimental results. A useful distribution of this type is the Weibull distribution, a generalization of the exponential distribution introduced by Weibull [1]. Weibull distribution is the easiest to introduce in terms of cumulative distribution function, which takes the form(2.16)F(x;β,α)=1-e-(x/α)βforx≥0=0forx<0where α and β are parameters α and β positive. This function is easy to see to be generalized to the cumulative distribution function for exponential distribution, which corresponds to the β =1 option.The probability density function for the weibull distribution can then be obtained as a derivation of F(x;β,α) with respect to x:(2 .17)f(x;β,α)=βα-βxβ-1e-(x/α)βforx≥0=0forx<0When β=1, The Weibull distribution is reduced to an exponential distribution with the identification of the exponential parameter λ with 1/α.Parameter β is a shape parameter affecting the shape of the distribution, while α is a scale parameter that affects the scale. It is also possible to change the location of the Weibull distribution by replacing the variable x x-x0. The mean and dispersion of the Weibull distribution have complicated shapes:E(X)=αΓ(1+1β)andV(X)=α2[Γ(1+2β)−Γ2(1+1β)], where Γ(β)=∫0∞xβ-1e−xdx is gamma Weibull distribution is widely used at the time of modeling failure, because a large number of probability curve shapes can be generated by different choices of two parameters, β and α. Figure 13 gives three examples of Weibull distributions. Weibull distribution ranges from increasing exponential divisions to curves resembling normal divisions. The exponential distribution limit corresponds to a memory-free failure rate (the failure rate of an individual item is independent of its current age), while other Weibull distributions correspond to the distribution of fault times, which can peak at a certain age and bemoved in different modes.Fig. a) Weibull probability density functions for three sets of parameters: (β, σ) = (1, 0.2), (1,5,0,15) and (10.0,5). b) Weibull cumulative distribution functions for the same three sets of parameters. When installing Weibull distribution on experimental data, it is worth noting that from the cumulative distribution function F(x;β,α) Eq. (2.16) we can easily infer the relationship(2.18)ln(1-F(x;β) <<>>)=βln(x/α)=-βlnα+βlnxIt gives a straight line, when lnln[1-F(x;β,α)]-1 is rendered against ln x, a useful method for determining whether the Weibull distribution is appropriate and, if so, specifying the parameters β and α from the intersection and slope of the line. This image also identifies an exponential function by obtaining the β=1.A special property of the Weibull distribution, which is that the natural logarithm of the Weibull variable has the least extreme value, as described in Chapter 7.Example 2.8:An example of distribution by a well-fit Weibull distribution is plotted in Figure 14. A large number of 3,3 microfaradic solid tantalizing capacitors were operated continuously at high temperature to determine their failure rate [2]. It was found that 5% failed after 4 hours, 10% after 13 hours, 15% after 26 hours, 20% after 36 hours, 25% after 51 hours, 30% after 75 hours, 35% after 100 hours, 40% after 111 hours, 45% after 162 hours and 50% after 174 hours. Settings x = 4, 13, . . . , 174 and F = 0.05, 0.10, . . . , 0.50 and rendering[1-F(x;β,α)]-1versuslnxFig. 14. Graph of capacitor failure data [2]. The random variable is from hours to failure. The line corresponds to the choice of weibull distribution β = 0.70 and α = 310. The fact that the rendered values fit well into the straight line (which corresponds to (2.18) with β =0.70 and α = 310) shows that weibull distribution is suitable for modeling the failure rate of these capacitors. Nancy Brandon Tuma, in the Encyclopedia of Social Measurement, 2005Explorative analyses rely primarily on estimating the statistics defined in the previous section and then examining how estimates differ over time and across subsets of cases differentiated on the basis of the proposed Variables. These methods are especially useful in analyzing event history because patterns of variation over time and across cases are complex and are not easily captured by a single statistic. If true censorship occurs and is independent of the occurrence of the event studied, an estimate of the product limit S(t) proposed by E. L. Kaplan and Paul Meier (KM) in 1958 are impartial and asymptotically consistent:(8)S €KM(t)=∏t(i)<t[1(d(i)n(i))](</t)</t) where i-t refers to an event where events are arranged in an unit time schedule, t(i) indicates the time (i)th of the event, d(i) is the number of events that occurred in t(i), and n(i) is the number at risk just before t(i), which by convention includes events that are censored by convention to t(i). Although ŜKM(t) is a step function, connection estimates for subsequent time points by line segments usually gives an image that better reflects the actual survivor function, provided it is continuous. Greenwood's formula indicates asymptotic deviation S(t) at time t:(9)Var[S€KM(t)]=[S€KM(t)]2∑t(i)<t(d(i)n(i)[n(i)−d(i)])(t−1)</t</t). The equation (9) is often used to estimate the two-sided (1 - α)-100% point confidence interval of the probability of survival over time t:(10)SKM(t)±zα/2Var[S€KM(t)], where z has a standard Gaussian distribution. This formula implicitly assumes that the Kaplan-Meier estimate has a Gaussian distribution and asymptotically does so. Eq. (10) However, it underestimates the width of the confidence interval when the number at risk at time t is too small to use asymptotic properties. The pointwise confidence interval is the confidence interval at one time t. Typically, a simultaneous reliability band around S(t) is preferable to the time interval. Point confidence intervals βKM(t) and βKM(u) at the time t and you, respectively, are not statistically independent in estimating from the same data. As a result, reusing the Greenwood formula on a time point set using the same dataset overestimates the actual level of reliability and underestimates the actual bandwidth of reliability. Several authors have suggested ways to estimate the current trust band for ŜKM(t). All images of survivors [i.e. S(t) graphs versus time t] tend to look similar; S(t) equals 1 at the initial time and tends to fall to zero as t increases. All the plots of the survivors have approximately a backdeer shape of S. Due to their roughly similar shape, the surviving plots rarely give much insight into the process that is being studied. Analysts can identify selected percentile values for survival, such as when S(t) = 0.5 (half-life). If the observation period is long enough, and the land of the estate may also indicate well whether the CDF is defective. At the highest monitored times, S(t) is close to zero if the probability distribution is not defective, and non-zero asymptota if the distribution is defective. Since the probability of survival is an adjunct of CDF, an impartial and asymptotically consistent estimate of CDF 1 − ŝKM(t). A relative frequency distribution or event time histogram provides an empirical approximation to the event time probability density function. If censorship is extensive, relative frequency distribution provides a biased pdf estimate. There is no advisable to estimate the PDF in another way. For example, pdf can be estimated as the product of hazard and probability of survival estimates that consider censorship [see Eq. The H(t) estimate with good asymptotic properties was first proposed by Wayne Nelson in 1972 and proved as asymptotically impartial in 1978. This estimate, commonly called nelson-aalen (NA), is (11)HĖNA(t)=−lnS€NA(t)=∑t(i)<td(i)n(i),t(i-1)<t≤t(i). Except when the number of substances at risk is small at the time of t, The AM(t) differs only slightly from −ln ŝKM(t). The point confidence interval of the integrated hazard rate can be calculated by estimating its asymptotic dispersion:(12)Var[HĖNA(t)]=∑t(i)<t[d(i)n(i)[n(i)−d(i)]]2,t(i-1)<t≤t(i). Examining the integrated hazard estimates at time t provides useful information about the time change in the probability of an event. If the probability of an event does not change depending on time, the integrated hazard plotted against the time should be close to a straight line. If the integrated danger increases at an increasing rate as time increases (i.e. there is upward bending), it indicates that the probability of the event increases with time (mortality of older adults has this pattern). If the integrated hazard increases at a decreasing rate and then increases (i.e. it bends downwards), it indicates that the probability of an event decreases as time increases (the rate of marriage breakdown usually has this pattern). If the integrated danger increases at an increasing rate as time increases, but then shifts and increases with decreasing speed, it indicates that the level of danger is a non-tonic function of time (the speed of the first marriage has this pattern). If the integrated hazard increases at a decreasing rate and then keeps increasing, it also indicates that the level of danger is a non-totonic function of time and that it has the shape of a bath. In many cases, broad trends can be identified in how hazard rates change over time by directly estimating and plotting and plotting time, as described in the next section. However, empirical graphs of hazard rate estimates over time tend to be very jagged if the number of cases at risk and the number of events are quite large. When hazard level images are jagged, wide trends in time variability the speed of hazards can often be more easily identified by the integrated hazard rate graph over time, not by the hazard rate graph over time. There is no clear best estimate of the level of danger. One estimate is based on Kaplan-Meier's estimate of the probability of survival over time t:(13)ĦKM(t)=1Δt(i)ln[S(i)]-ln[S(i)]t(i-1)<t≤t(i). Another corresponds to Nelson-Aamann's estimate of H(t):(14)ĦNA(t)=1Δt(i)d(i)n(i),t(i−1)<t≤t(i). An earlier estimate, traditional with demographers, is life table estimate (LT):(15)ĦLT(t)=1Δt(i)d(i)n(i)−0.5d(i),t(i−1)<t≤t(i). The life table estimate was originally developed for applications that contain information about the risk number and number of events in a series of time intervals, but not the exact time of events. In the classic mortality application there are data on the number of live at the beginning of the interval (e.g. age a) and the number who die before the end of this interval (e.g. in the five-year interval from age and up to age + 5). Adjustment to d(i) in denominator Eq. (15) to be corrected in view of the fact that not all n(i) cases are at risk throughout the interval. Images of estimated hazard rates over time tend to be jagged, especially when the number of events at risk and the number of events are small. The smoothing of empirical estimates provides a better representation of the basic hazard level when it comes to the continuous functioning of time. The estimation of the service life table shall be smoothed by calculating the hazard speed for the time interval, not at the time point. Alternatively, smoothing algorithms can be used to estimate hazard rates in a set of adjacent time points in an analogous way to calculate the running average. If there are competitive risks (i.e. when multiple types of events may occur), the probability of a conditional transition, mk(t) can be estimated as other probabilities. For example, it can be estimated as the relative frequency of an event to occur between all events that occur at or around time t.The rate of transition to the state k, rk(t), is estimated using analogues on Eqs. (13)-(15), with the exception of d(i) in these equations is replaced by dk(i), the number of events consisting of transition to state at time t(i). For example, Nelson-Aalen's estimate of the rate of transition to k is:(16)rĒ(t)=1Δt(i)dk(i)n(i),t(i−1)<t≤t(i). Rudolf J. Freund, ... Donna L. Mohr, in statistical methods (Third edition), 2010A discrete probability distribution shows the probability associated with each value of the random variable Y. This display can be presented as a table, as illustrated by previous examples, such as a graph or as a formula. For example, the probability distribution in Table 2.6 can be expressed as a formula, also called a function, asp(y)=y−6,y=1,2,3,p(t)=0,for all other values y.It can be in graphic form, as shown in Fig. Bar chart of probability distribution in Table 2.6.Table 2.6. Distribution of discrete probabilities a formula p(s) that means the probability for discrete values of variable Y can be considered a probability distribution.All probability distributions listed above are displayed to meet both conditions. Since the empirical and theoretical probability distribution can be described by similar tables of relative frequencies and/or histograms, it is logical to expect that the numeric descriptors of both are the same. Because the theoretical distribution essentially describes the base file, the descriptors of those distributions are called parameters. For example, we use greek μ and σ for the mean and standard deviation of the theoretical probability distribution as well as for the empirical probability distribution referred to in point 1.5. Specifically, and its variance, which we refer to as σ2, is calculated as the place where the scale is valid Y values.For example, if the probability distribution in the measles example is valid, the average number of cases of measles in a couple who had measles calculated from the theoretical distribution is μ= 0 (0.64) + 1 (0.32) + 2 (0.04) = 0.4.That is, the average number of individuals per couple who had measles is 0.4 for the whole city. Dispersion isσ2=(0−0.4)2(0.64)+(1−0.4)2(0.32)+(2−0.4)2(0.04)=0.1024+0.1152+0.1024=0.320,and σ=0.566.The probability distribution average is often called the expected value of a random variable. For example, the expected number of individuals in a couple who had measles is 0.4. This is a long-range expectation in the sense that if we took a large number of couples, the expected (average) number of individuals who had measles would be 0.4. Note that the expected value can be (and often is) a value that a random variable can never reach. Now we can solve the problem faced by the expert in example 2.1. A random variable is the cost of replacing screws on one part for four results, which we calculate as follows:OutcomePossibilityCostA defective, B not defective 0.008 * 0.996 = 0.007968 $0.23A not defective, B defective 0.004*0.992= 0.003968$0.69Two screws defective 0.008*0.004= 0.000032$0.92The screw is not defective 0.992 * 0.996 = 0.988032 $0.00Now we can find the expected cost of replacing defective screws on one part:μ=0.23 (0.007968)+0.69(0.003968)+0.92(0.000032)+0(0.988032)=0.0046.1000 parts were produced per day; therefore, the expected daily cost is 1000 ($0.0046)=$4.60.Suppose that the possible values of a random variable from an experiment are a set of integable values occurring at the same frequency. This means that 1 to occur with the same probability. Then the probability of getting a specific integer in this range is 1.k.k. and the probability distribution can be writtenIt is called a discrete uniform (or rectangular) distribution and can be used for all populations of this type, with k depending on the range of existing variable values. Note that we are able to represent many different distributions with one function using a letter (k in this case) to represent any value of an important characteristic. This characteristic is the only thing that differs between distributions and is called aparameterof distribution. All probability distributions are characterized by one or more parameters, and descriptive parameters, such as diameter and deviation, are known functions of these parameters. For example, for this splitand a simple example of an experiment that results in a random variable with a discrete uniform distribution consists of feasting on a fair cube. Let Y be a random variable describing the number of spots on the top of the cube. Thenwhich is a discrete uniform distribution with k = 6. The mean Y is a deviation is a note that this is an example where a random variable can never take a mean value. Example 2.5A current even distribution is often used in simulation studies. A simulation study is exactly what it sounds like, a study that uses a computer to simulate an actual phenomenon or process as close as possible. The use of simulation studies can often eliminate the need for costly experiments, and is also often used to study problems where actual experimentation is impossible. When a simulated process requires the use of probability distribution to describe it, the technique is often referred to as the Monte Carlo method. For example, Monte Carlo methods were used to simulate collisions between photons and electrons, the disintegration of radioactive isotopes, and the effect of dropping an atomic bomb on the city. The basic component of the Monte Carlo simulation is the generation of random numbers (see, for example, Owen, 1962). For example, random numbers can be generated to consist of single digits with a discrete even distribution with k=10. Using the digits 0 through 9, these random digits can be used to simulate the results of example 2.2. For each simulated conversation, we generate a random digit. If the value of the digit is 0 or 1, the result is had childhood measles; otherwise (digits 2 to 9) the result is No. The result should then occur with a probability of 0.2. The result of an experiment involving one pair is then simulated using a pair of such cells, one for each individual. Simulation studies usually involve a large number of simulated events, but we use only 10 pairs for illustrative purposes. Suppose we have the following 10 pairs of random numbers (from a table or generated by a computer):In the first pair (15), the first digit 1 means should, while the second digit 5 indicates no; therefore for this pair, y = 1. For the second pair y=0 and so on. The relative frequency distribution for this simulated sample of ten pairs is shown in Table 2.7. Simulation of the probability of measlesThis result differs somewhat from the theoretical distribution obtained by means of probability theory, since small samples are expected to be highly variability. A sample of 1,000 would have come much closer, but it still wouldn't have made a theoretical distribution accurately. In a few examples in this chapter, the result included only two options. This means that the individual had or did not have childhood measles, the coin landed with its head or tail up, or the test sample did or did not have cancer cells. This dichotomy result is quite common in experimental work. For example, questionnaires often have questions requiring simple yes or no answers, medical tests have positive or negative results, banks either succeed or fail after the first 5 years, and so on. In each of these cases there are two results for which we will arbitrarily accept the general designation of success and failure. An example of measles is such an experiment where every individual in a couple is a trial, and each attempt produces a dichotomous result (yes or no). Binomial probability distribution describes the distribution of random variable Y, the number of successes in n studies, if the experiment meets the following conditions:1.The experiment consists of n identical studies.2.Each study results in one of two mutually exclusive results, one of which is marked as success, the other failure. 3.The probability of success in one study is equal to p. The p value remains constant during the experiment.4.Tests are independent. The formula or function for calculating probabilities for binomial probability distribution is given byp(s)=n!! (n−y)!py(1−p)n−y,fory=0.1,...,n.Notation n!, called factorial n, is the quantity obtained by multiplying n by each non-zero intenumber less than n. For example, 7!=7⊘ 6⊘ 3⊘⊘ 2=5040. By definition 0!=1.Binomial distribution is a distribution that can be derived using the simple probability rules listed in this chapter. Although remembering this inference is not needed, being able to track it provides insight into the use of probability rules. The formula for binomial probability distribution can be developed first by observing that p(s) is the probability of obtaining exactly y achievements from n tests. We know that there are n tests, so there must be (n−y) failures occurring at the same time. Since the tests are independent, the probability of success is the product of the probability of individual successes, which is py and the probability (n−y) of failures is (1−p)n−y. There is the probability of success and (n−y) failures py(1−p)n−y. However, this is the probability of only one of the many sequences of successes and (n−y) failures, and the definition of p(s) is the probability of any sequence of successes and (n−y) failures. The number of such sequences can be calculated using a counting rule called a combination. This rule says that there are any items that we can get y items from n items. So, if we have 5 tests there are5!2! (5-2)!=5⊘ 4⊘ 2⊘ 1(2)(3⊘ 2)=10ways arrangement of 2 successes and 3 failures. (The reader may want to list these and verify that there are ten of them.) The probability of success is then obtained by repeatedly applying the addition rule. This means that the probability of success is obtained by multiplying the probability of the sequence by the number of possible sequences, resulting in the above formula. Note that the measles example meets the conditions for a binomial experiment. This means that we indicate having childhood measles success, the number of trials is two (the pair is an experiment and an individual trial) and p =0.2, using a value from a national health study. We also assume that each individual has the same chance of having measles as a child, therefore p is constant for all studies, and we have previously assumed that the incidence of measles is independent among individuals. Random variable Y is the number in every couple who had measles. Using the binomial distribution function, we getP(Y=0)=2!0! (2-0)! (0.2)0(0.8)2−0=0.64,P(Y=1)=2!1! (2-1)! (0,2)1(0,8)2−1=0,32,P(Y=2)=2!2! (2-2)! (0.2)2(0.8)2−2=0.04.These probabilities exactly match those previously obtained from the basic principles as they should. For small to medium sample sizes, many scientific calculators and spreadsheets have binomial probability distribution as a function. For larger samples, there is approximation, which is useful both in practice and in deriving methods of statistical derivation. The application of this approximation is indicated in point 2.5 and other applications are given in the following chapters. Binomial distribution has only one parameter, p(n is usually considered a fixed value). The diameter and variance of binomial distribution are expressed in the letter p asFor example of our study state, n = 2 and p = 0.2 givesμ = 2(0.2) = 0.4,σ2 = (2) (0.2) (0.8)=0.32.Again these results are identical to the values previously calculated for this example. Binomial distribution describes a situation where observations are assigned to one of two categories and the measurement of interest is the frequency of observations in each category. Some data frequency, but do not necessarily have a category assignment. Examples of such data include the monthly number of fatal car accidents in the city, the number of bacteria per microscopic slide, the number of fish caught by tradies, or the number of phone calls per day to the switchboard. The common thread is that we work with the number of occurrences in any unit of space and / or time (moon in the city, microscope image, tradies, day). The analysis of this data can be solved by means of the Poisson distribution. Consider the variable number of fatal car accidents in a given month.. Since an accident can occur in every fraction of a second, there are basically an infinite number of chances of an accident. If we consider an event fatal accident to occur as a success (!), we have a binomial experiment in which n is infinite. However, the probability of a fatal accident that occurs at any given time is essentially zero. Then we have a binomial experiment with an almost infinite sample and almost zero value for p, but np, the number of occurrences, is the final number. In fact, the formula for the Poisson distribution can be inferred by finding the boundary of the binomial formula when n is approaching infinity and p is approaching zero Wackerly et al. (1996). The probability calculation formula for the Poisson distribution is where y represents the number of occurrences in a fixed time period and μ is the average number of occurrences in the same time period. The letter e is a Naperian constant that is approximately equal to 2.71828. For poisson distributions, both medium and dispersion are μ.Example 2.6Payment and bridge operators need information for toll device personnel services to minimize queues (waiting lines) without using too many operators. Suppose that in a specified time period the number of cars per minute approaching the toll booth has an average of 10. Traffic technicians are interested in the probability that exactly 11 cars in a minute from noon to 12:01 will approach the toll booth. Suppose an unacceptable queue develops as 14 or more cars approach the toll booth at any moment. The probability of such an event can be calculated as the sum of the probabilities of 14 or more cars approaching the toll booth, or more practically by calculating the complement. That is, P(Y≥14)=1−P(Y≤13). We can use the above formula or computer package with Poisson option such as Microsoft Excel. Using Excel, we find P(Y≤13)=0.8645 or the resulting probability is 1−0.8645=0.1355. 1−0.8645=0.1355.

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