Case 1 - Medical Malpractice:
Descriptive Statistics, Graphics, and Exploratory Data Analysis

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Background

According to a recent study published in the US News and World Report the cost of medical malpractice in the United States is $55.6 billion a year, which is 2.4 percent of annual health-care spending. Another 2011 study published in the New England Journal of Medicine revealed that annually, during the period 1991 to 2005, 7.4% of all physicians licensed in the US had a malpractice claim. These staggering numbers not only contribute to the high cost of health care, but the size of successful malpractice claims also contributes to high premiums for medical malpractice insurance.

An insurance company wants to develop a better understanding of its claims paid out for medical malpractice lawsuits. Its records show claim payment amounts, as well as information about the presiding physician and the claimant for a number of recently adjudicated or settled lawsuits.

The Task

Using descriptive statistics and graphical displays, explore claim payment amounts, and identify factors that appear to influence the amount of the payment.

The Data MedicalMalpractice.jmp

The data set contains information about the last 118 claim payments made, covering a six month period. The eight variables in the data table are described below:

Amount	Amount of the claim payment in dollars
Severity	The severity rating of damage to the patient, from 1 (emotional trauma) to 9 (death)
Age	Age of the claimant in years
Private Attorney	Whether the claimant was represented by a private attorney
Marital Status	Marital status of the claimant
Specialty	Specialty of the physician involved in the lawsuit
Insurance	Type of medical insurance carried by the patient
Gender	Patient Gender

The variables are coded in JMP with a *Continuous*, *Ordinal* or *Nominal* modeling type. This coding helps to make sure that JMP performs the correct analysis and produces appropriate graphs.

A first step in any analysis is to ensure that your variables have the correct Modeling Type:

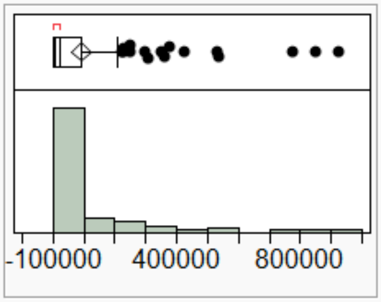
- Continuous variables, like **Amount**, have numeric values (e.g.; 2, 5, 3.35, 159.667,…).
- Ordinal variables, such as **Severity**, have either numeric or character values which represent ordered categories (e.g.; small, medium and large; 1-9 severity rating scales,…).
- Nominal variables, like **Gender**, can also have either numeric or character values, and represent unordered categories or labels (e.g.; the names of states, colors of M&Ms, machine numbers,…).

Analysis

We begin by looking at the key variable of interest, the amount of claim payment. Exhibit 1 displays a histogram and summary statistics for **Amount**.

Exhibit 1 Distribution of **Amount**

Amount



Quantiles

100.0%	maximum	926500
99.5%		926500
97.5%		778375
90.0%		256004
75.0%	quartile	92670
50.0%	median	22750
25.0%	quartile	7500
10.0%		2407
2.5%		1572.85
0.5%		1550
0.0%	minimum	1550

Moments

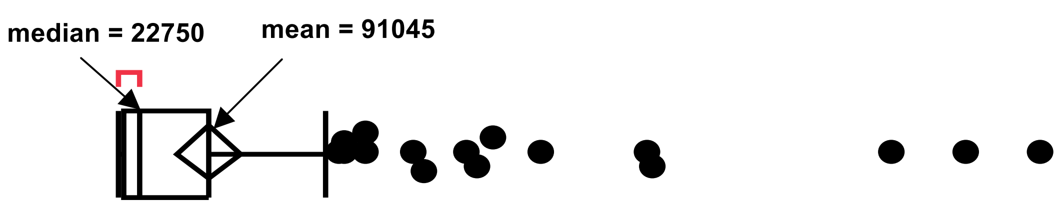
Mean	91044.915
Std Dev	164501.8
Std Err Mean	15143.618
Upper 95% Mean	121036.06
Lower 95% Mean	61053.774
N	118

*(Analyze > Distribution; Select **Amount** as Y, Columns, and click OK. For a horizontal layout select Stack under the top red triangle.)*

From Exhibit 1 we see that the histogram of **Amount** is skewed right, meaning that there is a long tail, with several very high payments. The *mean* (average) payment is $91,045, while the *median* (middle) is $22,750. When a histogram is right skewed, as is the case here, the mean will exceed the median. This is because the mean is influenced by extreme values – the high payments that we observe in the histogram inflate the mean.

A measure of the spread of the data is the *standard deviation* (StdDev in Exhibit 1). The higher the standard deviation, the larger the spread, or variation, in the data. When the data are skewed, the standard deviation, like the mean, will be inflated.

Other useful summary statistics are the *quartiles*. The first quartile (next to 25.0% in Exhibit 1) is $7,500 and the third quartile (next to 75.0%) is $92,670. The *interquartile range*, defined as Q3 – Q1, is a measure of the amount of spread or variability in the middle 50% of the data. This value is displayed graphically in the *outlier box plot* (above the histogram). A larger version of this plot is displayed below.



The left edge of the box is the first quartile, the center line is the median or second quartile, and the right edge of the box is the third quartile. Hence, the *width* of the box is the interquartile range, or IQR.

(Notes: The center of the diamond is the mean. We will discuss this in a few moments. The red bracket at the top, which we won't discuss further, denotes the "densest" region of the data.)

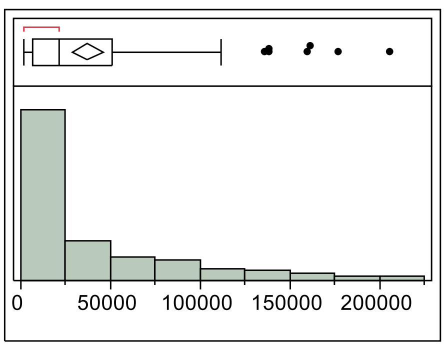
The outlier box plot helps us to visually identify potential outliers. The rule of thumb used to distinguish outliers from non-outliers is this: *if the histogram is approximately normal, or bell-shaped*, outliers are those points that extend beyond 1.5 IQRs of the box. The line extending from the right edge of the box, called a whisker, is roughly 1.5 IQRs in length (we say "roughly", because it is actually drawn to the furthest point within that range, so it may not be quite 1.5 IQRs).

Let's ignore, for sake of illustration, the fact that our data are right skewed. There are 16 points beyond the whisker, which we will consider to be outliers. In this case, the outliers are those points that are much *larger* than the rest.

Having identified several outliers, what should we do about them? Let's consider removing them from the analysis. To do so, we will hide and exclude the points (rather than simply deleting them). *Hide* removes points from graphs, while *Exclude* removes them from future calculations.

Exhibit 2 is the new histogram for **Amount** after excluding and hiding the 16 outliers.

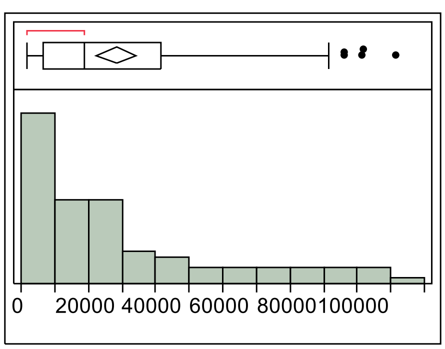
Exhibit 2 **Amount** after excluding and hiding 16 outliers



(To exclude and hide, draw a box around the points in the boxplot to select them. Then, select Rows > Hide and Exclude. Return to Analyze > Distribution and re-generate the histogram.)

Note that there are now seven (7) new outliers! We might as well get rid of those seven outliers as well. The result is shown in Exhibit 3.

Exhibit 3 **Amount** after excluding and hiding a total 23 outliers



OK, so now we have six *more* outliers. How long can this game go on? You're welcome to continue excluding and hiding outliers as you see fit. Or perhaps you've gotten the message: discarding outliers from a skewed distribution is an exercise in futility, since observations that didn't stand out at first will appear to be outliers after excluding the most extreme observations. Removing observations in this situation just forces other observations to take their place.

There's an even more important reason not to exclude outliers from the analysis. There's nothing *wrong* with those "outliers" — they're just bigger than most of the other payments. By excluding the 23 outliers, we have removed the really high claim payments made by the insurance company. The average calculated on the remaining observations is $28,306, a number less than one-third the original average. Imagine that the company uses the average and range of the truncated data set to forecast future payments. Upper management will be unpleasantly surprised to find many year-end actual payments greatly exceeding the predicted payments and you, as the firm statistician, may well be out of a job.

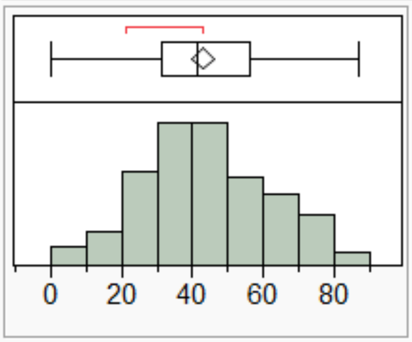
In other words, why discard data points just because they're unusual or inconvenient? There is great danger in the knee-jerk exclusion of outliers. We'll see some examples in future cases in which excluding outliers might make sense. The message here is to avoid doing so without good reason.

Let's now turn to other variables in the data set.

First, we make sure none of the observations are hidden or excluded. The distribution of Age is shown in Exhibit 4.

Exhibit 4 Distribution of **Age**

Age



Quantiles

100.0%	maximum	87
99.5%		87
97.5%		78.05
90.0%		69.1
75.0%	quartile	56.25
50.0%	median	41.5
25.0%	quartile	31
10.0%		21
2.5%		6.875
0.5%		0
0.0%	minimum	0

Summary Statistics

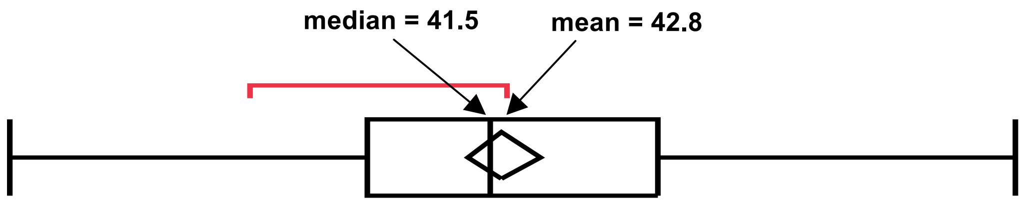
Mean	42.830508
Std Dev	18.004418
Std Err Mean	1.657441
Upper 95% Mean	46.112984
Lower 95% Mean	39.548033
N	118

(Use Rows > Clear Row States to unhide and unexclude.)

The oldest patient in the data set is 87, the youngest a newborn. The average age is 42.8 and the median age is 41.5 years.

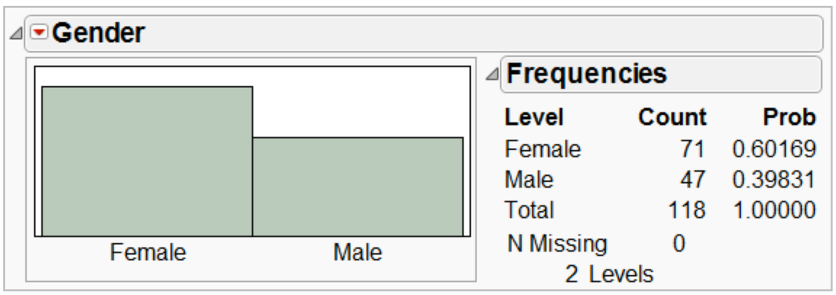
The shape of this histogram is quite different from that of Amount, which was highly skewed right. Age doesn't appear overly skewed, and the histogram is nearly symmetric. A symmetric distribution looks about the same on the right side as the left.

Now, we'll examine the outlier box plot of Age. Once again, we've reproduced the box plot below. Recall that the peak of the diamond is the position of the mean. This outlier box plot tells us that the mean and median are quite close and, therefore, that the distribution is nearly symmetric. Because no points are shown beyond the whiskers, this outlier box also indicates an absence of potential outliers.



We will next examine the distribution of **Gender**. Recall that for **Amount** and **Age**, which are continuous variables, we used histograms and summary statistics to characterize the shape, center and spread of the distributions. Since **Gender** is Nominal, we use a bar chart and a frequency distribution (Exhibit 5).

Exhibit 5 Distribution of **Gender**

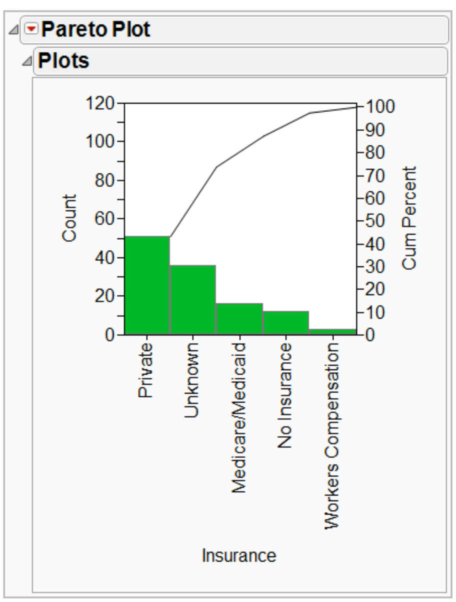


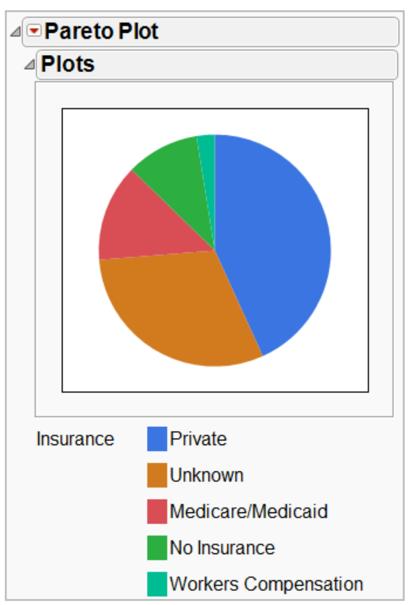
(Analyze > Distribution)

From the bar chart and its accompanying frequency table we see that 71 of the 118 (60.2%) patients in this sample are female and 39.8% are male.

Along with bar charts, Pareto plots and pie charts can be used to display information about nominal (categorical) variables. Exhibit 6 shows a Pareto plot and pie chart for **Insurance** type.

Exhibit 6 Pareto Plot (Left) and Pie Chart (Right) of **Insurance**





(Analyze > Quality and Process > Pareto Plot, use ***Insurance*** *as Y, Cause. Pie Chart is an option under the red triangle.)*

Both plots sort the categories of the variable in descending order of frequency. Patients with private insurance coverage are the largest group in this sample, although apparently the type of insurance held by many patients is unknown. Workers compensation patients comprise the smallest group in this sample.

Now, we turn our attention to the key question being asked by management: Do any of the variables appear to influence to the size of the claim payment? Or, asked another way, are any of the variables related to payment amount? For example, do payments tend to be higher when the claimant is married? Or, are they higher for female claimants than for males?

A number of tools are available for exploring potential relationships between variables. At the end of the day, many graphical and analytic techniques may be used to explore relationships, depending on the data, the business problem, and the preferences of the analyst. In this section, we'll use:

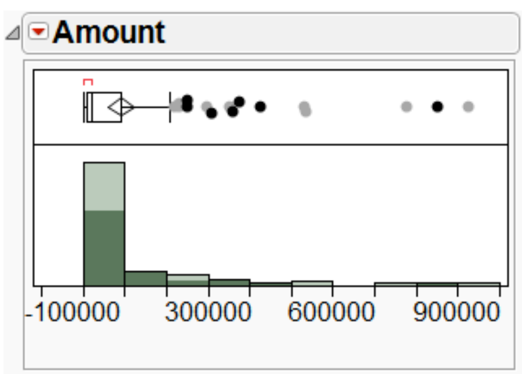
a. Dynamic plot-linking
b. Data Filter
c. Side-by-Side (Comparative) Box Plots
d. Graph Builder

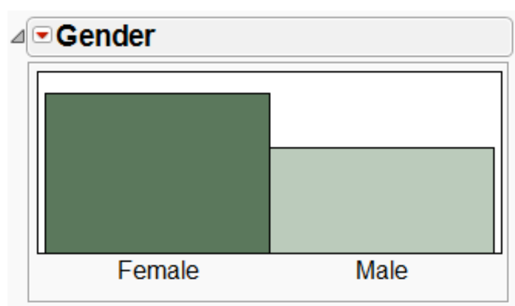
Dynamic plot-linking

If we select observations in a data table, those observations are also selected in all open graphs. Likewise, if we select observations in a plot, those observations are also selected in other plots and in the data table.

This dynamic linking can help us explore how different variables relate to one another. Consider the histogram of Amount and the bar graph of **Gender** in Exhibit 7 below. By clicking on the bar for Females, those same observations are highlighted in the histogram of Amount. Click on the bar for Males, and the observations for males are selected.

Exhibit 7 Distributions of **Amount** and **Gender**, Females



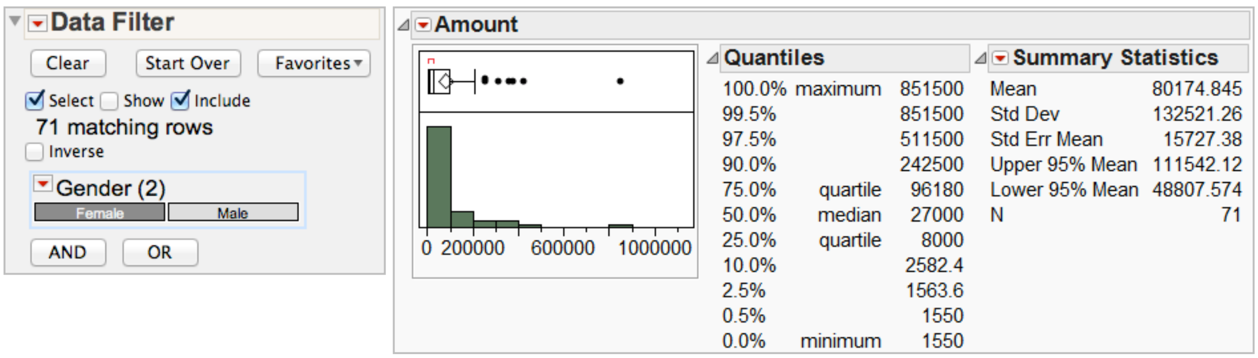


Are males and females distributed in a similar manner across the payment amounts? If so, we would conclude that **Amount** and **Gender** are *not* related, since males and females received roughly the same number of low, medium and high payment amounts. We explore this question further using the Data Filter.

The Data Filter

The Data Filter provides another method for exploring the distribution of one variable across the levels of another variable. For example, we can use the Data Filter to show the distribution of **Amount** for each **Gender**. In Exhibit 8 we see the Data Filter and results for females only.

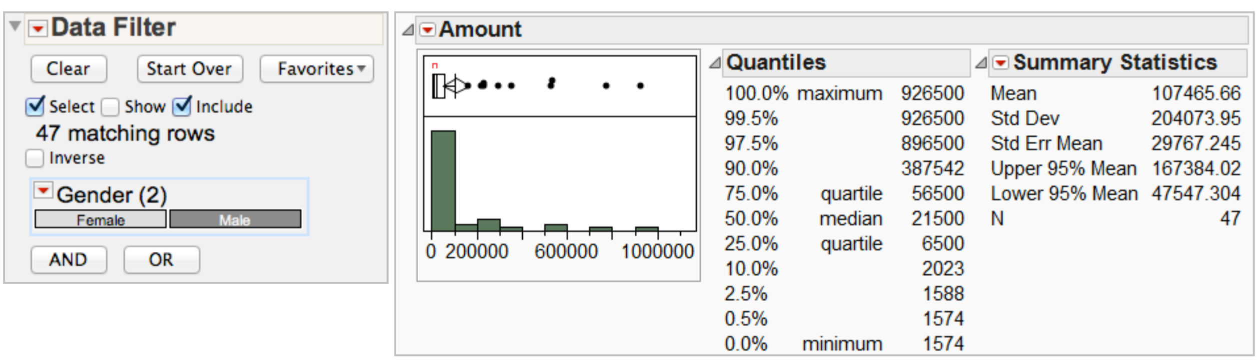
Exhibit 8 **Amount** with Data Filter, **Gender**, Females



(Rows > Data Filter; select ***Gender*** *and click Add. Then, select* ***Female*** *to select the values for the females in the histogram. To update the Distribution output with the* ***Amount*** *values for females only, check the Include box in the data filter. Then, in the Distribution window select Automatic Recalc under the top red triangle > Script.)*

When we select males in the Data Filter, the Distribution window will show only the amounts paid for males.

Exhibit 9 **Amount** with Data Filter, **Gender**, Males



Compare the output for females and males. The histograms for females and males look similar, with the possible exception of a few more extreme points for males (note that the scales are different). What about the summary statistics? The mean for males ($107,466) is much higher than for females ($80,175). But, recall that **Amount** is highly skewed, and extreme observations will have a large influence on the mean.

Does the information under *Quantiles* provide any additional insights (Exhibit 10)? Do females and males have roughly the same minimum and maximum values? What about the median and the first and third quartiles? Are they similar? In the same ball park?

Exhibit 10 Quantiles of **Amount** for Females (left) and Males (right)

Quantiles

100.0%	maximum	851500
99.5%		851500
97.5%		511500
90.0%		242500
75.0%	quartile	96180
50.0%	median	27000
25.0%	quartile	8000
10.0%		2582.4
2.5%		1563.6
0.5%		1550
0.0%	minimum	1550

Quantiles

100.0%	maximum	926500
99.5%		926500
97.5%		896500
90.0%		387542
75.0%	quartile	56500
50.0%	median	21500
25.0%	quartile	6500
10.0%		2023
2.5%		1588
0.5%		1574
0.0%	minimum	1574

From this analysis, there does not seem to be a notable difference in the distribution of **Amount** for males and females. Both distributions are right skewed, and the bulk of claim payments fall below $400,000 for both genders. We will examine this again in another case that uses more formal statistical methods, and will revisit this analysis in an exercise.

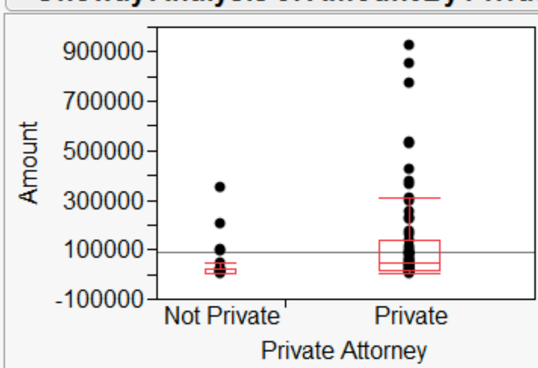
Side-by-Side (Comparative) Box Plots

Let's now consider other variables. We'll investigate whether payment amounts are related to whether or not a private attorney represented the claimant. In a complete analysis, we would start by exploring distributions of all variables. We'll jump ahead and introduce a third method for comparing distributions: side-by-side box plots, also known as comparative box plots.

We will use box plots to explore the relationship between **Private Attorney** and **Amount**. In Exhibit 11, we show box plots and quantiles. Note that 40 cases did not use a private attorney (**Not Private**), and 78 did use a private attorney (**Private**).

Exhibit 11 Fit Y by X, **Amount** and **Private Attorney**

Oneway Analysis of Amount By Private Attorney



*(Analyze > Fit Y by X; use **Private Attorney** as X, Factor and **Amount** as Y, Response. Then, select Quantiles under the top red triangle).*

Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
Not Private	1550	1581	2057.5	6500	22437.5	96468	351500
Private	2776	7950	16500	44000	139000	363000	926500

Both the box plots and the quantiles indicate that the amount of the claim payment had a lot to do with whether a private attorney was used. This makes a lot of sense. Would you rather have your own (paid!) attorney, or take your chances?

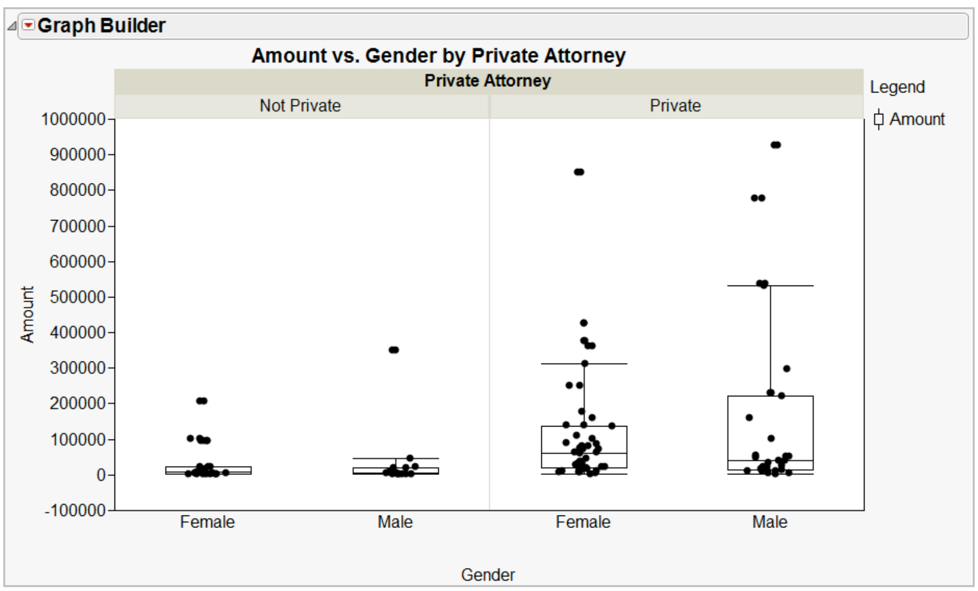
The Graph Builder

The final method we'll introduce is a graphing platform unique to JMP, the Graph Builder. In this platform you can drag and drop variables to dynamically explore relationships between two or more variables.

Thus far, we've investigated the relationship between **Gender** and **Amount**, and between **Private Attorney** and **Amount**. But, do we draw different conclusions if we look at all three variables at once?

In Exhibit 12, we see the relationship between **Gender** and **Amount**. The data are broken down by **Private Attorney**.

Exhibit 12 Graph Builder, **Amount** vs. **Gender** by **Private Attorney**



*(Graph > Graph Builder; Drag and drop Amount in Y, **Gender** in X, and **Private Attorney** in Group X. Click on the box plot icon at the top. Or, right-click in the graph and select Points > Change to > Box Plot.)*

Earlier, we concluded that there didn't appear to be a relationship between **Gender** and **Amount**. And, we found that the amount paid was related to whether a private attorney was used.

When we include both variables in the same analysis, do we draw the same conclusions? It appears that the relationship between **Private Attorney** and **Amount** is consistent for females and males. In other words, it doesn't matter if someone was female or male, if a private attorney was used the payout was generally much higher.

A word of caution: oftentimes, the relationship between one variable and another depends upon a third variable. For this reason, it is important to use tools like Graph Builder, in conjunction with the graphical tools introduced earlier, to explore more than two variables at a time.

We will continue investigation of this data in the exercises to follow.

Summary

Statistical Insights

- In this case we provided an introduction to descriptive statistics and graphs.
- For a skewed distribution, the mean and the median will be very different. The median is more representative of the center of the data for skewed distributions.
- For a symmetric distribution, the mean and the median will be similar.
- The 1.5 x IQR outlier rule says that points beyond 1.5 interquartile ranges of the outlier box are outliers (if the distribution is roughly normal).
- Don't automatically exclude outliers. There should be a very good reason to eliminate data!

Managerial Implications

The skills learned in this case can be used to prepare all sorts of summary statistics and graphs for the variables in the data set. For example, the average level of claim payments is $91,045 although there were a few large payments made, one as big as $926,500. About 40% of the sample is male patients.

Thus far, we've learned that we should expect to pay higher claims when a private attorney represents the claimant. Further analysis may lead insights that will guide future business decisions.

JMP Features and Hints

- Before you begin any statistical analysis in JMP, check that *each* variable in the data set has the appropriate modeling type. By default, all numeric columns are set to continuous and all character columns are set to nominal. Discrete variables may need to be changed to nominal or ordinal modeling types.

- JMP will produce graphs and analyses based on your chosen modeling types. JMP will go down a different path if you fail to set the appropriate modeling type.

- Don't be quick to delete rows from the data set. It's easier to temporarily exclude or hide them. In JMP, to *exclude* an observation means to prevent it from being used in subsequent calculations such as those for the mean. To *hide* a row means to remove it from graphs. You can exclude and not hide (and vice versa).

- You now know how to use JMP to create: histograms, bar graphs, Pareto plots and pie charts, dynamically-linked plots, side-by-side box plots, and graphs involving more than two variables at a time.

Exercises

Use the MedicalMalpractice.jmp data set to answer the following questions:

1. What percentage of the sample involved Anesthesiologists? Dermatologists? Orthopedic surgeons?
2. What percent of the patients in the sample were divorced? Widowed?
3. Is there any relationship between age of the patient and size of the payment?
4. Is there any relationship between size of the payment and severity? Does this depend on whether a private attorney was used?

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