(2.1) There are two definitions of "statistics" that are possible here. A statistic is simply a number computed from data; for example, the sample mean or sample median. The subject of statistics is that branch of science that deals with the analysis of data. There is much that can be said about the role of statistics in modern society: it is hard to imagine life without statistics. Politicians and public officials use statistics to make policy decisions in fields as diverse as: defense, health care, and transportation, etc. Companies use statistics to market their products, and television producers are obsessed with the Nielsen ratings as a measure of a TV show's success. It is hard to listen to a sporting event without the announcer commenting on the "statistics" of a particular team or player: penalty minutes, first downs, runs batted in, free throw percentage....
(2.3) When given a data set, it is wise to begin by visually examining the data. Become familiar with the data: What measurement is being taken? and What is being observed? Is the data quantitative (numerical) or categorical (labels)? Are there any outliers? Often a graphical display reveals many patterns. There might be clusters or outliers. The data could be symmetric or skewed; unimodal or multi-modal. If the data are paired, then a scatterplot may reveal a relationship: linear or otherwise. Also, it is straightforward to compute the summary statistics (as appropriate): mean, median, mode, standard deviation, interquartile range, maximum, minimum, range, correlation and/or covariance. Most of this is easily accomplished with a computer and statistical software such as SAS.
(2.4) A statistic is a number computed from data, while a parameter is a number associated with a population. Most often, a parameter is unknown, and a statistic is used to estimate a particular parameter.
(2.5) By definition,

$$
s^{2}=\frac{1}{n-1} \sum_{i=1}^{n}\left(y_{i}-\bar{y}\right)^{2} .
$$

Squaring, we see that $\left(y_{i}-\bar{y}\right)^{2}=y_{i}^{2}-2 y_{i} \bar{y}+\bar{y}^{2}$, and distributing the sum gives

$$
s^{2}=\frac{1}{n-1} \sum_{i=1}^{n}\left(y_{i}-\bar{y}\right)^{2}=\frac{1}{n-1}\left[\sum_{i=1}^{n} y_{i}^{2}-2 \bar{y} \sum_{i=1}^{n} y_{i}+\sum_{i=1}^{n} \bar{y}^{2} .\right]
$$

Since $\bar{y}$ is constant, and since $\sum y_{i}=n \bar{y}$, we see that

$$
\frac{1}{n-1}\left[\sum_{i=1}^{n} y_{i}^{2}-2 \bar{y} \sum_{i=1}^{n} y_{i}+\sum_{i=1}^{n} \bar{y}^{2}\right]=\frac{1}{n-1}\left[\sum_{i=1}^{n} y_{i}^{2}-2 \bar{y} \cdot n \bar{y}+n \bar{y}^{2}\right]=\frac{1}{n-1}\left[\sum_{i=1}^{n} y_{i}^{2}-n \bar{y}^{2}\right]
$$

as required.
(2.13) Very briefly:
(a) The average is $M / R$, and each average is exact (having factored the billions and thousands into the computation). Ordered by state we have:

| State | average |
| :--- | :--- |
| Alaska | 8492.6 |
| New York | 11053.1 |
| Rhode Island | 11146.5 |
| Florida | 11422.8 |
| California | 11593.9 |

(b) The average across the 5 states is $491000000000 / 43103000=11391.3$.
(c) Yes, the 15000 mile figure seems reasonable because the average in (b) is close (enough) to 10000.
(2.14) If a statistic is viewed as a random variable (as opposed to deterministic) sampled from a population, then the distribution of that statistic is known as its sampling distribution.
(2.17) Very briefly:
(a) Compare the column totals for exercise vigorously and cigarette smoking. Since 10907 and 11092 are nearly the same, and 11017 and 11014 are nearly the same, the randomization scheme did a good job in controlling these variables.
(b) No, since $5431 / 11017 \approx 0.49$ and $5488 / 11014 \approx 0.50$ are nearly the same.
(c) No, since $2997 / 10907 \approx 0.27$ and $3060 / 10921 \approx 0.28$ are nearly the same.
(2.21) An estimator is a statistic that is computed in an attempt to estimate a particular parameter.
(2.22) In order to evaluate the goodness of an estimator $\hat{\theta}$, one should compute both $E(\hat{\theta})$ and $\operatorname{Var}(\hat{\theta})$.
(2.23) Suppose that $\hat{\theta}$ is used an estimator of $\theta$. Two desirable properties of $\hat{\theta}$ are that $E(\hat{\theta})=\theta$ and that $\operatorname{Var}(\hat{\theta})$ is as small as possible.
(2.24) We call $\hat{\theta}$ an unbiased estimator of $\theta$ if $E(\hat{\theta})=\theta$.
(2.25) The error of estimation made when using $\hat{\theta}$ to estimate $\theta$ is given by the (random) quantity $|\hat{\theta}-\theta|$.
(2.26) Since Chebychev's theorem tells us that for any distribution, $75 \%$ of the observations must fall within 2 standard deviations of the mean, it seems reasonable to use $2 \sigma_{\hat{\theta}}$ as a bound on the error of estimation. In the particular case of the normal distribution, we see that just over $95 \%$ of the data lie within 2 standard deviations of the mean. (Actually, $95 \%$ lies within 1.96 SDs of the mean.) This is how the magic " $95 \%$ confidence interval" is often justified.
(2.27) By definition,

$$
\operatorname{Var}(y)=\sum_{x}(x-\mu)^{2} P(y=x)
$$

where $\mu=E(y)$ and $P(y=x)=p(x)$ is the probability density function of the random variable $y$. In the case given, the possible values of the random variable $y$ are $u_{1}, u_{2}, \ldots, u_{N}$, and each occurs with probability $P\left(y=u_{i}\right)=1 / N$. Hence, we conclude that

$$
\operatorname{Var}(y)=\sum_{x}(x-\mu)^{2} P(y=x)=\sum_{i=1}^{N}\left(u_{i}-\mu\right)^{2} P\left(y=u_{i}\right)=\frac{1}{N} \sum_{i=1}^{N}\left(u_{i}-\mu\right)^{2}
$$

