1. Reading: K. Rosen Discrete Mathematics and Its Applications, 4.5
2. The main message of this lecture:

## Probability with not necessarily equally likely outcomes, conditional probability, independent events: all have natural and extremely useful mathematical definitions.

The classical definition of probability (Laplace) assumes that the sample space is finite $S=$ $\left\{s_{1}, s_{2}, \ldots, s_{n}\right\}$, that all the outcomes $s_{i}$ are equally likely and introduces the formula for the probability of an event $E$ :

$$
p(E)=\frac{|E|}{|S|} .
$$

We can present the same formula in a somewhat more natural way, via the probabilities of individual outcomes. Note that the probability of each single outcome $p_{i}=p\left(s_{i}\right)=1 / n$, and that $p_{1}+p_{2}+\ldots+p_{n}=1$. Then $p(E)$ equals to the sum of those $p(s)$ for which $s \in E$ :

$$
p(E)=\sum_{s \in E} p(s)=|E| \cdot \frac{1}{n}=\frac{|E|}{|S|} .
$$

Definition 20.1. Imagine that $S$ is still finite $S=\left\{s_{1}, s_{2}, \ldots, s_{n}\right\}$, but the outcomes $s_{i}$ are not necessarily equally likely. We assume that the probability of individual outcomes $p_{i}=p\left(s_{i}\right)$ are given and that

1. $0 \leq p(s) \leq 1$ for each $s \in S$
2. $p\left(s_{1}\right)+p\left(s_{2}\right)+\ldots+p\left(s_{n}\right)=1$.

Then the formula number two for the probability of an event $E$ still applies:

$$
p(E)=\sum_{s \in E} p(s) .
$$

Example 20.2. Biased coin: heads come up twice as often as tails. $S=\{H, T\}, p(H)+p(T)=$ $1, p(H)=2 p(T), 2 p(T)+p(T)=1$, therefore, $3 p(T)=1, p(T)=1 / 3, p(H)=2 / 3$.

Theorem 20.3. $p\left(E_{1} \cup E_{2}\right)=p\left(E_{1}\right)+p\left(E_{2}\right)-p\left(E_{1} \cap E_{2}\right)$
Proof. Similar to the Inclusion-Exclusion Principle, in

$$
p\left(E_{1}\right)+p\left(E_{2}\right)=\sum_{s \in E_{1}} p(s)+\sum_{s \in E_{2}} p(s)
$$

each element of the intersection $E_{1} \cap E_{2}$ is counted twice. Subtracting $p\left(E_{1} \cap E_{2}\right)$ to compensate this overcount we get the desired formula for $p\left(E_{1} \cup E_{2}\right)$.
Corollary 20.4. $p(\bar{E})=1-p(E)$. Indeed, since $p(S)=1$, by 20.3 , we have $1=p(S)=$ $p(E \cup \bar{E})=p(E)+p(\bar{E})$. Thus $p(\bar{E})+p(E)=1$ and $p(\bar{E})=1-p(E)$.
Example 20.5. Flipping a fair coin the probability of having at least one $T$ (event $E$ ) is $7 / 8$. Suppose we know that the first flip came up heads (event $F=\{H T T, H T H, H H T, H H H\}$ ) and we want to evaluate the "new" probability of $E$ given $F$. A new provisional sample set is
now down to $F$, we have four equally likely outcomes. Some of the outcomes from $E$ (namely $T H H, T T H, T H T, T T T)$ are no longer possible. To evaluate the "conditional" probability of $E$ given $F$ we have to take the ratio of what is left of $E$ to what is left of $S$ :

$$
\frac{|E \cap F|}{|F|}=\frac{|E \cap F| /|S|}{|F| /|S|}=\frac{p(E \cap F)}{p(F)}=\frac{3 / 8}{4 / 8}=3 / 4 .
$$

Definition 20.6. Conditional probability $p(E \mid F)$ ("the probability of $E$ given $F$ ") is

$$
p(E \mid F)=\frac{p(E \cap F)}{p(F)} .
$$

The reason for this definition is similar to the one used in example 20.5: given a condition $F$ we may regard it as a new sample space and adjust the formula accordingly.
Example 20.7. What is the conditional probability that a family of three children has more than one boy given they have at least one boy. $E=\{B B B, B B G, B G B, G B B\}, F=$ $\{B B B, B B G, B G B, G B B, B G G, G B G, G G B\}$. Then $E \cap F=E$, since $E \subset F$.

$$
p(E \mid F)=\frac{p(E \cap F)}{p(F)}=\frac{p(E)}{p(F)}=\frac{4 / 8}{7 / 8}=4 / 7 .
$$

What if the condition $F$ is "the first child is a girl"? Then $F=\{G B B, G B G, G G B, G G G\}$, $E \cap F=\{G B B\}, p(E \mid F)=p(E \cap F) / p(F)=(1 / 8) /(4 / 8)=1 / 4$.
Definition 20.8. If a condition $F$ does not change the probability of an event $E$, we say that $E$ and $F$ are independent: $p(E)=p(E \mid F)$. Note that in a full accord to intuition, independence is symmetric: $E$ is independent from $F$ if and only if $F$ is independent from $E$ :

$$
p(E)=\frac{p(E \cap F)}{p(F)} \Leftrightarrow p(E) \cdot p(F)=p(E \cap F) \Leftrightarrow p(F)=\frac{p(E \cap F)}{p(E)}
$$

therefore, $p(E)=p(E \mid F) \quad \Leftrightarrow \quad p(F)=p(F \mid E)$.
Example 20.9. A fair coin is flipped twice. $E=$ "the first flip come up tails" $=\{T T, T H\}$, $F=$ "the second flip comes up tails" $=\{T T, H T\}$. Intuitively, $E$ and $F$ are independent. Let us check the formula. On one hand, $p(E)=1 / 2$. On the other hand, $p(E \cap F)=p(\{T T\})=1 / 4$, $p(E \mid F)=p(E \cap F) / p(F)=(1 / 4) /(1 / 2)=1 / 2$. Alternatively, one could check the condition $p(E \cap F)=p(E) \cdot p(F): 1 / 4=(1 / 2) \cdot(1 / 2)$.
Example 20.10. The events $E=$ " more then one boy out of three kids" and $F=$ "the first baby is a girl" are not independent. Indeed, $p(E \cap F)=p(\{G B B\})=1 / 8$, whereas $p(E) \cdot p(F)=$ $(1 / 2) \cdot(1 / 2)=1 / 4$. So, $p(E \mid F)=(1 / 8) /(1 / 2)=1 / 4$, i.e. $E$ given $F$ is twice less likely then $E$.

Definition 20.11. Bernoulli trial is an experiment with two outcomes: Success (probability $p$ ) and Failure (probability $q=1-p$ ). Examples: fair coin $p=q=1 / 2$, biased coin $p=2 / 3$, $q=1 / 3$, etc.
Theorem 20.12. The probability of $k$ successes in $n$ independent Bernoulli trials with probability of success $p$ is $C(n, k) \cdot p^{k} \cdot q^{n-k}$.
Proof. Each $n$-trail with $k$ successes can be labelled by a string of $k S$ 's and $(n-k) F$ 's with the probability of such a string $p^{k} q^{n-k}$. There are $C(n, k)$ such trials, the event $E$ consists of all of them, therefore, $p(E)=C(n, k) p^{k} q^{n-k}$.
Homework assignments. (due Friday 03/16).
20A:Rosen4.5-6; 20B:Rosen4.5-10; 20C:Rosen4.5-16; 20D:Rosen4.5-26ac.

