BADG 2: A Perfect Game

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Abstract

An earlier paper (http://fettermania.com/math/bdice.pdf) focused on a near-optimal strategy for maximizing expected value in gameplay for *Bitches: A Dice Game*. This paper focuses on a different question: what is the probability of playing a perfect game (and is there any subtlety to doing so)? Using standard recursive calculation, we calculate the probabilities with the out-of-box game setup. Then we venture into a related question: What's the expected win probability with r standard dice remaining of side count d as $r \to \infty$? We give poor bounds, prove convergence, and find surprising results along the way.

1 Introduction and the Commercial Game

Outside of ideological patron Larry Waldman, the publication of my original b. a. d. g. paper (http://fettermania.com/math/bdice.pdf) received little fanfare from humans. However, the robots somehow picked up on this and brought it to the attention of Samuel Cox, creator of the game. After dispensing mild praise about the paper and strong confusion about my interest in it, Mr. Cox suggested another problem.

Instead of "how does one play the game with high/maximum expected value?" (addressed in the first paper), Mr. Cox wondered how often a *perfect game* (one in which the best possible score is achieved at the end) occurs if played optimally. Though optimal play looks obvious (pick up all your maximum rolls), Mr. Cox has also debated with his class: "is it always best to pick up all your maximum-roll dice?"

I took this on and a day or so later, the solution to this particular question surfaced. As usual, twinkly subproblems appeared along the way, and I left to find a solution to a related problem: does the probability of a perfect game converge to a positive number as the number of dice increase to infinity?

We'll briefly review this subgame's rules and the solution method for the commercially offered game before diving in to a discovered second quest: asymptotic behavior of infinite dice. We'll note surprising or interesting findings in **bold-italic**.

1.1 The Game

Though the rules to the multi-player game are detailed in the original paper referenced above, we will reformulate this for a solitaire-style game, which follows this pattern:

- 1. Begin with 12 standard dice of six sides, along with one eight-, one ten-, and one twelve-sided die.
- 2. On each turn, roll all remaining dice in play.
- 3. If there are no dice with a maximum side showing (e.g. a six-sided die showing six pips), you have lost ("busted").
- 4. Set aside some number of dice which have achieved their maximum roll.
- 5. Continue until no dice remain (you have a perfect game) or you have busted out.

The question "how likely am I to get a perfect score?" therefore relies on the strategy one employs in picking up dice.

1.2 Mistake 1: The Strategy Assumption

Proposition 1.1 (Smoke 'em if you got 'em). The best strategy to achieve a perfect game is to always pick up as many dice with maximum face value as the turn allows.

This proposition is:

- 1. Simple
- 2. Obvious
- 3. The strategy any reasonable person would employ
- 4. Initially assumed for the calculations in the next section
- 5. Mathematically false

In the next section, we assume this simple, deterministic strategy in calculating the expected value of any state reachable from the standard b. a. d. g. starting configuration and show where it goes wrong.

1.3 Solution Method for the Commercial Game

The following definitions will help us write a program to get our solution for the commercial game:

- The "state" $\vec{s} := [a, b, c, d]$ is how many dice of size 6, 8, 10, and 12 remain, respectively¹. We start at $\vec{S} = [12, 1, 1, 1]$. A perfect game ends at $\vec{s} = \vec{0}$. A failure to roll any max roll ends the game in an unlisted 'losing' state \varnothing .
- The "probability vector" $\vec{p} := [1/6, 1/8, 1/10, 1/12]$ is the chance of getting a max roll from each of the dice sizes, again here assumed to be 6, 8, 10, 12.
- With a win defined as value 1 $(F(\vec{0}) = F([0,0,0,0]) = 1)$ and a loss as value 0 $(F(\varnothing) = 0)$, the "expected game value" of any other state \vec{s} is denoted as $F(\vec{s})$. Said another way, $F(\vec{s})$ is the probability of ending up in winning state $\vec{0}$ from state \vec{s} .
- We call any state $\vec{t} := [t_1, t_2...t_z]$ reachable from state $\vec{s} := [s_1, s_2...s_z]$ if $t_i \leq s_i$ for all $1 \leq i \leq z$, but $\vec{s} \neq \vec{t}$. More intuitively, if you can start at state \vec{s} and get to state \vec{t} in one roll (and corresponding pickup) of your dice, then \vec{t} is reachable from \vec{s} . This is just any non-bust state "smaller than" where you are now.

1.4 Probability Lemmas

First, let's limit ourselves to a game (or state) with only a single flavor of dice, say d-sided, collapsing state vector \vec{s} to a single integer r (r dice of size d left). Refer to Fig. 1 for a partial visualization of the states and transitions starting at r dice left of size d, with p := 1/d, q := 1 - p.

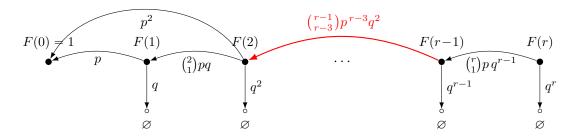


Figure 1: Transition graph of the dice game showing expected values F(r) and a few transition probabilities.

Lemma 1.2 (EV of r d-sided dice). The chance of a completing perfect game from a state of r standard dice of d sides each, with definitions $p := \frac{1}{d}$, $P_{single}(r, k, p) := \binom{r}{k} p^k (1-p)^{r-k}$, and F(0) = 1 is defined by the recurrence $F(r) = \sum_{k=1}^r P_{single}(r, k, p) F(r-k)$.

Proof: This a clear application of the binomial theorem. With the Smoke 'Em if you Got 'Em Strategy, the chance of transitioning to the state with r-k remaining dice from that with r is the chance of rolling exactly k max rolls and r-k non-max rolls among your

¹We refer to this often as an arbitrarily-sized vector as well

d-sided dice, or $P_{single}(r, k, p)$. The expected value of being in this new state is defined as F(r-k). The value of this state transition possibility is $P_{single}(r, k, p)F(r-k)$. The total expected value of being in state r is therefore the sum of the values of all possible state transitions. Note that k=0 implies a roll with no maxes, and thus a loss (value 0), and F(0)=1 since no dice remaining (outside of a loss case) means a victory, or unit value of expectation.

Extending this to dice of z different sizes is clear:

Lemma 1.3 (State Transition lemma). $P_{transition}(\vec{s}, \vec{t}, \vec{p})$, the chance of transitioning from state $\vec{s} = [s_1, s_2, \ldots s_z]$ to state $\vec{t} = [t_1, t_2 \ldots t_z]$ with probability vector $\vec{p} = [p_1, p_2 \ldots p_z]$ is equal to $\prod_{i=1}^{z} P_{single}(\vec{s}_i, \vec{t}_i, \vec{p}_i)$.

Proof: Divide the turn's roll into z independent subrolls, each rolling all s_i dice, $1 \le i \le z$, themselves each with p_i chance of hitting a max. The outcomes of these z subrolls are all mutually independent, so $P_{transition}$ can be expressed as the product of P_{single} quantities.

1.5 Simple recursive algorithm

With these easy proofs and definitions in hand, the algorithm follows readily - build up each state from $F(\vec{0})$ to $F(\vec{S})$ by applying the State Transition Lemma and previously computed values of F in Algorithm 1. Notes:

- Steps 1 5 are definitions from the lemmas above.
- Step 6 creates a set of all states reachable from state \vec{s} , including \vec{s} itself.
- Thinking of the states as a directed graph where a state points to all the states reachable from it, Step 7 creates an ordered list of states $\vec{s_1}, \vec{s_2}, \vec{s_3}...$, like [0,0,0,0], [0,0,1,0], [0,1,0,0], [0,1,1,0]... where, when $\vec{s_i}$ is encountered in the list, all states reachable from $\vec{s_i}$ occur before $\vec{s_i}$ in the list. There are many such possible orders. This is required for step 9's $F(\vec{t})$ values to be defined.
- Step 9 uses Lemma 1.3 to calculate $F(\vec{s})$ from the values of previously calculated substates.

1.6 Results for Commercial Game

Using the Smoke 'Em if you Got 'Em strategy, the chance of winning² $F(\vec{s})$ for every state \vec{s} , with \vec{s} ranging from $\vec{0}$ to $\vec{S} = [12, 1, 1, 1]$ is listed in Figures 2 and 3. These are computed with a simple python program³.

²Alternatively, expected value of being in state $F(\vec{s})$, with $F(\vec{0}) = 1, F(\emptyset) = 0$

³https://github.com/fettermania/mathnotes/blob/main/bdice2/bdice2.py

Algorithm 1 Dynamic program for $F(\vec{S})$

```
1: \vec{S} \leftarrow [12, 1, 1, 1]
2: \vec{p} \leftarrow \left[\frac{1}{6}, \frac{1}{8}, \frac{1}{10}, \frac{1}{12}\right]
3: P_{\text{single}}(r, k, p) := \binom{r}{k} p^k (1 - p)^{r - k}
4: P_{\text{transition}}(\vec{s_1}, \vec{s_2}, \vec{p}) := \prod_{i=0}^{\dim(\vec{s})} P_{\text{single}}(\vec{s_1}_i, \vec{s_2}_i, \vec{p_i})
5: F(\vec{0}) \leftarrow 1
6: substates(\vec{s}) := \underset{i=0}{\overset{dim(s)}{\times}} [0, s_i]
7: states \leftarrow topological_sort(substates(\vec{S})\{[0, 0, 0, 0]})
8: for \vec{s} \in states do
9: F(\vec{s}) \leftarrow \sum_{\vec{t} \in (\text{substates}(\vec{s}) \setminus \{\vec{s}\})} P_{\text{transition}}(\vec{s}, \vec{t}) \cdot F(\vec{t})
10: end for
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Note that this state table is *four-dimensional*, with each dimension i corresponding to the count of dice s_i in each state. Since the number of 8-, 10-, and 12-sided dice is either zero or one, we've collapsed these into four 12 by 2 tables, where d_k notes the number of dice of size k.

Our main initial result for $F(\vec{S})$ is in the bottom-right corner of Fig. 3.

$d_6 \backslash d_8$	0	1	$d_6 ackslash d_8$	0	1
0	1	0.125	0	0.1	0.03469
1	0.1667	0.05642	1	0.04556	0.02046
2	0.07407	0.03244	2	0.02644	0.01425
3	0.04192	0.02206	3	0.01815	0.01109
4	0.02809	0.01679	4	0.01392	0.009299
5	0.02107	0.01378	5	0.01152	0.008218
6	0.01708	0.01195	6	0.01006	0.007537
7	0.01463	0.01076	7	0.009124	0.0071
8	0.01303	0.009966	8	0.008506	0.006818
9	0.01195	0.009423	9	0.00809	0.006638
10	0.01119	0.009044	10	0.007809	0.006529
11	0.01065	0.008779	11	0.007618	0.006468
12	0.01025	0.008591	12	0.007491	0.006441

Figure 2: Expected values for $(d_{10}, d_{12}) = (0, 0)$ (left) and (1, 0) (right).

$d_6 \backslash d_8$	0	1	$d_6 ackslash d_8$	0	1
0	0.08333	0.02908	0	0.02347	0.01087
1	0.03819	0.01726	1	0.01406	0.007809
2	0.02231	0.01209	2	0.009946	0.006252
3	0.0154	0.009464	3	0.007849	0.005385
4	0.01188	0.00798	4	0.006672	0.004879
5	0.009888	0.007088	5	0.005971	0.00458
6	0.008677	0.006532	6	0.005542	0.004408
7	0.007907	0.006181	7	0.005278	0.004318
8	0.007404	0.00596	8	0.00512	0.004283
9	0.007071	0.005825	9	0.005033	0.004284
10	0.006851	0.00575	10	0.004994	0.004312
11	0.006707	0.005715	11	0.004988	0.004356
12	0.006618	0.005709	12	0.005005	0.004413

Figure 3: Expected values for $(d_{10}, d_{12}) = (0, 1)$ (left) and (1, 1) (right).

1.7 Observations

Observations from Figs. 2 and 3:

- Most of the time, starting with some state \vec{s} and picking up one or more dice will increase the expected value of winning.
- However, we do note some non-monotonicity: there are two surprising "critical points" at [12,0,1,1] and [9,1,1,1], where instead of the EV decreasing as d_6 increases, the EV increases instead. This means that, for example, the best strategy when rolling two max-sixes and no other max dice in state [10,1,1,1] is to *leave one max die on the table* so as to end up in slightly higher EV state [9,1,1,1] over [8,1,1,1]. We will revisit these in the next section.
- At all states reachable from [12,0,1,1], the best strategy is confirmed: pick up as many max-rolled dice as possible. Deviating from this strategy produces an F-value smaller than those in the table. Note: The "bend" at [11,0,1,1] does not affect this; you have no alternative from [12,0,1,1] than to pick up if [11,0,1,1] if you roll one max-six.
- At all states reachable from [10, 1, 1, 1], the simple strategy remains best.
- We can confirm that holding d_6 steady, it's always better to have zero than one of each of the 8, 10, and 12-sided dice.

What The Creator Asked For: The chance of getting a perfect run the commercial game using the Smoke 'Em strategy is about 0.004413, or a little more than 4.4%.

1.8 Re-examining The optimal strategy

From examining the table it becomes clear that there are expected values for states \vec{s}, \vec{t} such that \vec{t} is reachable from \vec{s} yet $F(\vec{t}) < F(\vec{s})$.

This means we need to refine our formula to choose the best selectable EV state from state \vec{s} , not just the furthest from \vec{s} . With this definition in hand:

$$selectable_states(\vec{s}, \vec{t}) := (substates(\vec{s}) - \vec{s}) - substates(\vec{t}) + \vec{t}$$

update Step 9 of Algorithm 1 above to:

$$F(\vec{s}) \leftarrow \sum_{\vec{t} \in \text{(substates}(\vec{s}) - \{\vec{s}\})} P_{\text{transition}}(\vec{s}, \vec{t}) \cdot max_{\vec{u} \in selectable_states(\vec{s}, \vec{t})} F(\vec{u})$$

Because F monotonically decreases as all of d_6 , d_8 , d_{10} , d_{12} increase up to these critical points, these two functions will be equal on states reachable from [10, 1, 1, 1] and [12, 0, 1, 1].

We then need to recursively reevaluate F on "bigger" states than [9, 1, 1, 1], shown in Fig. 4.

$d_6 \backslash d_8$	0	1
0	0.02347	0.01087
1	0.01406	0.007809
2	0.009946	0.006252
3	0.007849	0.005385
4	0.006672	0.004879
5	0.005971	0.00458
6	0.005542	0.004408
7	0.005278	0.004318
8	0.00512	0.004283
9	0.005033	0.004284
10	0.004994	$0.004312 \rightarrow 0.004312$
11	0.004988	$0.004356 \rightarrow 0.004366$
12	0.005005	$0.004413 \rightarrow 0.004446$

Figure 4: Expected values for $(d_{10}, d_{12}) = (0, 1)$ (left) and (1, 1) (right).

What The Creator Really Asked For: The chance of getting a perfect run the commercial game using the very best strategy (smoke 'em except leave a second and final unsupported six on $[d_6 \in \{10, 11, 12\}, d_8 = 1, d_{10} = 1, d_{12} = 1]$) is about 0.004446, or a little more than 4.4%, a 0.73% relative improvement on the smoke 'em strategy.

So it turns out Mr. Cox's students are correct - you may indeed want to "save" future six rolls if your rarer "onesies" remain. The difference on the commercial game begins at [10,1,1,1], and occurs exactly when you roll exactly 2 sixes on 6-sided dice and no other maxes.

- [10, 1, 1, 1]: Naive: Take both sixes (EV = 0.0043116537). **Optimal**: Take only 1 six (EV = 0.0043120029).
- [11, 1, 1, 1]: Naive: Take both sixes (EV = 0.0043564817). **Optimal**: Take only 1 six (EV = 0.0043662025).
- [12, 1, 1, 1]: Naive: Take both sixes (EV = 0.0044132805). **Optimal**: Take only 1 six (EV = 0.0044456381).

It's nice to see the game is complex and non monotonic even in this constrained scenario. There are configurations with more dice yielding other critical points in their spaces, especially as more dimensions (dice types) are added. Though the difference is minuscule in the commercial game, expanding \vec{S} to something like $\vec{S}^* = [24, 2, 2, 2]$ yields a wider EV difference between simple and optimal strategies⁴.

2 The Second Quest: $d_6 \to \infty$

But can we say nothing more definitive than that? Looking at the left column on the first table (Fig. 2) with only one type of die, it looks like a higher dice count both decreases our chance of winning, but may only do so asymptotically.

Let's run $\vec{S} = [r, 0, 0, 0], r \to \infty$ and see (Table 1).

It certainly looks like there is an asymptote to which $F(\vec{s})$ converges. This will be the thrust of the rest of this paper: examining the infinite game of $F(\vec{s})$ with one type of die. But can we prove there is an asymptote?

Two notes:

• We only have one type of die now, and if we have r of them left, the EV of that state is given as F(r) (we changed F to take integers now instead of vectors).

 $^{^4}F(\vec{S^*})=0.0033078600$ using the basic strategy and 0.0038614244 using its corresponding optimal strategy, a 17% improvement

r	F(r)
0	1.00000000000000000
1	0.1666666666666666666666666666666666666
2	0.074074074074074
3	0.041923868312757
4	0.028091341512981
5	0.021074519393544
6	0.017084426737672
7	0.014629278661270
8	0.013031406311202
9	0.011947904221376
10	0.011190349681739
:	:
90	0.009033527660227
91	0.009033527656758
92	0.009033527653985
93	0.009033527651768
94	0.009033527649995
95	0.009033527648578
96	0.009033527647444
97	0.009033527646538
98	0.009033527645813
99	0.009033527645234
100	0.009033527644770

Table 1: Values of F(r) with $p = \frac{1}{6}$

- Unless we see an inflection point (F(r)) reverses direction and starts *increasing* past a certain point), the simple strategy and optimal strategy (from section 1) are equivalent.
- If we can find $\lim_{r\to\infty} F_d(r)$, with dice of size d and $\lim_{r\to\infty} F_g(r)$ with dice of size g>d, then it's clear that an infinite proportional mix of these dice will fall between them; this is not examined further.

2.1 Mathematical Lemmas

Note: For some d-sided die, we assume p := 1/d, q := 1 - p for the rest of the paper.

To restate F for a single die value:

Definition 2.1 (EV of Game at state r). The expected value of the game with r fixed

d-sided dice is 1 at r=0, and when r>0, is defined by $F(r)=\sum_{k=1}^r {r \choose k} p^k q^{r-k} F(r-k)$.

Lemma 2.2 (Easy Cases Lemma). If p = 0, F(r) = 0. If p = 1, F(r) = 1. If $p = \frac{1}{2}$, for any r > 0, $F(r) = \frac{1}{2}$.

Proof: Though we won't be flipping infinite (p = 0) or 1-sided (p = 1), dice, these algebraic identities are obvious (can't succeed, can't fail, respectively) and will be useful later.

Base case for $p = \frac{1}{2}$: $F(1) = \frac{1}{2}$ since a perfect game occurs if and only if the 2-die (coin, really) shows 2 instead of 1.

Inductive case for $p = \frac{1}{2}$: Assuming $F(k) = \frac{1}{2}$ for all 0 < k < r, and F(0) = 1:

$$F(r) = \sum_{k=1}^{r-1} {r \choose k} p^k q^{r-k} F(r-k) + {r \choose r} p^r q^0 F(0)$$

$$= \left[{r \choose 1} + {r \choose 2} + \dots + {r \choose r-1} \right] \frac{1}{2^r} (\frac{1}{2}) + \frac{1}{2^r} 2(\frac{1}{2})$$

$$= (2^r - 2) \frac{1}{2^r} (\frac{1}{2}) + 2 \frac{1}{2^r} (\frac{1}{2})$$

$$= (2^r) \frac{1}{2^r} (\frac{1}{2})$$

$$= \frac{1}{2}$$

For simplicity, we consider only $p \leqslant \frac{1}{2}$ from here on out⁵.

Lemma 2.3 (Lazy Upper Bound for F(r)). With $r \ge 1$ dice left, $F(r) \le p$.

Proof: See Fig. 1. Any successful path from state r>0 to state 0 has a final jump of the form $p^k, k \leqslant r$. For instance, the "low" path in Fig. 1 would have probability $F(r) = {r \choose 1} pq^{r-1} {r \choose 1} {r \choose 1} pq^{r-3} q^2 {r \choose 1} pq {r$

Lemma 2.4 (Lazy Lower Bound for F(r) (Pochhammer form)). With $r \ge 1$ dice remaining, $F(r) \ge \prod_{i=1}^k (1-q^k)$.

Proof: See Fig. 1. Any successful path passes through a set of these stages $r \dots 0$ without once falling into the state \varnothing . This means that if state k is included in the path, that there was a $(1-q^k)$ chance of not busting at that stage. So, assuming our successful path visited every single stage (picking up exactly one die each time), the chance of success would be at least $F(r) = \prod_{i=1}^k (1-q^k)$, since we survived every "bust trap". However,

⁵Swap "q" for "p" in all statements if $p > \frac{1}{2}$ and you'll find mirrored results (e.g. p converges upward)

we need not visit every stage (we could possibly pick up more than one die). Therefore, $F(r) \ge \prod_{i=1}^k (1-q^k)$.

Interestingly enough, this lower bound for F(r) is a known quantity called the q-Pochhammer symbol $(q;q)_{\infty} = \prod_{i=1}^{k} (1-q^k)$, with known convergence properties, appearing in areas like quantum algebra and physics. News to me. Neato.

However, this symbol does not have a closed form evaluation. Let's try to find a closed form bound that's even WORSE than this one.

Lemma 2.5 (Closed Form Lower Bound Lemma). For an unbounded set of r > 0 dice, $p \leq \frac{1}{2}$, the probability F(r) of getting a perfect game has a lower bound of $\exp(-\frac{q}{(1-q)^2})$.

Proof:

- First we have $F(r) \ge \prod_{k=1}^r (1-q^k)$ from the Lazy Lower Bound lemma.
- This means $\log(F(r)) \geqslant \sum_{k=1}^{r} \log(1 q^k)$

Often, $\log(1-z)$ is approximated by -z near zero, but we are most concerned with z near one, since 1-z approaches 0, and $\log(1-z)$ explodes. Therefore, let's look at the expansion of $\log(1-z)$:

- Identity 1: $f(z) = -\frac{1}{1-z} = -1 z z^2 \dots$
- Identity 2: $\int f(z) = \log(1-z) = -z \frac{z^2}{2} \frac{z^3}{3} \dots$

So when summing $\sum_{i=1}^{k} \log(1-q^k)$, we can instead sum:

$$\log(F(r)) = \log(1 - q^{1}) + \log(1 - q^{2}) + \log(1 - q^{3}) + \cdots$$

$$= \left(-q - \frac{q^{2}}{2} - \frac{q^{3}}{3} - \cdots\right) + \left(-q^{2} - \frac{q^{4}}{2} - \frac{q^{6}}{3} - \cdots\right)$$

$$+ \left(-q^{3} - \frac{q^{6}}{2} - \frac{q^{9}}{3} - \cdots\right) + \cdots$$
(2)

$$> (-q - q^2 - q^3 - \cdots) + (-q^2 - q^4 - q^6 - \cdots) + (-q^3 - q^6 - q^9 - \cdots) + \cdots$$
 (3)

$$= \frac{-q}{1-q} + \frac{-q^2}{1-q^2} + \frac{-q^3}{1-q^3} + \cdots$$
 (4)

$$> \frac{-q}{1-q} + \frac{-q^2}{1-q} + \frac{-q^3}{1-q} + \cdots$$
 (5)

$$= \frac{1}{1-q} \left[-q - q^2 - q^3 - \dots \right]$$
 (6)

$$=\frac{-q}{(1-q)^2}\tag{7}$$

- (2) follows from (1) by substitution using Identity 2 above.
- (3) follows from (2) since the denominators of (2) are larger.
- (4) follows from (3) when dividing each sequence by $-q^k$ and applying identity 1.
- (5) follows from (4) since the denominators of (4) are larger.
- (6) and (7) follow from (5) by dividing out $\frac{1}{1-q}$ and applying Identity 2.

Since $\log(F(r)) > \frac{-q}{(1-q)^2}$, $F(r) > \exp(\frac{-q}{(1-q)^2})$.

q	$P(\infty)$	$(q;q)_{\infty}$	$\exp\left(-\frac{q}{(1-q)^2}\right)$
1/2	5.0000×10^{-1}	2.8879×10^{-1}	1.3534×10^{-1}
2/3	1.9827×10^{-1}	6.9272×10^{-2}	2.4788×10^{-3}
3/4	7.3137×10^{-2}	1.5545×10^{-2}	6.1442×10^{-6}
4/5	2.5997×10^{-2}	3.3680×10^{-3}	2.0612×10^{-9}
5/6	9.0335×10^{-3}	7.1400×10^{-4}	9.3576×10^{-14}
6/7	3.0912×10^{-3}	1.4913×10^{-4}	5.7495×10^{-19}
7/8	1.0461×10^{-3}	3.0815×10^{-5}	4.7809×10^{-25}
8/9	3.5109×10^{-4}	6.3155×10^{-6}	5.3802×10^{-32}
9/10	1.1705×10^{-4}	1.2861×10^{-6}	8.1940×10^{-40}

This is a very poor bound, especially when compared to $(q;q)_{\infty}$. But being able to prove Lemma 2.3 and 2.5 in closed form (or without relying on the Pochhammer result) yields this surprising result:

Corollary 2.6 (Bounded Results for F(r) as $r \to \infty$). As $p \to 0$, F(r) can be made arbitrarily close to 0. However, for fixed p > 0, $F(r) > \epsilon$ as $r \to \infty$ for some $\epsilon > 0$.

The upshot: Though increasing the number of sides of the dice can drive F(r) to zero, increasing the number of dice (r) to infinity will never drive F(r) below some fixed constant dependent only on p.

There are a few ways to make this stronger:

- 1. Find a closed form solution for F(r).
- 2. Find a solution for the asymptote of F(r) as $r \to \infty$.
- 3. Prove that F(r) actually converges (instead of just "is bounded") as $r \to \infty$.

We will show why (1) is unlikely, that (3) is true, and hope to one day get better bounds for (2) than lemmas 2.3 and 2.5.

2.2 An Unlikely Closed Form

Definition 2.1, again is
$$F(r) = \sum_{k=1}^{r} {r \choose k} p^k q^{r-k} F(r-k), r > 0$$
, with $F(0) = 1$.

Definition 2.1 is a complicated recurrence; each successive F(r) depends not only on the previous result F(r-1) but all previous results F(r-j), $0 \le j \le r$.

Applying Definition 2.1 by hand yields:

Table A: List of F(r):

$$F(0) = 1,$$

$$F(1) = p,$$

$$F(2) = p^{2} (1 + 2q),$$

$$F(3) = p^{3} (1 + 3q + 3q^{2} + 6q^{3}),$$

$$F(4) = p^{4} (1 + 4q + 6q^{2} + 16q^{3} + 12q^{4} + 12q^{5} + 24q^{6}),$$

$$F(5) = p^{5} (1 + 5q + 10q^{2} + 30q^{3} + 35q^{4} + 50q^{5} + 90q^{6} + 80q^{7} + 60q^{8} + 60q^{9} + 120q^{10}),$$

$$F(6) = p^{6} (1 + 6q + 15q^{2} + 50q^{3} + 75q^{4} + 126q^{5} + 240q^{6} + 300q^{7} + 360q^{8} + 390q^{9} + 660q^{10} + 540q^{11} + 480q^{12} + 360q^{13} + 360q^{14} + 720q^{15}).$$

This pattern in this form isn't yet obvious. Let's look at differences F(r) - F(r+1); if these converge or are bounded, we have hope for a closed form solution:

Table B: List of F(r) - F(r+1):

$$F(0) - F(1) = 1 (1 - p),$$

$$F(1) - F(2) = p (1 - p - 2pq),$$

$$F(2) - F(3) = p^{2} (1 + 2q - p - 3pq - 3pq^{2} - 6pq^{3}),$$

$$F(3) - F(4) = p^{3} (1 + 3q + 3q^{2} + 6q^{3} - p - 4pq - 6pq^{2} - 16pq^{3} - 12pq^{4} - 12pq^{5} - 24pq^{6}),$$

$$F(4) - F(5) = p^{4} (1 + 4q + 6q^{2} + 16q^{3} + 12q^{4} + 12q^{5} + 24q^{6} - p - 5pq - 10pq^{2} - 30pq^{3} - 35pq^{4} - 50pq^{5} - 90pq^{6} - 80pq^{7} - 60pq^{8} - 60pq^{9} - 120pq^{10}),$$

$$F(5) - F(6) = p^{5} (1 + 5q + 10q^{2} + 30q^{3} + 35q^{4} + 50q^{5} + 90q^{6} + 80q^{7} + 60q^{8} + 60q^{9} + 120q^{10} - p - 6pq - 15pq^{2} - 50pq^{3} - 75pq^{4} - 126pq^{5} - 240pq^{6} - 300pq^{7} - 360pq^{8} - 390pq^{9} - 660pq^{10} - 540pq^{11} - 480pq^{12} - 360pq^{13} - 360pq^{14} - 720pq^{15}).$$

Proposition 2.7 (F(r) does not have a closed form).

Thoughts, not a proof:

- Since the degree of p in F(r) is $\frac{r(r+1)}{2}$, this suggests F's successive functions become more complicated than a closed from allows.
- The successive differences are also complicated, as in Table B. By Lemma 2.2, the differences collapse at $p = \frac{1}{2}$ for any r > 0, but must be nonzero at some $p = \frac{1}{2} \epsilon$, but summing these to produce a closed form looks even less tenable.

Though not a proof, these suggest there may not be a fundamentally simpler way to capture our multi-way recurrence than a polynomial whose degree is a triangle number in r! Then, my next failed attempt to find a solution focused instead on the seemingly monotonic behavior of $F(r), r \to \infty$ for fixed $p < \frac{1}{2}$.

2.3 F(r) is non-monotonic

Theorem 2.8 (Incorrect Blind Alley: F(r+1) < F(r), r > 0). If $p < \frac{1}{2}, F(r+1) < F(r)$ for r > 0.

Failed Proof: This certainly seems obvious. Perhaps there are reformulations or combinatorial identities that allow the reduction of Definition 2.1 to something manageable.

The bugbear of $F(r)(\frac{1}{2}) = \frac{1}{2}$ made sure, however, that successive differences had to be extremely small near $\frac{1}{2}$, so no real daylight poked through. Additionally, there are countervailing forces as well: you are *less* likely to fail on stage r+1 (immediate bust probability: q^{r+1}) than stage r (immediate bust probability: q^r), but more likely to land further away from stage 0 than at stage r, presumably worse EV by induction.

All hope was lost when the counterexample was found.

Proposition 2.9 (Counterexample to Monotonicity). F(r) < F(r+1) for certain values of $r > 0, p < \frac{1}{2}$.

Consider that at $p = \frac{1}{2}$, $F(r) = F(s) = \frac{1}{2}$ for any r, s > 0, and therefore, F(r) - F(r+1) = 0. If F(r) > F(r+1) when $p < \frac{1}{2}$, we can know with p at any distance ϵ below $\frac{1}{2}$, that the difference will be positive.

First, reformulate each of the expressions in **Table B** as dependent on this ϵ : with $p \to \frac{1}{2} - \epsilon, q \to \frac{1}{2} + \epsilon$:

List of F(r) - F(r+1), as a function ϵ :

$$F(1) - F(2) = -2e^3 + \frac{1}{2}e^3$$

$$F(2) - F(3) = 6\epsilon^6 + 3\epsilon^5 - 3\epsilon^4 - \frac{3}{2}\epsilon^3 + \frac{3}{8}\epsilon^2 + \frac{3}{16}\epsilon$$

$$F(3) - F(4) = -24\epsilon^{10} - 36\epsilon^{9} + 20\epsilon^{7} + 11\epsilon^{6} - \frac{5}{2}\epsilon^{5} - 4\epsilon^{4} - \frac{1}{4}\epsilon^{3} + \frac{13}{22}\epsilon^{2} + \frac{3}{64}\epsilon,$$

$$F(4) - F(5) = 120\epsilon^{15} + 360\epsilon^{14} + 330\epsilon^{13} - 40\epsilon^{12} - \frac{485}{2}\epsilon^{11} - \frac{267}{2}\epsilon^{10} - \frac{7}{8}\epsilon^{9} + 50\epsilon^{8} + \frac{925}{32}\epsilon^{7} - \frac{9}{32}\epsilon^{6} - \frac{801}{128}\epsilon^{5} - \frac{71}{32}\epsilon^{4} + \frac{185}{512}\epsilon^{3} + \frac{135}{512}\epsilon^{2} + \frac{3}{2048}\epsilon,$$

$$\begin{split} F(5) - F(6) &= -720\epsilon^{21} - 3600\epsilon^{20} - 7200\epsilon^{19} - 6420\epsilon^{18} - 315\epsilon^{17} + 4560\epsilon^{16} + 3810\epsilon^{15} + 720\epsilon^{14} \\ &- \frac{6285}{8}\epsilon^{13} - \frac{6205}{8}\epsilon^{12} - \frac{2893}{8}\epsilon^{11} + \frac{231}{32}\epsilon^{10} + \frac{13305}{128}\epsilon^{9} + \frac{1985}{32}\epsilon^{8} \\ &+ \frac{1387}{128}\epsilon^{7} - \frac{1273}{128}\epsilon^{6} - \frac{21449}{4096}\epsilon^{5} - \frac{1405}{4096}\epsilon^{4} + \frac{425}{1024}\epsilon^{3} \\ &+ \frac{2047}{16384}\epsilon^{2} - \frac{423}{65536}\epsilon. \end{split}$$

We're looking to see if F(r) - F(r+1) is ever negative, and we need look no further than F(5) - F(6), for small ϵ . Notice that if ϵ is almost zero, the final term in each sum $C \cdot \epsilon$ for some C will dominate the expression, as ϵ^2, ϵ^3 ... will be exceedingly small. For F(1) - F(2), F(2) - F(3), F(3) - F(4) and F(4) - F(5), the final C is positive, but for F(5) - F(6), $C = -\frac{423}{65536}$. This means that for small epsilon, looking at $p = \frac{1}{2} - \epsilon$ may yield an increase in EV as we move from 5 to 6 dice left.

Sure enough, for $\epsilon = .005, (p = .495)$, we see that F(r + 1) can be greater than F(r) in Table 2:

r	F(r)
0	1.0000000000000000
1	0.495
2	0.49250025
3	0.49155356436553116
4	0.4913090668731703
5	0.4912951070978062
6	0.4913242043135742
7	0.4913441989090334
8	0.49135032152170444
9	0.4913486656274434
10	0.4913447466697759

Table 2: Values of F(r) with p = 0.495

We can see that F(r) will reverse directions (yellow cells) as r increases, though it does asymptotically approach something like 0.4913417493573063 as $r \to \infty$.

With monotonicity and bounds, convergence is assured. Without it, we must show convergence another way.

2.4 F(r) converges as $r \to \infty$

Theorem 2.10 (F(r) convergence). : F(r) converges when $p \leq \frac{1}{2}$.

Notice that each term F(k) in table A is of the form $F(k) = p^k a_k$, where a_k is completely a function of q.

$$a_0 = 1, F(0) = 1 = p^0 a_0$$
 (8)

$$a_1 = 1, F(1) = p = p^1 a_1$$
 (9)

$$a_2 = 1 + 2q, F(2) = p^2 a_2 (10)$$

$$a_3 = 1 + 3q + 3q^2 + 6q^3, F(3) = p^3 a_3$$
(11)

Let's look again at definition 2.1 and an equivalent way to write it:

$$F(r) = p^r a_r \tag{12}$$

$$F(r) = \sum_{k=1}^{r} {r \choose k} p^k q^{r-k} F(r-k)$$
 (13)

$$F(r)/p^{r} = \sum_{k=1}^{r} {r \choose k} p^{k-r} q^{r-k} p^{r-k} a_{r-k}$$
(14)

$$a_r = \sum_{k=1}^r \binom{r}{k} q^{r-k} a_{r-k} \tag{15}$$

$$= \sum_{m=0}^{r-1} {r \choose m} q^m a_m.$$
 (16)

The final line works when reindexing as m = r - k. Now the pattern of successive functions from Table A emerges a little more clearly.

If we can find the a ratio of $\frac{F(r+1)}{F(r)} = p\frac{a_{r+1}}{a_r}$, $r \to \infty$ of constant or decreasing magnitude, we can assert convergence. We will show that $R_r := \frac{a_{r+1}}{a_r}$ approaches $\frac{1}{1-q} = \frac{1}{p}$, so the ratio of $\frac{F(r+1)}{F(r)} \to 1$.

Note: I used ChatGPT-40 for this section to help formalize this more clearly.

Step 1: Express a_{r+1} in terms of a_r . Using Pascal's identity,

$$a_{r+1} = \sum_{k=0}^{r} {r+1 \choose k} q^k a_k$$

$$= \sum_{k=0}^{r} {r \choose k} + {r \choose k-1} q^k a_k$$

$$= \sum_{k=0}^{r-1} {r \choose k} q^k a_k + q^r a_r + q \sum_{k=0}^{r-1} {r \choose k} q^k a_{k+1}.$$

Dividing by a_r gives

$$R_r = 1 + q^r + q \sum_{k=0}^{r-1} {r \choose k} q^k \frac{a_{k+1}}{a_r}.$$

Step 2: Two-sided bounds. Let

$$m_{r-1} := \min_{0 \leqslant k \leqslant r-1} \frac{a_{k+1}}{a_k}, \qquad M_{r-1} := \max_{0 \leqslant k \leqslant r-1} \frac{a_{k+1}}{a_k}.$$

Since $\frac{a_{k+1}}{a_r} = \frac{a_{k+1}}{a_k} \cdot \frac{a_k}{a_r}$ and $\sum_{k=0}^{r-1} {r \choose k} q^k a_k = a_r$, equation (1) implies $1 + q^r + q m_{r-1} \leqslant R_r \leqslant 1 + q^r + q M_{r-1}, \qquad (r \geqslant 1).$

Step 3: Take limits. Let $L := \limsup_{r \to \infty} R_r$ and $\ell := \liminf_{r \to \infty} R_r$. Since $q^r \to 0$, inequality (2) yields

$$L \leqslant 1 + qL, \qquad \ell \geqslant 1 + q\ell.$$

Thus $(1-q)L \le 1$ and $(1-q)\ell \ge 1$, so $\ell \ge \frac{1}{1-q} \ge L$. Therefore $\ell = L = \frac{1}{1-q}$, i.e.

$$\lim_{r \to \infty} \frac{a_{r+1}}{a_r} = \frac{1}{1 - q}.$$

Direction for $q > \frac{1}{2}$. From the upper bound in (2),

$$R_r \leqslant 1 + q M f_{r-1} \leqslant 1 + \frac{q}{1-q} = \frac{1}{1-q},$$

so the approach is from below when $q>\frac{1}{2}$ (equivalently $p<\frac{1}{2}$).