Cookie Monster Meets the Fibonacci Numbers. Mmmmmm – Theorems!

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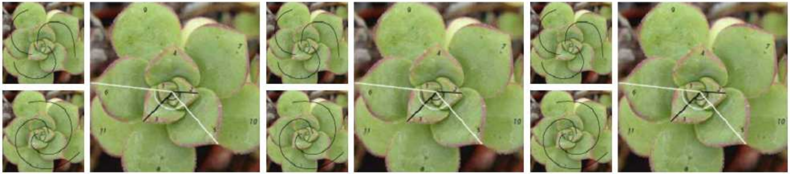
AMS Special Session on Undergraduate Research
Holy Cross, April 9, 2011

Introduction

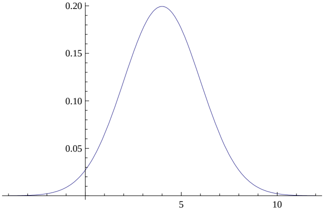
Goals of the Talk

- Chat about ‘fun’ properties of Fibonacci numbers.
- Right perspective: misleading proofs.
- Often enough to ask *any* question, not just right one.
- Several techniques: generating fns, partial fractions.
- Some open problems.



Thanks to colleagues from the Williams College 2010 SMALL REU program (especially Ed Burger, David Clyde, Cory Colbert, Carlos Dominguez, Gea Shin and Nancy Wang).

Pre-requisites: Probability Review



- Let X be random variable with density $p(x)$:
  - $\diamond$ $p(x) \geq 0$; $\int_{-\infty}^{\infty} p(x)dx = 1$;
  - $\diamond$ $\text{Prob}\,(a \leq X \leq b) = \int_a^b p(x)dx$.

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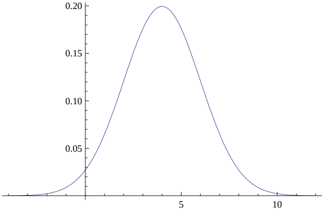

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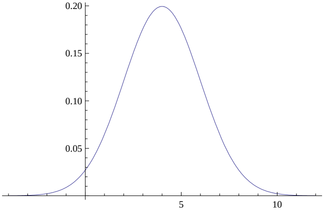

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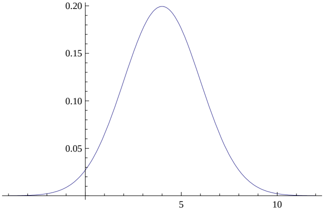

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- Gaussian: Density $(2\pi\sigma^2)^{-1/2} \exp(-(x-\mu)^2/2\sigma^2)$.
- Combinatorics: $\binom{n}{k} = \frac{n!}{k!(n-k)!}$, $n! \approx n^n e^{-n}\sqrt{2\pi n}$.

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Lekkerkerker's Theorem (1952)

The average number of summands in the Zeckendorf decomposition for integers in $[F_n, F_{n+1})$ tends to $\frac{n}{\varphi^2+1} \approx .276n$, where $\varphi = \frac{1+\sqrt{5}}{2}$ is the golden mean.

New Results

Central Limit Type Theorem

As $n \to \infty$, the distribution of the number of summands in the Zeckendorf decomposition for integers in $[F_n, F_{n+1})$ is Gaussian (normal).

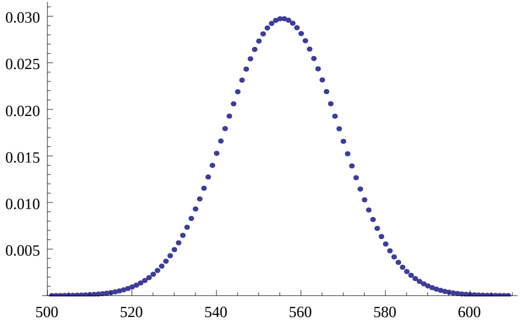

Figure: Number of summands in $[F_{2010}, F_{2011})$; $F_{2010} \approx 10^{420}$.

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Reinterpreting the Cookie Problem

The number of solutions to $x_1 + \cdots + x_P = C$ with $x_i \geq 0$ is $\binom{C+P-1}{P-1}$.

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Let $p_{n,k} = \# \{N \in [F_n, F_{n+1})$: the Zeckendorf decomposition of N has exactly k summands$\}$.

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$$N = F_{i_1} + F_{i_2} + \cdots + F_{i_{k-1}} + F_n,$$
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$$d_1 := i_1 - 1,\ d_j := i_j - i_{j-1} - 2\ (j > 1).$$

$$d_1 + d_2 + \cdots + d_k = n - 2k + 1,\ d_j \geq 0.$$

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Cookie counting $\Rightarrow p_{n,k} = \binom{n-2k+1-k-1}{k-1} = \binom{n-k}{k-1}$.

An Erdos-Kac Type Theorem
(note slightly different notation)

Generalizing Lekkerkerker

Theorem (KKMW 2010)

As $n \to \infty$, the distribution of the number of summands in Zeckendorf's Theorem is a Gaussian.

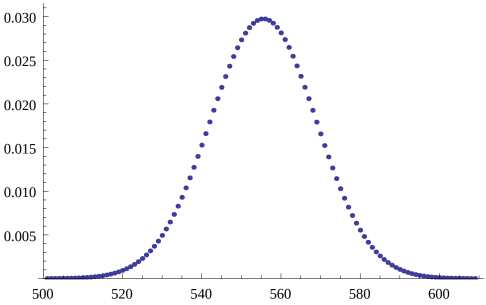

Figure: Number of summands in $[F_{2010}, F_{2011})$

Generalizing Lekkerkerker: Erdos-Kac type result

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Numerics: At $F_{100,000}$: Ratio of $2m^{\text{th}}$ moment σ_{2m} to $(2m-1)!!\sigma_2^m$ is between .999955 and 1 for $2m \leq 10$.

Sketch of proof: Use Stirling’s formula,

$$n! \approx n^n e^{-n}\sqrt{2\pi n}$$

to approximates binomial coefficients, after a few pages of algebra find the probabilities are approximately Gaussian.

(Sketch of the) Proof of Gaussianity

The probability density for the number of Fibonacci numbers that add up to an integer in $[F_n, F_{n+1})$ is $f_n(k) = \binom{n-1-k}{k}/F_{n-1}$. Consider the density for the $n+1$ case. Then we have, by Stirling

$$\begin{aligned} f_{n+1}(k) &= \binom{n-k}{k}\frac{1}{F_n} \\ &= \frac{(n-k)!}{(n-2k)!k!}\frac{1}{F_n} = \frac{1}{\sqrt{2\pi}}\frac{(n-k)^{n-k+\frac{1}{2}}}{k^{(k+\frac{1}{2})}(n-2k)^{n-2k+\frac{1}{2}}}\frac{1}{F_n}\end{aligned}$$

plus a lower order correction term.

Also we can write $F_n = \frac{1}{\sqrt{5}}\phi^{n+1} = \frac{\phi}{\sqrt{5}}\phi^n$ for large n, where ϕ is the golden ratio (we are using relabeled Fibonacci numbers where $1 = F_1$ occurs once to help dealing with uniqueness and $F_2 = 2$). We can now split the terms that exponentially depend on n.

$$f_{n+1}(k) = \left(\frac{1}{\sqrt{2\pi}}\sqrt{\frac{(n-k)}{k(n-2k)}}\frac{\sqrt{5}}{\phi}\right)\left(\phi^{-n}\frac{(n-k)^{n-k}}{k^k(n-2k)^{n-2k}}\right).$$

Define

$$N_n = \frac{1}{\sqrt{2\pi}}\sqrt{\frac{(n-k)}{k(n-2k)}}\frac{\sqrt{5}}{\phi}, \quad S_n = \phi^{-n}\frac{(n-k)^{n-k}}{k^k(n-2k)^{n-2k}}.$$

Thus, write the density function as

$$f_{n+1}(k) = N_n S_n$$

where N_n is the first term that is of order $n^{-1/2}$ and S_n is the second term with exponential dependence on n.

(Sketch of the) Proof of Gaussianity (cont)

Model the distribution as centered around the mean by the change of variable $k = \mu + x\sigma$ where μ and σ are the mean and the standard deviation, and depend on n. The discrete weights of $f_n(k)$ will become continuous. This requires us to use the change of variable formula to compensate for the change of scales:

$$f_n(k)dk = f_n(\mu + \sigma x)\sigma dx.$$

Using the change of variable, we can write N_n as

$$\begin{aligned} N_n &= \frac{1}{\sqrt{2\pi}}\sqrt{\frac{n-k}{k(n-2k)}}\frac{\phi}{\sqrt{5}} \\ &= \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{1-k/n}{(k/n)(1-2k/n)}}\frac{\sqrt{5}}{\phi} \\ &= \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{1-(\mu+\sigma x)/n}{((\mu+\sigma x)/n)(1-2(\mu+\sigma x)/n)}}\frac{\sqrt{5}}{\phi} \\ &= \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{1-C-y}{(C+y)(1-2C-2y)}}\frac{\sqrt{5}}{\phi} \end{aligned}$$

where $C = \mu/n \approx 1/(\phi+2)$ (note that $\phi^2 = \phi + 1$) and $y = \sigma x/n$. But for large n, the y term vanishes since $\sigma \sim \sqrt{n}$ and thus $y \sim n^{-1/2}$. Thus

$$N_n \approx \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{1-C}{C(1-2C)}}\frac{\sqrt{5}}{\phi} = \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{(\phi+1)(\phi+2)}{\phi}}\frac{\sqrt{5}}{\phi} = \frac{1}{\sqrt{2\pi n}}\sqrt{\frac{5(\phi+2)}{\phi}} = \frac{1}{\sqrt{2\pi\sigma^2}}$$

since $\sigma^2 = n\frac{\phi}{5(\phi+2)}$.

(Sketch of the) Proof of Gaussianity (cont)

For the second term S_n, take the logarithm and once again change variables by $k = \mu + x\sigma$,

$$\begin{aligned}
\log(S_n) &= \log\left(\phi^{-n}\frac{(n-k)^{(n-k)}}{k^k(n-2k)^{(n-2k)}}\right) \\
&= -n\log(\phi) + (n-k)\log(n-k) - (k)\log(k) \\
&\quad - (n-2k)\log(n-2k) \\
&= -n\log(\phi) + (n-(\mu+x\sigma))\log(n-(\mu+x\sigma)) \\
&\quad - (\mu+x\sigma)\log(\mu+x\sigma) \\
&\quad - (n-2(\mu+x\sigma))\log(n-2(\mu+x\sigma)) \\
&= -n\log(\phi) \\
&\quad + (n-(\mu+x\sigma))\left(\log(n-\mu) + \log\left(1-\frac{x\sigma}{n-\mu}\right)\right) \\
&\quad - (\mu+x\sigma)\left(\log(\mu) + \log\left(1+\frac{x\sigma}{\mu}\right)\right) \\
&\quad - (n-2(\mu+x\sigma))\left(\log(n-2\mu) + \log\left(1-\frac{x\sigma}{n-2\mu}\right)\right) \\
&= -n\log(\phi) \\
&\quad + (n-(\mu+x\sigma))\left(\log\left(\frac{n}{\mu}-1\right) + \log\left(1-\frac{x\sigma}{n-\mu}\right)\right) \\
&\quad - (\mu+x\sigma)\log\left(1+\frac{x\sigma}{\mu}\right) \\
&\quad - (n-2(\mu+x\sigma))\left(\log\left(\frac{n}{\mu}-2\right) + \log\left(1-\frac{x\sigma}{n-2\mu}\right)\right).
\end{aligned}$$

(Sketch of the) Proof of Gaussianity (cont)

Note that, since $n/\mu = \phi + 2$ for large n, the constant terms vanish. We have $\log(S_n)$

$$\begin{aligned}
= \quad & -n\log(\phi) + (n-k)\log\left(\frac{n}{\mu} - 1\right) - (n-2k)\log\left(\frac{n}{\mu} - 2\right) + (n-(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-\mu}\right) \\
& - (\mu + x\sigma)\log\left(1 + \frac{x\sigma}{\mu}\right) - (n - 2(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-2\mu}\right) \\
= \quad & -n\log(\phi) + (n-k)\log(\phi+1) - (n-2k)\log(\phi) + (n-(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-\mu}\right) \\
& - (\mu + x\sigma)\log\left(1 + \frac{x\sigma}{\mu}\right) - (n - 2(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-2\mu}\right) \\
= \quad & n(-\log(\phi) + \log\left(\phi^2\right) - \log(\phi)) + k(\log(\phi^2) + 2\log(\phi)) + (n-(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-\mu}\right) \\
& - (\mu + x\sigma)\log\left(1 + \frac{x\sigma}{\mu}\right) - (n - 2(\mu+x\sigma))\log\left(1 - 2\frac{x\sigma}{n-2\mu}\right) \\
= \quad & (n-(\mu+x\sigma))\log\left(1 - \frac{x\sigma}{n-\mu}\right) - (\mu + x\sigma)\log\left(1 + \frac{x\sigma}{\mu}\right) \\
& - (n - 2(\mu+x\sigma))\log\left(1 - 2\frac{x\sigma}{n-2\mu}\right).
\end{aligned}$$

(Sketch of the) Proof of Gaussianity (cont)

Finally, we expand the logarithms and collect powers of $x\sigma/n$.

$$\begin{aligned}
\log(S_n) &= (n-(\mu+x\sigma))\left(-\frac{x\sigma}{n-\mu}-\frac{1}{2}\left(\frac{x\sigma}{n-\mu}\right)^2+\dots\right) \\
&\quad -(\mu+x\sigma)\left(\frac{x\sigma}{\mu}-\frac{1}{2}\left(\frac{x\sigma}{\mu}\right)^2+\dots\right) \\
&\quad -(n-2(\mu+x\sigma))\left(-2\frac{x\sigma}{n-2\mu}-\frac{1}{2}\left(2\frac{x\sigma}{n-2\mu}\right)^2+\dots\right) \\
&= (n-(\mu+x\sigma))\left(-\frac{x\sigma}{n\frac{(\phi+1)}{(\phi+2)}}-\frac{1}{2}\left(\frac{x\sigma}{n\frac{(\phi+1)}{(\phi+2)}}\right)^2+\dots\right) \\
&\quad -(\mu+x\sigma)\left(\frac{x\sigma}{\frac{n}{\phi+2}}-\frac{1}{2}\left(\frac{x\sigma}{\frac{n}{\phi+2}}\right)^2+\dots\right) \\
&\quad -(n-2(\mu+x\sigma))\left(-\frac{2x\sigma}{n\frac{\phi}{\phi+2}}-\frac{1}{2}\left(\frac{2x\sigma}{n\frac{\phi}{\phi+2}}\right)^2+\dots\right) \\
&= \frac{x\sigma}{n}n\left(-\left(1-\frac{1}{\phi+2}\right)\frac{(\phi+2)}{(\phi+1)}-1+2\left(1-\frac{2}{\phi+2}\right)\frac{\phi+2}{\phi}\right) \\
&\quad -\frac{1}{2}\left(\frac{x\sigma}{n}\right)^2 n\left(-2\frac{\phi+2}{\phi+1}+\frac{\phi+2}{\phi+1}+2(\phi+2)-(\phi+2)+4\frac{\phi+2}{\phi}\right) \\
&\quad +O\left(n\,(x\sigma/n)^3\right)
\end{aligned}$$

(Sketch of the) Proof of Gaussianity (cont)

$$\begin{aligned}
\log(S_n) &= \frac{x\sigma}{n} n \left(-\frac{\phi+1}{\phi+2}\frac{\phi+2}{\phi+1} - 1 + 2\frac{\phi}{\phi+2}\frac{\phi+2}{\phi} \right) \\
&\quad -\frac{1}{2}\left(\frac{x\sigma}{n}\right)^2 n(\phi+2)\left(-\frac{1}{\phi+1} + 1 + \frac{4}{\phi}\right) \\
&\quad + O\left(n\left(\frac{x\sigma}{n}\right)^3\right) \\
&= -\frac{1}{2}\frac{(x\sigma)^2}{n}(\phi+2)\left(\frac{3\phi+4}{\phi(\phi+1)} + 1\right) + O\left(n\left(\frac{x\sigma}{n}\right)^3\right) \\
&= -\frac{1}{2}\frac{(x\sigma)^2}{n}(\phi+2)\left(\frac{3\phi+4+2\phi+1}{\phi(\phi+1)}\right) + O\left(n\left(\frac{x\sigma}{n}\right)^3\right) \\
&= -\frac{1}{2}x^2\sigma^2\left(\frac{5(\phi+2)}{\phi n}\right) + O\left(n\,(x\sigma/n)^3\right).
\end{aligned}$$

(Sketch of the) Proof of Gaussianity (cont)

But recall that

$$\sigma^2 = \frac{\phi n}{5(\phi+2)}.$$

Also, since $\sigma \sim n^{-1/2}$, $n\left(\frac{x\sigma}{n}\right)^3 \sim n^{-1/2}$. So for large n, the $O\left(n\left(\frac{x\sigma}{n}\right)^3\right)$ term vanishes. Thus we are left with

$$\begin{aligned}\log S_n &= -\frac{1}{2}x^2 \\ S_n &= e^{-\frac{1}{2}x^2}.\end{aligned}$$

Hence, as n gets large, the density converges to the normal distribution:

$$\begin{aligned}f_n(k)dk &= N_n S_n dk \\ &= \frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{1}{2}x^2}\sigma dx \\ &= \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}x^2}dx.\end{aligned}$$

□

Generalizations

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Generalizing from Fibonacci numbers to linearly recursive sequences with arbitrary nonnegative coefficients.

$$H_{n+1} = c_1 H_n + c_2 H_{n-1} + \cdots + c_L H_{n-L+1}, \; n \geq L.$$

with $H_1 = 1$, $H_{n+1} = c_1 H_n + c_2 H_{n-1} + \cdots + c_n H_1 + 1, \; n < L$, coefficients $c_i \geq 0$; $c_1, c_L > 0$ if $L \geq 2$; $c_1 > 1$ if $L = 1$.

- Zeckendorf: Every positive integer can be written uniquely as $\sum a_i H_i$ with natural constraints on the a_i's (e.g. cannot use the recurrence relation to remove any summand).
- Lekkerkerker
- Central Limit Type Theorem

Generalizing Lekkerkerker

Generalized Lekkerkerker's Theorem

The average number of summands in the generalized Zeckendorf decomposition for integers in $[H_n, H_{n+1})$ tends to $Cn + d$ as $n \to \infty$, where $C > 0$ and d are computable constants determined by the c_i's.

$$C = -\frac{y'(1)}{y(1)} = \frac{\sum_{m=0}^{L-1}(s_m + s_{m+1} - 1)(s_{m+1} - s_m)y^m(1)}{2\sum_{m=0}^{L-1}(m+1)(s_{m+1} - s_m)y^m(1)}.$$

$$s_0 = 0, s_m = c_1 + c_2 + \cdots + c_m.$$

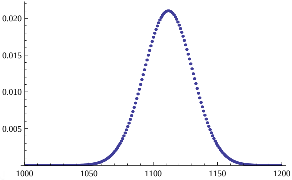
$y(x)$ is the root of $1 - \sum_{m=0}^{L-1} \sum_{j=s_m}^{s_{m+1}-1} x^j y^{m+1}$.

$y(1)$ is the root of $1 - c_1 y - c_2 y^2 - \cdots - c_L y^L$.

Central Limit Type Theorem

Central Limit Type Theorem

As $n \to \infty$, the distribution of the number of summands, i.e., $a_1 + a_2 + \cdots + a_m$ in the generalized Zeckendorf decomposition $\sum_{i=1}^{m} a_i H_i$ for integers in $[H_n, H_{n+1})$ is Gaussian.



Example: the Special Case of $L = 1$

$H_{n+1} = c_1 H_n$, $H_1 = 1$. $H_n = c_1^{n-1}$.

- Legal decomposition $\sum_{i=1}^{m} a_i H_i$:
  $a_i \in \{0, 1, \dots, c_1 - 1\}$ $(1 \le i < m)$, $a_m \in \{1, \dots, c_1 - 1\}$,
  equivalent to the c_1-base expansion.
- For $N \in [H_n, H_{n+1})$, $m = n$, i.e., the first term is $a_n H_n$.
- A_i: the corresponding random variable of a_i.
  The A_i's are independent.
- For large n, the contribution of A_n is immaterial.
  A_i $(1 \le i < n)$ are identically distributed random variables
  with mean $(c_1 - 1)/2$ and variance $(c_1^2 - 1)/12$.
- Central Limit Theorem: $A_2 + A_3 + \cdots + A_n \to$ Gaussian
  with mean $n(c_1 - 1)/2 + O(1)$
  and variance $n(c_1^2 - 1)/12 + O(1)$.

Far-difference Representation

Theorem (Alpert, 2009) (Analogue to Zeckendorf)

Every integer can be written uniquely as a sum of the $\pm F_n$'s, such that every two terms of the same (opposite) sign differ in index by at least 4 (3).

Example: $1900 = F_{17} - F_{14} - F_{10} + F_6 + F_2$.

K: # of positive terms, L: # of negative terms.

Generalized Lekkerkerker's Theorem

As $n \to \infty$, $E[K]$ and $E[L] \to n/10$. $E[K] - E[L] = \varphi/2 \approx .809$.

Central Limit Type Theorem

As $n \to \infty$, K and L converges to a bivariate Gaussian.

- $\text{corr}(K, L) = -(21 - 2\varphi)/(29 + 2\varphi) \approx -.551$, $\varphi = \frac{\sqrt{5}+1}{2}$.
- $K + L$ and $K - L$ are independent.

Future Research

Further Research

1. Are there similar results for linearly recursive sequences with arbitrary integer coefficients (i.e. negative coefficients are allowed in the defining relation)?
2. Lekkerkerker's theorem, and the Gaussian extension, are for the behavior in intervals $[F_n, F_{n+1})$. Do the limits exist if we consider other intervals, say $[F_n + g_1(F_n), F_n + g_2(F_n))$ for some functions g_1 and g_2?
3. For the generalized recurrence relations, what happens if instead of looking at $\sum_{i=1}^{n} a_i$ we study $\sum_{i=1}^{n} \min(1, a_i)$? In other words, we only care about how many distinct H_i's occur in the decomposition.
4. **What can we say about the distribution of the gaps / largest gap between summands in the Zeckendorf decomposition? Appropriately normalized, how do they behave?**

Appendix:
Combinatorial Identities and Lekkerkerker's Theorem

Needed Binomial Identity

Binomial identity involving Fibonacci Numbers

Let F_m denote the m^{th} Fibonacci number, with $F_1 = 1$, $F_2 = 2$, $F_3 = 3$, $F_4 = 5$ and so on. Then

$$\sum_{k=0}^{\lfloor \frac{n-1}{2} \rfloor} \binom{n-1-k}{k} = F_{n-1}.$$

Proof by induction: The base case is trivially verified. Assume our claim holds for n and show that it holds for $n+1$. We may extend the sum to $n-1$, as $\binom{n-1-k}{k} = 0$ whenever $k > \lfloor \frac{n-1}{2} \rfloor$. Using the standard identity that

$$\binom{m}{\ell} + \binom{m}{\ell+1} = \binom{m+1}{\ell+1},$$

and the convention that $\binom{m}{\ell} = 0$ if ℓ is a negative integer, we find

$$\begin{aligned}
\sum_{k=0}^{n} \binom{n-k}{k} &= \sum_{k=0}^{n} \left[\binom{n-1-k}{k-1} + \binom{n-1-k}{k} \right] \\
&= \sum_{k=1}^{n} \binom{n-1-k}{k-1} + \sum_{k=0}^{n} \binom{n-1-k}{k} \\
&= \sum_{k=1}^{n} \binom{n-2-(k-1)}{k-1} + \sum_{k=0}^{n} \binom{n-1-k}{k} = F_{n-2} + F_{n-1}
\end{aligned}$$

by the inductive assumption; noting $F_{n-2} + F_{n-1} = F_n$ completes the proof. □

Preliminaries for Lekkerkerker's Theorem

$$\mathcal{E}(n) \;:=\; \sum_{k=0}^{\lfloor \frac{n-1}{2} \rfloor} k \binom{n-1-k}{k}.$$

Average number of summands in $[F_n, F_{n+1})$ is

$$\frac{\mathcal{E}(n)}{F_{n-1}} + 1.$$

Recurrence Relation for $\mathcal{E}(n)$

$$\mathcal{E}(n) + \mathcal{E}(n-2) \;=\; (n-2)F_{n-3}.$$

Recurrence Relation

Recurrence Relation for $\mathcal{E}(n)$

$$\mathcal{E}(n)+\mathcal{E}(n-2) \;=\; (n-2)F_{n-3}.$$

Proof by algebra (details later):

$$\begin{aligned}
\mathcal{E}(n) &= \sum_{k=0}^{\lfloor \frac{n-1}{2} \rfloor} k\binom{n-1-k}{k} \\
&= (n-2)\sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor}\binom{n-3-\ell}{\ell} - \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor}\ell\binom{n-3-\ell}{\ell} \\
&= (n-2)F_{n-3}-\mathcal{E}(n-2).
\end{aligned}$$

Solving Recurrence Relation

Formula for $\mathcal{E}(n)$ (i.e., Lekkerkerker's Theorem)

$$\mathcal{E}(n) \ = \ \frac{nF_{n-1}}{\varphi^2+1} + O(F_{n-2}).$$

$$\sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^\ell \left(\mathcal{E}(n-2\ell) + \mathcal{E}(n-2(\ell+1))\right)$$

$$= \quad \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^\ell (n-2-2\ell) F_{n-3-2\ell}.$$

Result follows from Binet's formula, the geometric series formula, and differentiating identities: $\sum_{j=0}^m jx^j \ = \ x\frac{(m+1)x^m(x-1)-(x^{m+1}-1)}{(x-1)^2}$. Details later in the appendix.

Derivation of Recurrence Relation for $\mathcal{E}(n)$

$$
\begin{aligned}
\mathcal{E}(n) &= \sum_{k=0}^{\lfloor \frac{n-1}{2} \rfloor} k \binom{n-1-k}{k} \\
&= \sum_{k=1}^{\lfloor \frac{n-1}{2} \rfloor} k \frac{(n-1-k)!}{k!(n-1-2k)!} \\
&= \sum_{k=1}^{\lfloor \frac{n-1}{2} \rfloor} (n-1-k) \frac{(n-2-k)!}{(k-1)!(n-1-2k)!} \\
&= \sum_{k=1}^{\lfloor \frac{n-1}{2} \rfloor} (n-2-(k-1)) \frac{(n-3-(k-1)!}{(k-1)!(n-3-2(k-1))!} \\
&= \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (n-2-\ell) \binom{n-3-\ell}{\ell} \\
&= (n-2) \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} \binom{n-3-\ell}{\ell} - \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} \ell \binom{n-3-\ell}{\ell} \\
&= (n-2)F_{n-3} - \mathcal{E}(n-2),
\end{aligned}
$$

which proves the claim (note we used the binomial identity to replace the sum of binomial coefficients with a Fibonacci number).

Formula for $\mathcal{E}(n)$

Formula for $\mathcal{E}(n)$

$$\mathcal{E}(n) \;=\; \frac{nF_{n-1}}{\varphi^2+1} + O(F_{n-2}).$$

Proof: The proof follows from using telescoping sums to get an expression for $\mathcal{E}(n)$, which is then evaluated by inputting Binet's formula and differentiating identities. Explicitly, consider

$$\begin{aligned}
\sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^{\ell} \left(\mathcal{E}(n-2\ell) + \mathcal{E}(n-2(\ell+1))\right) \;&=\; \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^{\ell} (n-2-2\ell) F_{n-3-2\ell} \\
&= \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^{\ell} (n-3-2\ell) F_{n-3-2\ell} + \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^{\ell} (2\ell) F_{n-3-2\ell} \\
&= \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-1)^{\ell} (n-3-2\ell) F_{n-3-2\ell} + O(F_{n-2});
\end{aligned}$$

while we could evaluate the last sum exactly, trivially estimating it suffices to obtain the main term (as we have a sum of every other Fibonacci number, the sum is at most the next Fibonacci number after the largest one in our sum).

Formula for $\mathcal{E}(n)$ (continued)

We now use Binet's formula to convert the sum into a geometric series. Letting $\varphi = \frac{1+\sqrt{5}}{2}$ be the golden mean, we have

$$F_n \;=\; \frac{\varphi}{\sqrt{5}} \cdot \varphi^n - \frac{1-\varphi}{\sqrt{5}} \cdot (1-\varphi)^n$$

(our constants are because our counting has $F_1 = 1$, $F_2 = 2$ and so on). As $|1-\varphi| < 1$, the error from dropping the $(1-\varphi)^n$ term is $O(\sum_{\ell \le n} n) = O(n^2) = o(F_{n-2})$, and may thus safely be absorbed in our error term. We thus find

$$\begin{aligned}
\mathcal{E}(n) &= \frac{\varphi}{\sqrt{5}} \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (n-3-2\ell)(-1)^{\ell} \varphi^{n-3-2\ell} + O(F_{n-2}) \\
&= \frac{\varphi^{n-2}}{\sqrt{5}} \left[(n-3) \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} (-\varphi^{-2})^{\ell} - 2 \sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} \ell(-\varphi^{-2})^{\ell} \right] + O(F_{n-2}).
\end{aligned}$$

Formula for $\mathcal{E}(n)$ (continued)

We use the geometric series formula to evaluate the first term. We drop the upper boundary term of $(-\varphi^{-1})^{\lfloor \frac{n-3}{2} \rfloor}$, as this term is negligible since $\varphi > 1$. We may also move the 3 from the $n-3$ into the error term, and are left with

$$\begin{aligned}
\mathcal{E}(n) &= \frac{\varphi^{n-2}}{\sqrt{5}}\left[\frac{n}{1+\varphi^{-2}} - 2\sum_{\ell=0}^{\lfloor \frac{n-3}{2} \rfloor} \ell(-\varphi^{-2})^{\ell}\right] + O(F_{n-2}) \\
&= \frac{\varphi^{n-2}}{\sqrt{5}}\left[\frac{n}{1+\varphi^{-2}} - 2S\left(\left\lfloor \frac{n-3}{2} \right\rfloor, -\varphi^{-2}\right)\right] + O(F_{n-2}),
\end{aligned}$$

where

$$\mathcal{S}(m,x) = \sum_{j=0}^{m} jx^j.$$

There is a simple formula for $\mathcal{S}(m,x)$. As

$$\sum_{j=0}^{m} x^j = \frac{x^{m+1}-1}{x-1},$$

applying the operator $x\frac{d}{dx}$ gives

$$\mathcal{S}(m,x) = \sum_{j=0}^{m} jx^j = x\frac{(m+1)x^m(x-1)-(x^{m+1}-1)}{(x-1)^2} = \frac{mx^{m+2}-(m+1)x^{m+1}+x}{(x-1)^2}.$$

Formula for $\mathcal{E}(n)$ (continued)

Taking $x = -\varphi^{-2}$, we see that the contribution from this piece may safely be absorbed into the error term $O(F_{n-2})$, leaving us with

$$\mathcal{E}(n) \;=\; \frac{n\varphi^{n-2}}{\sqrt{5}(1+\varphi^{-2})} + O(F_{n-2}) \;=\; \frac{n\varphi^{n}}{\sqrt{5}(\varphi^{2}+1)} + O(F_{n-2}).$$

Noting that for large n we have $F_{n-1} = \frac{\varphi^n}{\sqrt{5}} + O(1)$, we finally obtain

$$\mathcal{E}(n) \;=\; \frac{nF_{n-1}}{\varphi^2+1} + O(F_{n-2}). \qquad \square$$