# Alice HH vs Bob HT using an Edgeworth Expansion 

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## 1 Definitions

| Symbol | Definition |
| :---: | :---: |
| $n \in \mathbb{N}$ | Number of coinflips in the sequence |
| $C_{1} C_{2}, \ldots, C_{n}$ | Sequence of coinflips $C_{i} \in\{H, T\}$ |
| $\begin{gathered} \Delta_{i}:= \\ 1_{C_{i} C_{i+1}=H H}-1_{C_{i} C_{i+1}=H T} \end{gathered}$ | The difference (Alice score - Bob score) due to the coinflips $C_{i}, C_{i+1}$ |
| $X_{n}=\sum_{i=1}^{n-1} \Delta_{i}$ | Alices total Score minus Bob's total Score. The total difference in score after the $n$ flips |
| $1_{H H \bullet}$ and 1 ${ }_{\bullet}{ }^{\text {H }}$ | Used as a shorthand notation for the indicators of the events like $1_{H H \bullet}:=$ $1\left\{C_{i} C_{i+1} C_{i+2}=H H \bullet\right\}$ when the value of $i$ is implicit. The bullet " $\bullet$ " stands for a "wildcard" that could be either $H$ or $T$, but makes calculations a bit easier to visualize when used in multiple places to keep $i$ constant. For example: $1_{H H \bullet} \cdot 1_{\bullet}{ }_{H H}=1_{H H H}$ or $1_{H H \bullet} \cdot 1_{\bullet}{ }_{H T}=1_{H H T}$ or $1_{H T \bullet} \cdot 1_{\bullet} \cdot H T=0$ (since the middle coinflip cannot be both H and T simultaneously). |

## 2 Moment Calculations

### 2.1 1st Moment

$$
\mathbf{E}\left[X_{n}\right]=(n-1) \mathbf{E}\left[\Delta_{i}\right]=0
$$

### 2.2 2nd Moment

Note that $\Delta_{i}$ and $\Delta_{j}$ are independent unless $i=j$ or $i=j \pm 1$ (i.e. the "range" of the interactions is only 1 coinflip.) From this it follows that we can expand to get:

$$
\mathbf{E}\left[X_{n}^{2}\right]=(n-1) \mathbf{E}\left[\Delta_{i}^{2}\right]+2(n-2) \mathbf{E}\left[\Delta_{i} \Delta_{i+1}\right]
$$

and we compuite:

$$
\mathbf{E}\left[\Delta_{i}^{2}\right]=\mathbf{E}\left[\left(1_{H H}-1_{H T}\right)^{2}\right]=\mathbf{E}\left[1_{H H}+1_{H T}+2 \cdot 0\right]=\frac{1}{4}+\frac{1}{4}=\frac{1}{2}
$$

and:

$$
\begin{aligned}
\mathbf{E}\left[\Delta_{i} \Delta_{i+1}\right] & =\mathbf{E}\left[\left(1_{H H \bullet}-1_{H T}\right)\left(1_{\bullet} \cdot H H-1_{\bullet}{ }_{H T}\right)\right] \\
& =\mathbf{E}\left[1_{H H H}-1_{H H T}-0+0\right] \\
& =\frac{1}{16}-\frac{1}{16}=0
\end{aligned}
$$

so combining gives:

$$
\mathbf{E}\left[X_{n}^{2}\right]=\frac{1}{2}(n-1)
$$

### 2.3 3rd Moment

Again, keeping track of only interactions at range 1 away, we have the expansion:

$$
\begin{aligned}
\mathbf{E}\left[X_{n}^{3}\right]= & \mathbf{E}\left[\sum_{i, j, k=1}^{n} \Delta_{i} \Delta_{j} \Delta_{k}\right] \\
= & (n-1) \mathbf{E}\left[\Delta_{i}^{3}\right]+3(n-3) \cdot 3!\cdot \mathbf{E}\left[\Delta_{i} \Delta_{i+1} \Delta_{i+2}\right] \\
& +(n-2) \cdot\binom{3}{1} \mathbf{E}\left[\Delta_{i}^{2} \Delta_{i+1}\right] \\
& +(n-2) \cdot\binom{3}{1} \mathbf{E}\left[\Delta_{i} \Delta_{i+1}^{2}\right]
\end{aligned}
$$

Now we notice that any expectation of the form $\mathbf{E}\left[\left(\ldots\right.\right.$ product of stuff...) $\cdot \Delta_{i+2}$ ] (i.e. it ends with a $\Delta$ on its own and not squared) is exactly 0 because the the last $\Delta$ is equally likely to be +1 or -1 (either both $50 \%$ or both $0 \%$ depending on whether the product of stuff at the beginning end is a H or ends in a T.) So the only surviving term here is the term $\mathbf{E}\left[\Delta_{i} \Delta_{i+1}^{2}\right]$ which gives:

$$
\begin{aligned}
\mathbf{E}\left[\Delta_{i} \Delta_{i+1}^{2}\right] & =\mathbf{E}\left[\left(1_{H H \bullet}-1_{H T}\right)\left(1_{\bullet H H}-1_{\bullet H T}\right)^{2}\right] \\
& =\mathbf{E}\left[\left(1_{H H \bullet}-1_{H T}\right)\left(1_{\bullet H H}+1_{\bullet H T}+2 \cdot 0\right)\right] \\
& =\mathbf{E}\left[1_{H H H}+1_{H H T}-0-0\right] \\
& =\frac{1}{8}+\frac{1}{8}=\frac{1}{4}
\end{aligned}
$$

So we have:

$$
\mathbf{E}\left[X_{n}^{3}\right]=\frac{3}{4}(n-2)
$$

## 3 Edgeworth Expansion

We use an expansion for the density function of the random variable of the form (see https://en.wikipedia.org/wiki/Edgeworth_se

$$
\rho_{X}(x) \approx \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(x-\mu)^{2}}{2 \sigma^{2}}}\left(1+\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x-\mu}{\sigma}\right)+\ldots\right)
$$

where $\mu=\mathbf{E}[X], \sigma=\sqrt{\operatorname{Var}[X]}$ and $\kappa_{3}=\mathbf{E}\left[(X-\mu)^{3}\right]$, and $H e_{3}(x)=x^{3}-3 x$ is the 3rd Hermite polynomial. In our case $\mu=0$ so this simplifies a bit to:

$$
\rho_{X}(x) \approx \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left(1+\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x}{\sigma}\right)+\ldots\right)
$$

### 3.1 A lemma about integrating He _3

Lemma 1. Have that:

$$
\int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}} H e_{3}\left(\frac{x}{\sigma}\right) d x=-\frac{1}{\sqrt{2 \pi}}
$$

Proof. Have:

$$
\begin{aligned}
\int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}} H e_{3}\left(\frac{x}{\sigma}\right) \mathrm{d} x & =\mathbf{E}_{Z \sim \mathcal{N}\left(0, \sigma^{2}\right)}\left[1_{Z>0} H e_{3}\left(\frac{Z}{\sigma}\right)\right] \\
& =\mathbf{E}_{Z \sim \mathcal{N}(0,1)}\left[1_{Z>0} H e_{3}(Z)\right] \\
& =\mathbf{E}_{Z \sim \mathcal{N}(0,1)}\left[1_{Z>0} Z^{3}\right]-3 \mathbf{E}_{Z \sim \mathcal{N}(0,1)}\left[1_{Z>0} Z\right] \\
& =\mathbf{E}_{Z \sim \mathcal{N}(0,1)}\left[\varphi(Z)^{3}\right]-3 \mathbf{E}_{Z \sim \mathcal{N}(0,1)}[\varphi(Z)] \\
& =(3-1)!!\frac{1}{\sqrt{2 \pi}}-3 \frac{1}{\sqrt{2 \pi}} \\
& =-\frac{1}{\sqrt{2 \pi}}
\end{aligned}
$$

where we have used the relu function $\varphi(x)=x 1_{\{x>0\}}$ and the result for Gaussias that (which can be proved by a nice integration by parts induction)

$$
\mathbf{E}\left[\varphi(Z)^{k}\right]= \begin{cases}\frac{(k-1)!!}{2} & k \text { is even } \\ \frac{(k-1)!!}{\sqrt{2 \pi}} & k \text { is odd }\end{cases}
$$

### 3.2 Alice - Bob using the Edgeworth Approximation.

Lemma 2. If we use the Edgeworth approximation:

$$
\rho_{X}(x) \approx \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left(1+\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x}{\sigma}\right)+\ldots\right)
$$

then we get:

$$
\mathbf{P}(X>0)-\mathbf{P}(X<0)=-\frac{2 \kappa_{3}}{3!\sigma^{3}} \frac{1}{\sqrt{2 \pi}}
$$

Proof. By making the chage of variable $x \rightarrow-x$ and using the fact that $H e_{3}(x)$ is an odd polynomial:

$$
\begin{aligned}
\mathbf{P}(X<0) & =\int_{-\infty}^{0} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left(1+\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x}{\sigma}\right)+\ldots\right) \mathrm{d} x \\
& =\int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left(1+\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{-x}{\sigma}\right)+\ldots\right) \mathrm{d} x \\
& =\int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left(1-\frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x}{\sigma}\right)+\ldots\right) \mathrm{d} x
\end{aligned}
$$

Hence, when we subtract the probabilieis we get:

$$
\begin{aligned}
\mathbf{P}(X>0)-\mathbf{P}(X<0) & =\int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}}\left((1-1)+(1-(-1)) \frac{\kappa_{3}}{3!\sigma^{3}} H e_{3}\left(\frac{x}{\sigma}\right)+\ldots\right) \mathrm{d} x \\
& =2 \frac{\kappa_{3}}{3!\sigma^{3}} \cdot \int_{0}^{\infty} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}} H e_{3}\left(\frac{x}{\sigma}\right) \mathrm{d} x+\ldots \\
& =-\frac{2 \kappa_{3}}{3!\sigma^{3}} \frac{1}{\sqrt{2 \pi}}
\end{aligned}
$$

by the Lemma.

Proposition 3. Suppose that the edgeworth approximation holds for the random variable $X_{n}$ which is Alice's Score minus Bob's score. Then:

$$
\mathbf{P}(\text { Alice wins })-\mathbf{P}(\text { Bob wins })=-\frac{1}{2 \sqrt{\pi n}}+\ldots
$$

Remark 4. Note that we know already from other methods that the result of the proposition is true. However, it is NOT YET PROVEN that the Edgeworth expansion actually holds (need to deal with the fact that the sequence $\Delta_{i}$ are not purely independent but are instead dependent)

Proof. By the lemmas we have:

$$
\begin{aligned}
\mathbf{P}(\text { Alice wins })-\mathbf{P}(\text { Bob wins }) & =\mathbf{P}\left(X_{n}>0\right)-\mathbf{P}\left(X_{n}<0\right) \\
& =-\frac{2 \kappa_{3}}{3!\sigma^{3}} \frac{1}{\sqrt{2 \pi}}+\ldots \\
& =-\frac{2\left(\frac{3}{4}(n-2)\right)}{3!\left(\frac{1}{2}(n-1)\right)^{3 / 2}} \frac{1}{\sqrt{2 \pi}}+\ldots \\
& =-\frac{2\left(\frac{3}{4}\right)}{3!\left(\frac{1}{2}\right) \sqrt{\frac{1}{2}}} \frac{1}{\sqrt{2 \pi}} \frac{(n-2)}{(n-1)^{3 / 2}}+\ldots \\
& =-\frac{1}{2 \sqrt{\pi n}}+\ldots
\end{aligned}
$$

where we have used $\frac{n-2}{(n-1)^{3 / 2}}=\frac{1}{\sqrt{n}}+\ldots$ as $n \rightarrow \infty$.

