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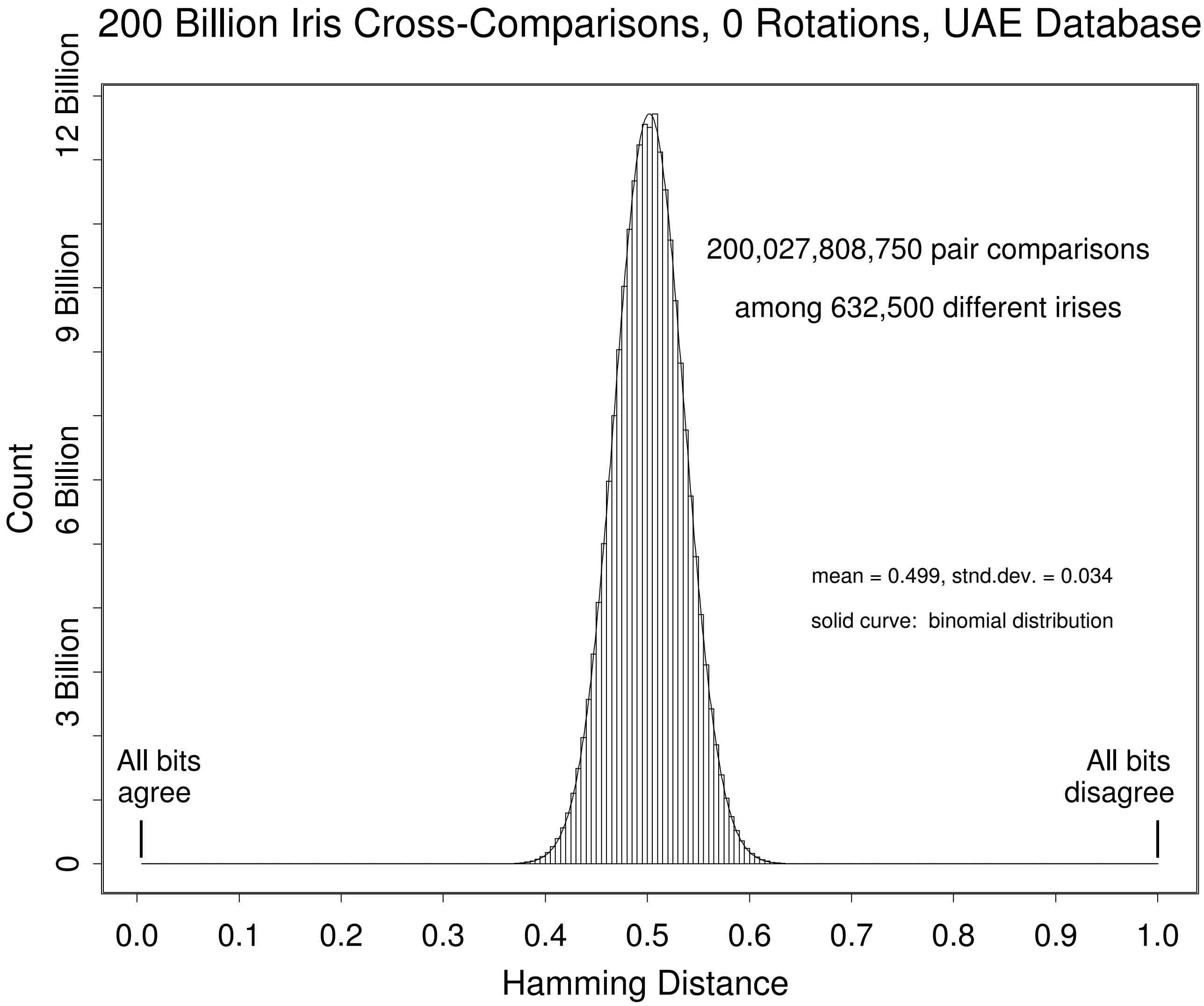


Binomial distribution (solid curve in histogram for 0 rotations):

$$f(x) = \frac{N!}{m!(N-m)!}\, p^m (1-p)^{(N-m)} \tag{1}$$

where $x = m/N$ (e.g. the fraction of 'heads' outcomes in N coin tosses).

Logic for computing raw Hamming Distance scores, incorporating masks:

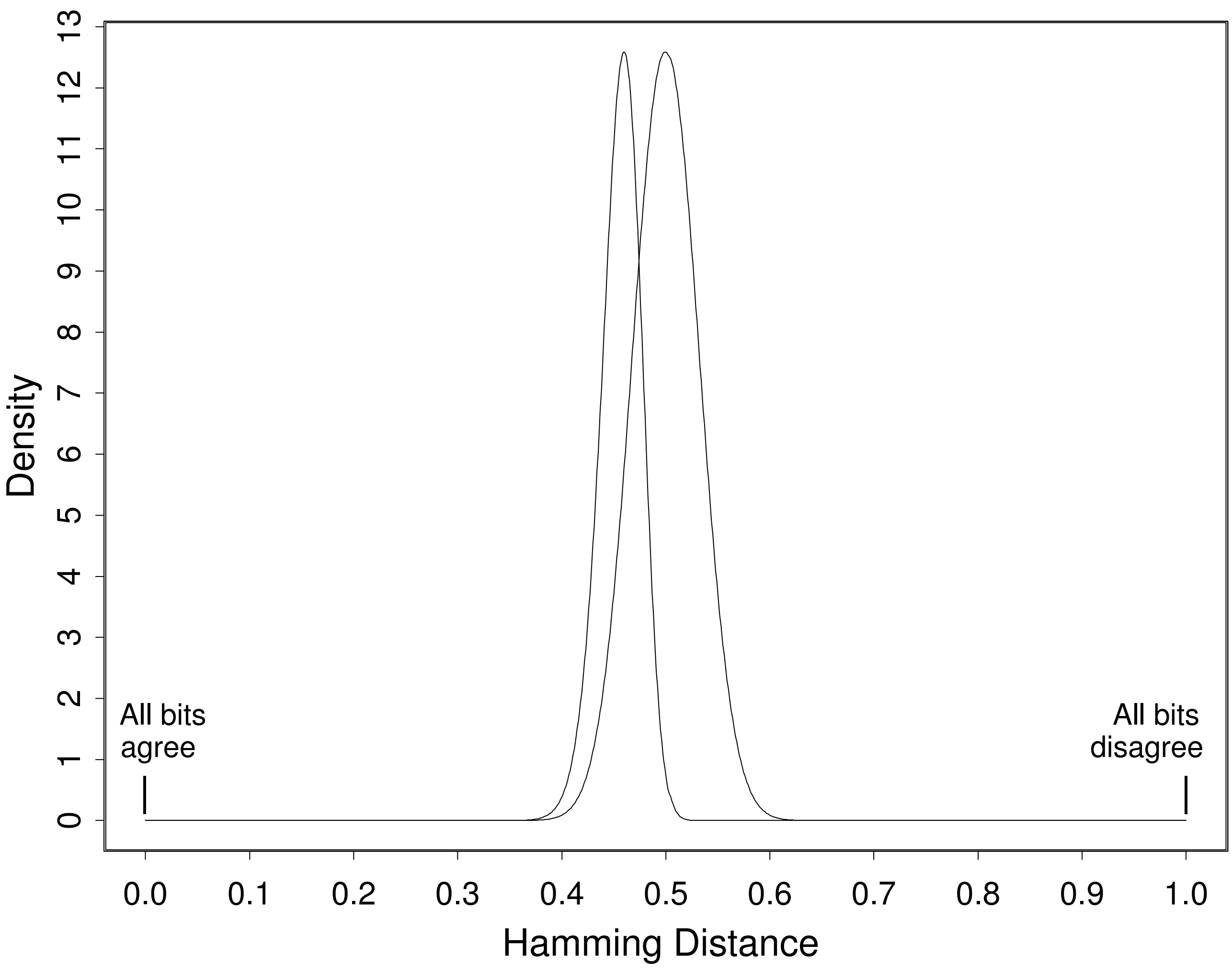
$$HD_{\text{raw}} = \frac{\|(codeA \otimes codeB) \cap maskA \cap maskB\|}{\|maskA \cap maskB\|} \tag{2}$$

where $\otimes$ is Exclusive-OR, $\cap$ is AND, and $\|\quad\|$ is the count of 'set' bits.

Score re-normalisation to compensate for number of bits compared:

$$HD_{\text{norm}} = 0.5 - (0.5 - HD_{\text{raw}})\sqrt{\frac{n}{911}} \tag{3}$$

Raw Binomial (p=0.5, N=249 DoF) and its Extreme-value Distribution



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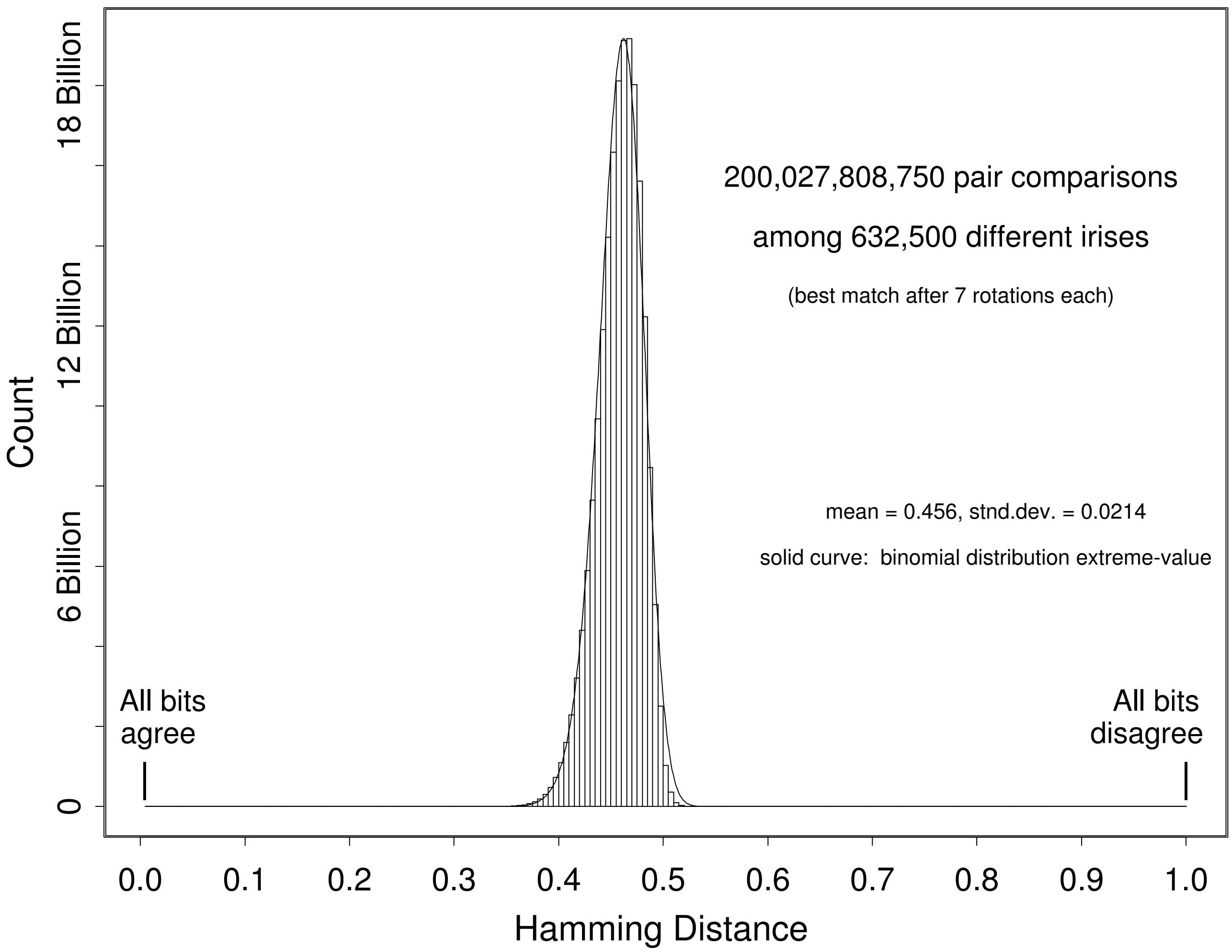
200 Billion Iris Cross-Comparisons, 7 Rotations, UAE Database



The new distribution after k rotations of IrisCodes in the search process still has a simple analytic form that can be derived theoretically. Let $f_0(x)$ be the raw density distribution obtained for the HD_{norm} scores between different irises after comparing them only in a single relative orientation; for example, $f_0(x)$ might be the binomial defined in Eqn (1). Then $F_0(x)$, the cumulative of $f_0(x)$ from 0 to x, becomes the probability of getting a False Match in such a test when using HD_{norm} acceptance criterion x:

$$F_0(x) = \int_0^x f_0(x)dx \tag{4}$$

or, equivalently,

$$f_0(x) = \frac{d}{dx}F_0(x) \tag{5}$$

Clearly, then, the probability of *not* making a False Match when using decision criterion x is $1 - F_0(x)$ after a single test, and it is $[1 - F_0(x)]^k$ after carrying out k such tests independently at k different relative orientations. It follows that the probability of a False Match after a "best of k" test of agreement, when using HD_{norm} criterion x, regardless of the actual form of the raw unrotated distribution $f_0(x)$, is:

$$F_k(x) = 1 - [1 - F_0(x)]^k \tag{6}$$

and the expected density $f_k(x)$ associated with this cumulative is:

$$\begin{aligned} f_k(x) &= \frac{d}{dx}F_k(x) \\ &= k f_0(x) \left[1 - F_0(x)\right]^{k-1} \end{aligned} \tag{7}$$

Observed False Match Rates in 200 billion comparisons

HD Criterion Policy	*Observed False Match Rate*
0.220	0 (*theor: 1 in* 5×10^{15})
0.225	0 (*theor: 1 in* 1×10^{15})
0.230	0 (*theor: 1 in* 3×10^{14})
0.235	0 (*theor: 1 in* 9×10^{13})
0.240	0 (*theor: 1 in* 3×10^{13})
0.245	0 (*theor: 1 in* 8×10^{12})
0.250	0 (*theor: 1 in* 2×10^{12})
0.255	0 (*theor: 1 in* 7×10^{11})
0.262	1 in 200 billion
0.267	1 in 50 billion
0.272	1 in 13 billion
0.277	1 in 2.7 billion
0.282	1 in 284 million
0.287	1 in 96 million
0.292	1 in 40 million
0.297	1 in 18 million
0.302	1 in 8 million
0.307	1 in 4 million
0.312	1 in 2 million
0.317	1 in 1 million

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