Chains of distributions and Benford's Law

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- If $f_{n,k}(x_n)$ is the probability density for X_n , then

$$f_{n,k}(x_n) = \begin{cases} \frac{\log^{n-1}(k/x_n)}{k\Gamma(n)} & \text{if } x_n \in [0, k] \\ 0 & \text{otherwise.} \end{cases}$$

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Theorem (JKKKM)

As $n \to \infty$ the distribution of digits of X_n rapidly tends to Benford's Law.

Uniform Density Example: n = 10 with 10,000 trials

 $\chi^2 = 7.35$ (critical threshold at 5% with 8 d.f. is 15.5)

Digit	Observed Probability	Expected Probability
1	0.298	0.301
2	0.180	0.176
3	0.127	0.125
4	0.097	0.097
5	0.080	0.079
6	0.071	0.067
7	0.056	0.058
8	0.048	0.051
9	0.044	0.046

Sketch of the proof

- First prove the claim for density $f_{n,k}$ by induction.
- Use Mellin Transforms and Poisson Summation to analyze probability.

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Differentiating yields $f_{2,k}(x_2) = \frac{\log(k/x_2)}{k}$.

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Further Comments

- Other distributions: exponential, one-sided normal.
- Densities of the form $f(x; \theta) = \theta^{-1}g(x/\theta)$.
- Weibull distribution: $f(x; \gamma) = \gamma x^{\gamma-1} \exp(-x^{\gamma})$.
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- Further areas of research Two parameter distribution, closed form for other single variable distributions

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$$\lim_{n\to\infty}\sum_{\ell=-\infty}^{\infty}\prod_{m=1}^{n}(\mathcal{M}f_{\mathcal{D}_{p(m)}(1)})\left(1-\frac{2\pi i\ell}{\log B}\right) = 0$$

Theorem (JKKKM)

- If conditions hold, as $n \to \infty$ the distribution of leading digits of X_n tends to Benford's law.
- The error is a nice function of the Mellin transforms: if $Y_n = \log_B X_n$, then

$$|\operatorname{Prob}(Y_n \bmod 1 \in [a,b]) - (b+a)| \le$$

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Follow Mellin transform proof of CLT mod 1 for product independent random variables.