

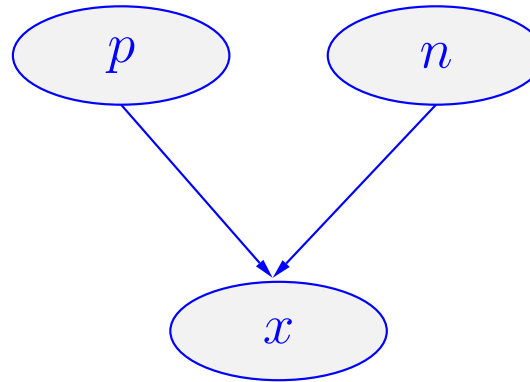
n independent Bernoulli processes

General case

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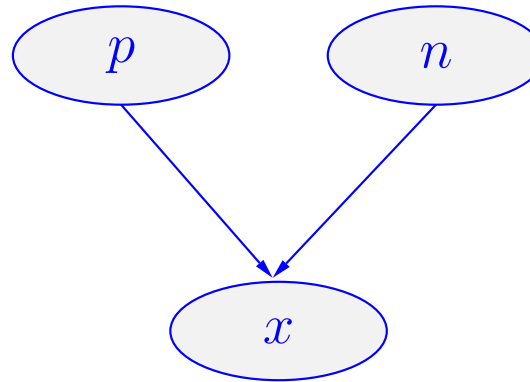
Model



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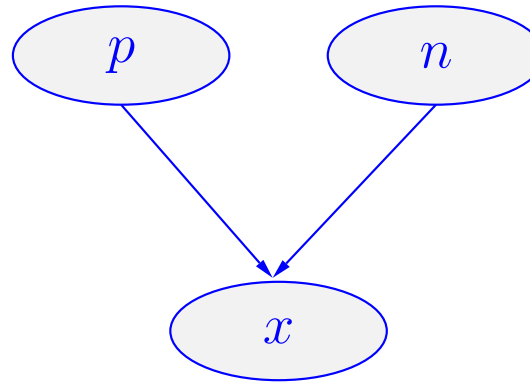
Joint pdf (omitting background condition I):

$$f(x, p, n) = f(x | p, n)$$

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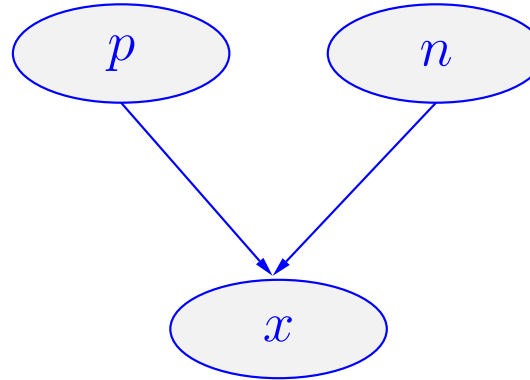
Joint pdf (omitting background condition I):

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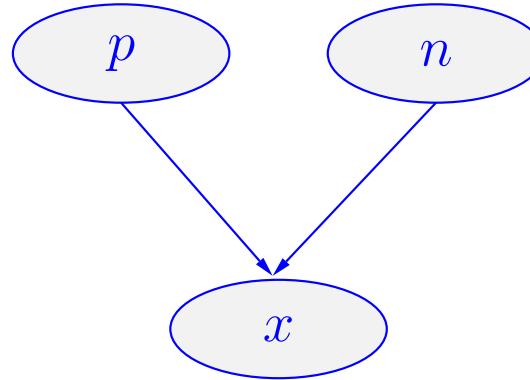
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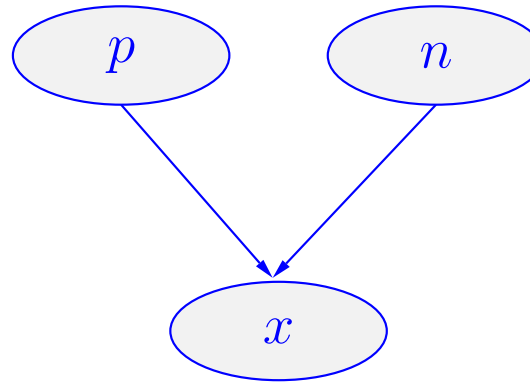
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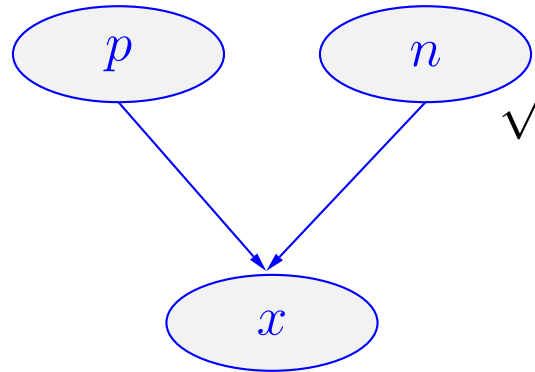
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(n and p are independent)

n independent Bernoulli processes

Usual case \rightarrow n fixed (for the moment)

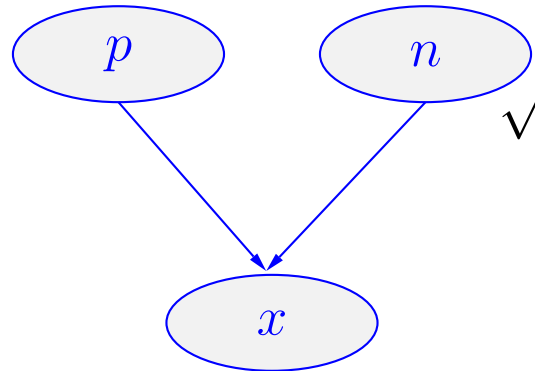
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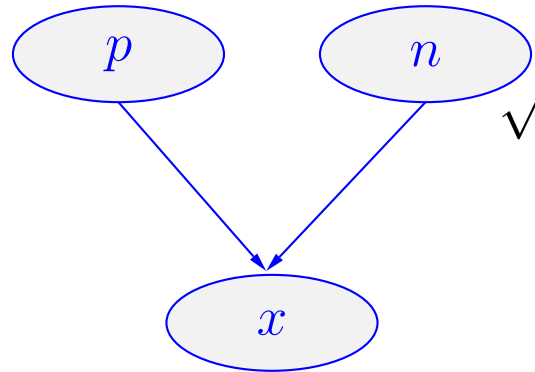
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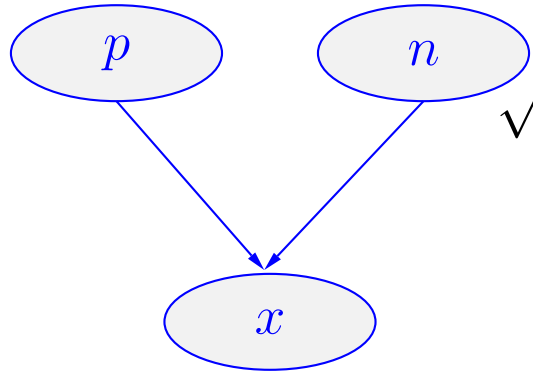
Typical problems

- p is assumed \rightarrow interested in $f(x | n, p)$
 \rightarrow well known binomial;

n independent Bernoulli processes

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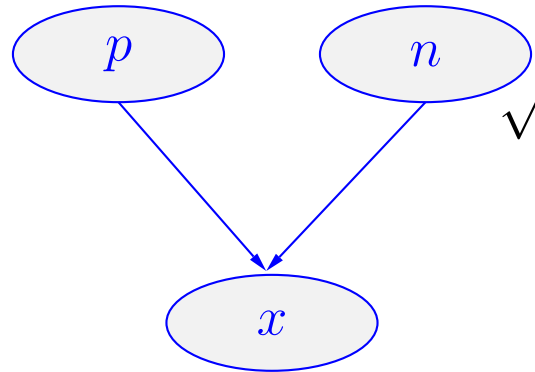
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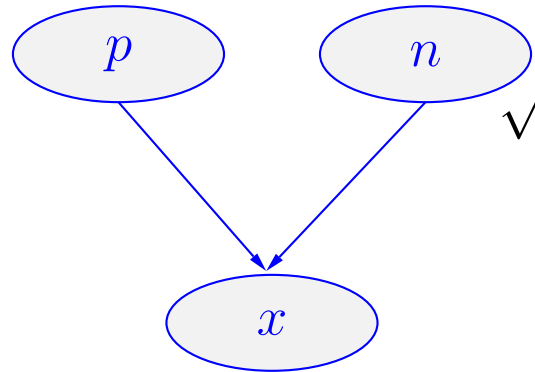
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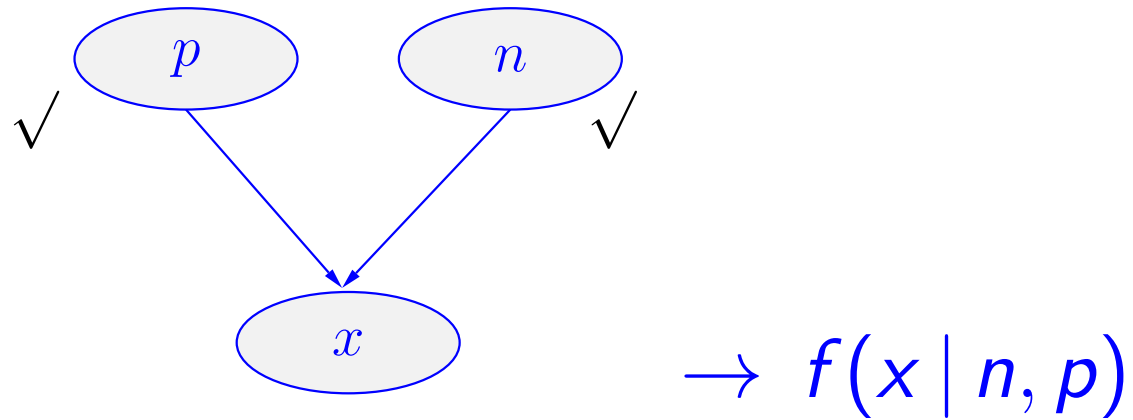
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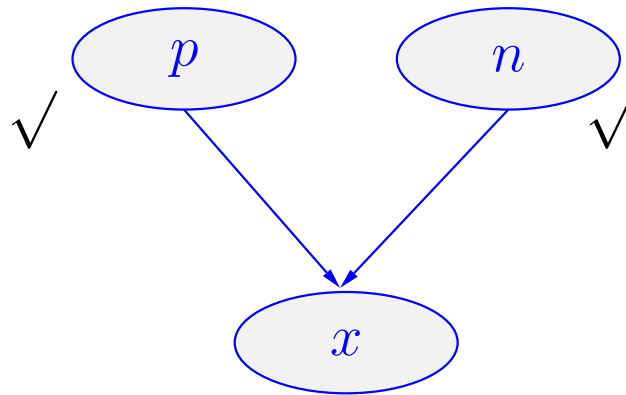
n independent Bernoulli processes

Graphical models of the typical problems

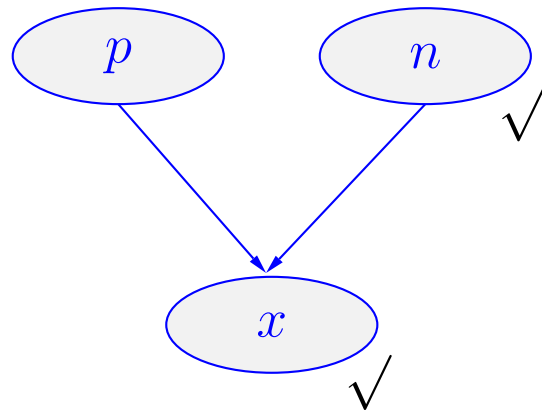


n independent Bernoulli processes

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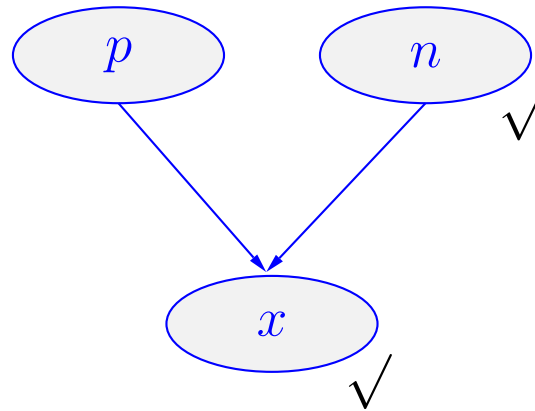
$$\rightarrow f(x \mid n, p)$$



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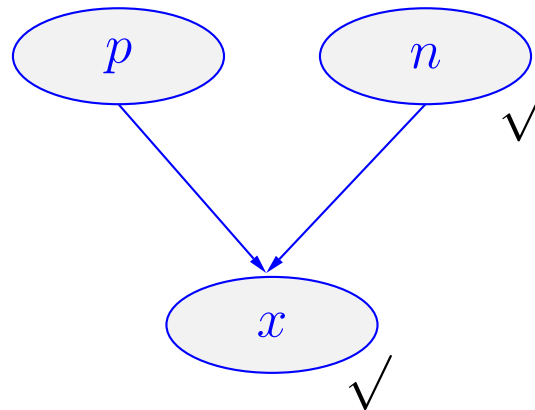
n independent Bernoulli processes

Inferring p



n independent Bernoulli processes

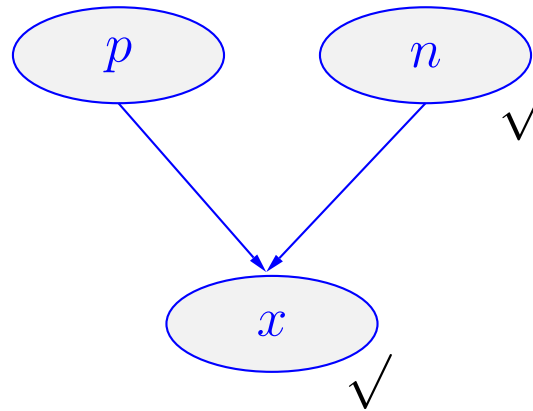
Inferring p



$$f(p | x, n) = \frac{f(p, x | n)}{f(x | n)}$$

n independent Bernoulli processes

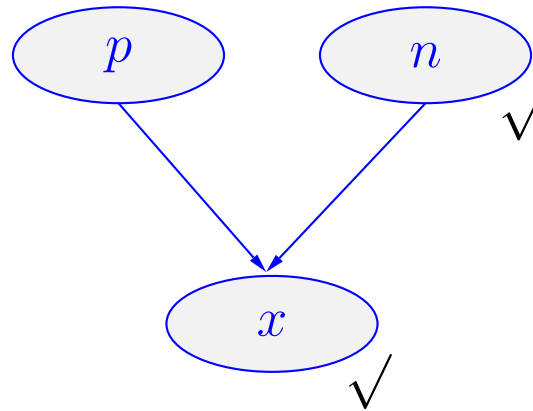
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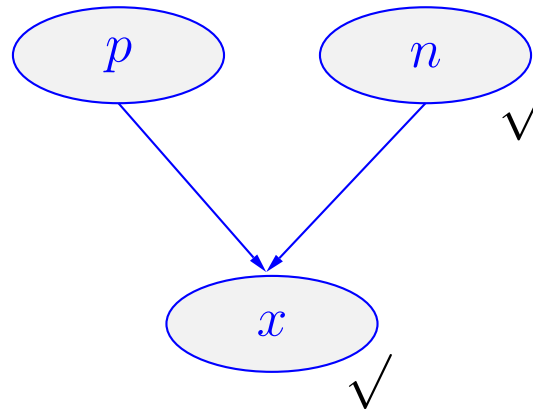
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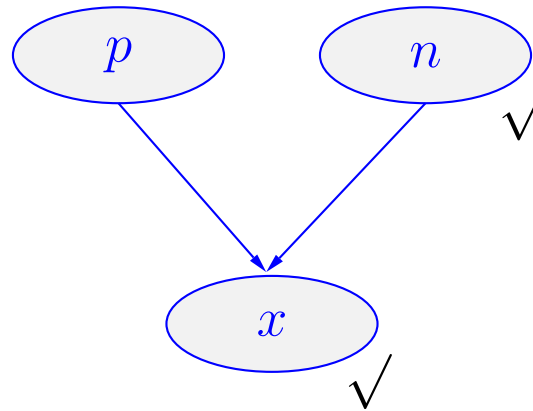
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(denominator just normalization!)

Inferring “Bernoulli’s p ”

We just need to make explicit $f(x \mid n, p)$:

$$f(x \mid n, p) = \binom{n}{x} p^x (1 - p)^{n-x}$$

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(The binomial coefficient is irrelevant, not depending on p)

Inferring “Bernoulli’s p ”

$$f(p \mid x, n) = \frac{p^x (1 - p)^{n-x} f_{\circ}(p)}{\int_0^1 p^x (1 - p)^{n-x} f_{\circ}(p) \, dp}$$

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For teaching purposes we start from a **uniform prior**,
i.e. $f_0(p) = 1$:

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- ▶ The integral at the denominator is the **special function “ β ”** (also defined for real values of x and n).
- ▶ In our case these two numbers are integer and the integral becomes equal to

$$\frac{x! (n - x)!}{(n + 1)!}$$

Inferring “Bernoulli’s p ”

Solution for uniform prior (think to **Bayes’ billard**)

$$f(p | x, n) = \frac{(n+1)!}{x! (n-x)!} p^x (1-p)^{n-x}$$

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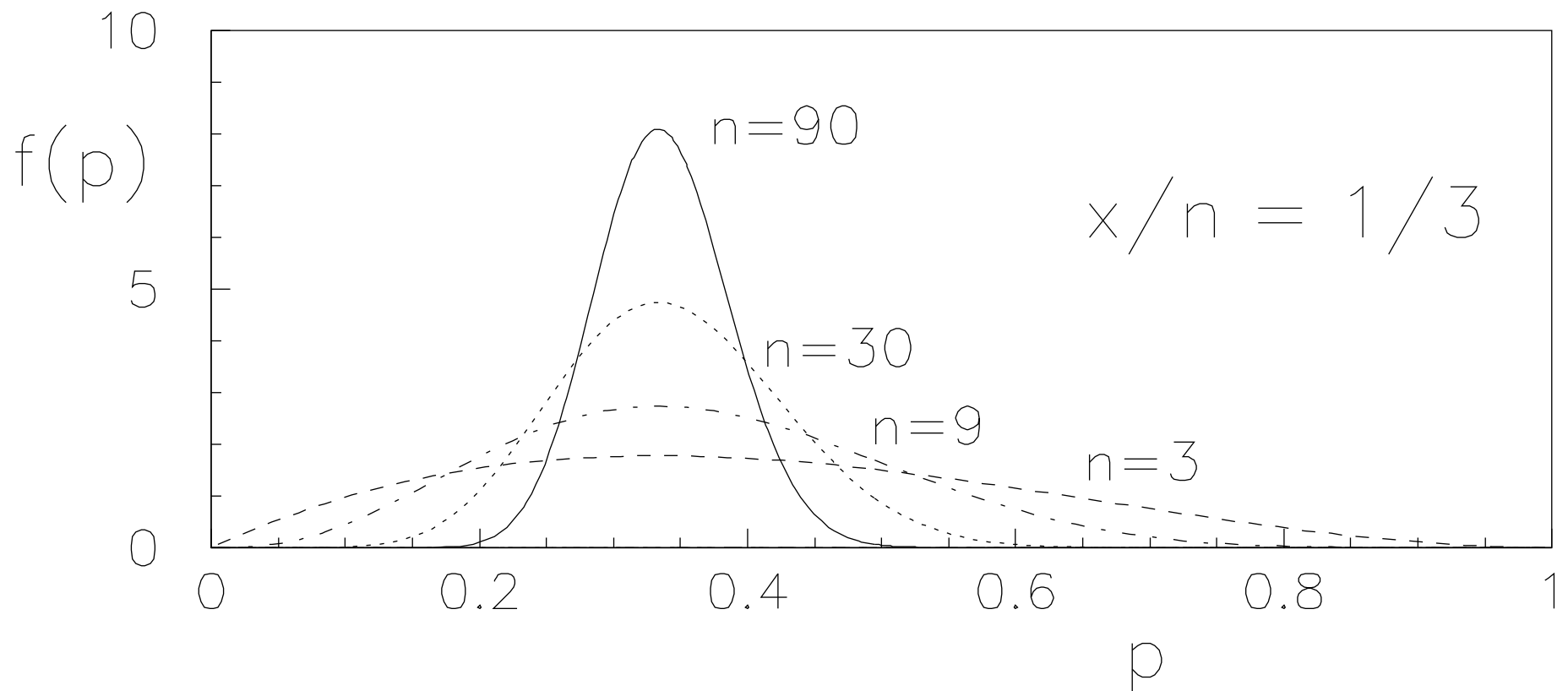
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Inferring “Bernoulli’s p ”

Summaries of the **posterior distribution**

$$p_m = \text{mode}(p) = \frac{x}{n}$$

Inferring “Bernoulli’s p ”

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$$\begin{aligned} \text{Var}(p) &= \frac{(x + 1)(n - x + 1)}{(n + 3)(n + 2)^2} \\ &= \frac{x + 1}{n + 2} \left(\frac{n + 2}{n + 2} - \frac{x + 1}{n + 2} \right) \frac{1}{n + 3} \\ &= E(p) (1 - E(p)) \frac{1}{n + 3} \end{aligned}$$

Inferring the “Bernoulli’s p ”

About the meaning of $E(p)$

- ▶ We have used the “first”^(*) n trials to learn about “ p ”.
- [^(*) “First” does not imply time order, but just order in usage.]

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$E(p)$ (and not the mode!) is the probability of every ‘future’ event which is believed to have the **same p** of the ‘previous’ ones.

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(But keep in mind the **inductivist turkey!**)

Inferring the “Bernoulli’s p ”

Large number behaviour

When the number of successes and the number of failures become ‘large’ (x large is not enough, as it can be easily understood from the symmetric properties of the binomial $p \leftrightarrow q$):

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Moreover $f(p)$ tends to a Gaussian distribution:

$$p \sim \mathcal{N}(p_m, \sigma_p)$$

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$$\text{Var}(p) \approx \frac{x}{n} \left(1 - \frac{x}{n}\right) \frac{1}{n} = \frac{p_m (1 - p_m)}{n}$$

$$\sigma(p)(= \sigma_p) \approx \sqrt{\frac{p_m (1 - p_m)}{n}} \propto \frac{1}{\sqrt{n}}$$

Moreover $f(p)$ tends to a Gaussian distribution:

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When $n \rightarrow \infty$, then $\sigma_p \rightarrow 0$,

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(Similarly to Bernoulli’s theorem, it is not a ‘mathematical’ limit!)

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- **No need of ‘frequentistic definition’ !**

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Frequency and probability are **related** in probability theory:

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- ▶ There is no need to identify the two concepts.
- ▶ It does not justify the frequentistic definition.