# Diversification and limited information in the Kelly game

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1 in one turn, a fraction *f* of the current wealth can be invested

- with the probability *p*, the invested amount is doubled
- with the probability 1 p, the invested amount is lost
- 2 repeat (infinitely) many times
- 3 winning probability *p* is constant and known

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question: how to find the optimal investment fraction?

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# in one turn, a fraction *f* of the current wealth can be invested with the probability *p*, the invested amount is doubled with the probability 1 - *p*, the invested amount is lost

- 2 repeat (infinitely) many times
- 3 winning probability *p* is constant and known
  - question: how to find the optimal investment fraction?
  - well-known answer: maximise the exponential growth rate

$$G(f) := \left\langle \ln\left(1 + f R_1\right) \right\rangle$$

 $R_1$  = game return on one-turn basis

optimal investment fraction

$$f^*(p) = egin{cases} 0 & p \in [0;rac{1}{2}] \ 2p-1 & p \in (rac{1}{2};1] \end{cases}$$

optimal growth rate

$$G^{*}(p) = \ln 2 + p \ln p + (1 - p) \ln(1 - p)$$

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Matúš Medo (University of Fribourg) Divers

Diversification and limited information

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in real life:

- simultaneous games
- unknown game properties

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## Insider vs outsider: intro

- M games simultaneously played
- insider strategy: know one game better
- outsider strategy: gain by diversification

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## Insider vs outsider: intro

- M games simultaneously played
- insider strategy: know one game better
- outsider strategy: gain by diversification
- when the outsider outperforms the insider?
  - 1 little insider's information
  - 2 extensive outsider's diversification

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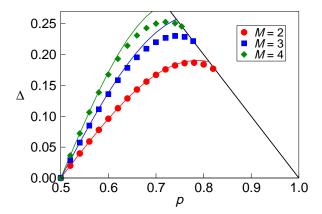
## Insider vs outsider: framework

## 1 M games

- 2 the winning probability of each game is either  $p \Delta$  or  $p + \Delta$  (changing each turn randomly)
- insider knows the exact winning probability for one game (no diversification)
- outsider knows only the average winning probability p (invests evenly in M games)

## Insider vs outsider: results

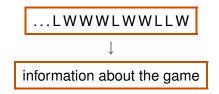
first approximation:  $\Delta \approx (p - \frac{1}{2})(\sqrt{2M} - 1)$ 



- even "noisy" information in the form  $p \pm \Delta$  is artificial
- let's assume that we use only *T* past turns for learning

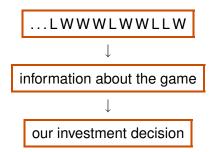
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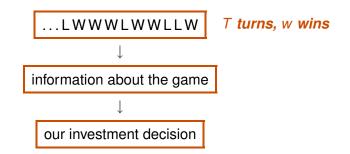
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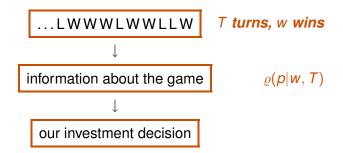
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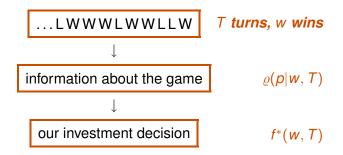
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## Limited information: derivation

• for any  $\rho(p)$ ,  $G := \langle \ln(1 + f R_1) \rangle$  is maximised by

$$f^*[\varrho] = 2\langle p \rangle_{\varrho} - 1$$

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■ observing *w* wins in *T* turns gives us the information

$$\varrho(\boldsymbol{p}|\boldsymbol{w},T) \propto \pi(\boldsymbol{p}) P(\boldsymbol{w}|\boldsymbol{p},T)$$

• here P(w|p, T) is the binomial distribution

$$P(w|p,T) = \binom{T}{w} p^w (1-p)^{T-w}$$

•  $\pi(p)$  is the prior distribution of p

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- the optimal investment fraction is

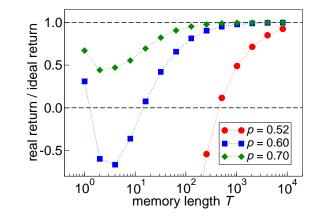
$$f^*(w, T) = \begin{cases} 0 & w \leq T/2 \\ rac{2w - T}{T + 2} & w > T/2 \end{cases}$$

two interesting cases:

$$\lim_{T \to \infty} f^*(w, T) = 2 \lim_{T \to \infty} \frac{w}{T} - 1 = 2p - 1$$
$$f^*(T, T) = \frac{T}{T + 2} < 1$$

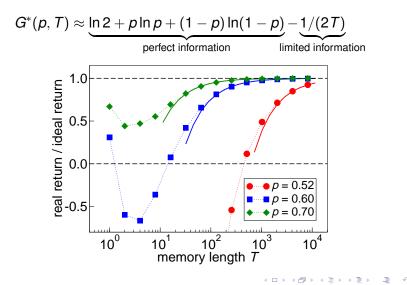
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# The role of prior information

## • what is $\pi(p)$ ?

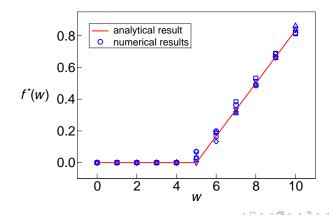
1 a way how to quantify our prior lack of information

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# The role of prior information

## • what is $\pi(p)$ ?

a way how to quantify our prior lack of information
 aggregate information about *p* evolving in time



## ■ simple pattern:

- 80 good turns (*p* = 0.8)
- 20 bad turns (*p* = 0.2)
- repeated many times

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- perfect information: return 16.7%

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- why necessary? because with enough data, prior beliefs are overruled!

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- set  $P(\text{crisis comes}) = P_C$
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- our framework is too simple to allow for more realistic considerations...

## Conclusion

#### we have seen:

- diversification and limited information in toy systems
- simple analytical results

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- all capabilities of the prior information  $\pi(p)$
- less frequent portfolio rebalancing
- transaction costs

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## Thank you for your attention