

# Insuring against loss of evidence and capital: review

Vladimir Vovk

Department of Computer Science  
Royal Holloway, University of London

Tokyo  
12 November, 2012

## Co-authors

Joint works with:

A. Philip Dawid, Steven de Rooij, Peter Grünwald, Wouter M. Koolen, Glenn Shafer, Alexander Shen, and Nikolai Vereshchagin

## Statistical testing in game-theoretic probability

It is usually framed as a perfect-information game between two players, Forecaster and Sceptic. On each round:

- Forecaster sets prices for various gambles;
- Sceptic chooses which gambles to make.

If Sceptic multiplies by a large factor the capital he puts at risk, he has evidence against Forecaster's ability; his capital at the end of each round is a measure of his evidence against Forecaster so far. However, his capital can go up and then back down. This is counterintuitive: evidence is supposed to be monotonic; evidence that can disappear is not really evidence.

## This talk 1

We will see that evidence found by Sceptic against Forecaster **is** monotonic, at least to some degree. Yes, reporting the maximum so far instead of the current value exaggerates the evidence against Forecaster. However, the exaggeration is not gross: Sceptic's strategy can be modified in such a way that actual evidence becomes almost as strong as the exaggerated evidence.

This gives a method for insuring against loss of evidence.

## This talk 2

Our results will have two main interpretations:

- Statistical:** Suppose you have a lot of evidence against Forecaster, or against a null hypothesis. How can you avoid losing all of it?
- Financial:** Suppose your current capital is large. Should you continue trading (risking losing all your money) or should you stop (preventing your capital from growing further)? Can we compromise? What trade-offs are open to us?

The same mathematics.

# Outline

- 1 Simple lookback adjusters
  - Definitions
  - Characterization of SLAs
  - Simple applications
  - Connection with Bayes factors and p-values
- 2 Lookback adjusters
- 3 Down-up adjusters
- 4 References

## Trading protocol

We are trading in one security  $X$  in a financial market. Normalize the initial price  $X_0$  to 1 and the investor's initial capital  $\mathcal{K}_0$  to 1. Trading protocol:

$X_0 := 1$  and  $\mathcal{K}_0 := 1$

FOR  $t = 1, 2, \dots$ :

Investor announces  $p_t \in \mathbb{R}$

Market announces  $X_t \in [0, \infty)$

$\mathcal{K}_t := \mathcal{K}_{t-1} + p_t(X_t - X_{t-1})$

END FOR

$\mathcal{K}_t$ : Investor's capital. **Trading strategy** is a strategy for Investor in this protocol.

Can be interpreted in terms of evidence.

## What we want to achieve

Set

$$X_t^* := \max_{s \leq t} X_s.$$

We would like to have a trading strategy that guarantees

$$\mathcal{K}_t \geq F(X_t^*)$$

for all  $t$ , where, as  $y \rightarrow \infty$ ,  $F(y) \rightarrow \infty$  almost as fast as  $y$ . If this inequality can be guaranteed,  $F$  is a **simple lookback adjuster (SLA)**.

We are interested only in nonnegative SLAs. Later in the talk: characterization of SLAs.



# Admissibility

The set of SLAs is too big. More manageable subset:  
admissible SLAs (**ASLAs**).

An SLA  $G$  **dominates** an SLA  $F$  if  $G \geq F$ .

$F$  is **admissible** if it is not dominated by any  $G$  different from  $F$ .

## Basic result

### Theorem

- Any SLA is dominated by an ASLA.
- A function  $F : [1, \infty) \rightarrow [0, \infty)$  is an ASLA if and only if it is increasing, right-continuous, and satisfies

$$\int_1^{\infty} \frac{F(y)}{y^2} dy = 1.$$

$F(y) = y$  is impossible (it would mean guaranteeing  $\mathcal{K}_t \geq X_t^*$  for all  $t$ ), but we want to come as close to this as possible.

## Examples

Let  $\alpha \in (0, 1)$ .

- There exists a trading strategy guaranteeing

$$\mathcal{K}_t \geq \alpha (X_t^*)^{1-\alpha}$$

for all  $t$ .

- There exists a trading strategy guaranteeing

$$\mathcal{K}_t \geq \alpha(1 + \alpha)^\alpha \frac{X_t^*}{\ln^{1+\alpha} X_t^*}$$

whenever  $X_t^* \geq e^{1+\alpha}$ .

## Idea of the proof, I: part “if”

For every threshold  $c$  we consider the trading strategy that buys 1 unit of  $X$  at the beginning and sells it when  $X_t$  reaches  $c$ . This strategy shows that  $F(y) = F_c(y) = c \mathbf{1}_{\{y \geq c\}}$  is an SLA. This function satisfies  $\int_1^\infty F(y) y^{-2} dy = 1$ . Moreover: any “regular” function that satisfies  $\int_1^\infty F(y) y^{-2} dy = 1$  can be represented as a mixture of  $F_c$ :  $F = \int_1^\infty F_c P(dc)$  for some probability measure  $P$  on  $[1, \infty)$ .

### Lemma

*An increasing right-continuous function  $F : [1, \infty) \rightarrow [0, \infty)$  satisfies  $\int_1^\infty F(y) y^{-2} dy = 1$  if and only if there exists a probability measure  $P$  on  $[1, \infty)$  such that  $F(y) = \int_{[1, y]} c P(dc)$  for all  $y \in [1, \infty)$ .*

## Idea of the proof, II: part “if”

Various values of  $c$ : our “experts”. We are trying to compete against the best of them.

A standard approach: mixing the experts (trivial in this setting). An example of mixing: suppose  $P(\{1\}) = P(\{2\}) = 1/2$ . The mixed strategy invests half of its initial capital into the strategy that sells its share of  $X$  when  $X_t$  reaches 1 and invests the other half of its initial capital into the strategy that sells its share of  $X$  when  $X_t$  reaches 2.

## Idea of the proof, III: part “only if”

Imagine that time  $t$  is continuous (this can always be approximated). If  $X_t$  is Brownian motion started from 1 and stopped when it hits 0, the distribution of  $X_\infty^*$  has density  $1/y^2$  on  $[1, \infty)$ . (Indeed, the probability that Brownian motion started at 1 hits level  $y > 1$ , before hitting 0 is  $1/y$ ; therefore, the distribution function of  $X_\infty^*$  is  $1 - 1/y$ , and its density is  $1/y^2$ .)

Since  $\mathcal{K}_t$  is a martingale,

$$\mathcal{K}_t \geq F(X_t^*)$$

implies

$$\int_1^\infty \frac{F(y)}{y^2} dy \leq 1.$$

(Set  $t = \infty$  and take expected values.)

# Applications to hypothesis testing for the Bernoulli model

$P_\theta$ : the probability measure on  $\{0, 1\}^\infty$  corresponding to tossing a coin with probability of 1 equal to  $\theta$ .

First we will test the hypothesis that the coin is fair,  $\theta = 1/2$ , against a simple alternative,  $\theta = 3/4$ . The likelihood ratio is

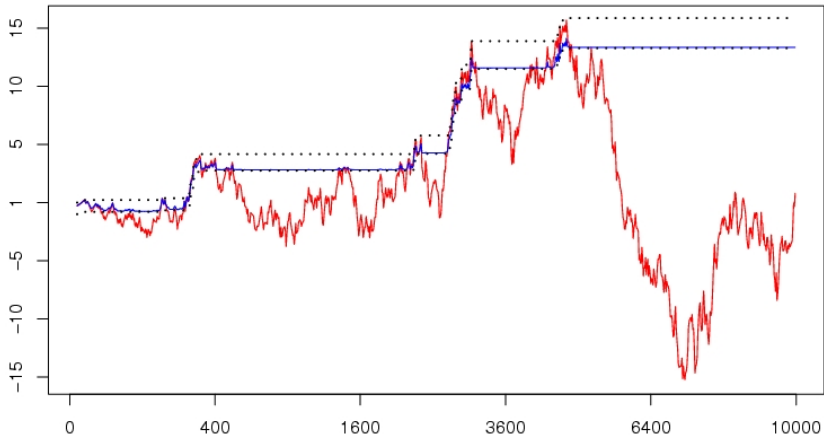
$$X_t := \frac{P_{3/4}(x_1, \dots, x_t)}{P_{1/2}(x_1, \dots, x_t)} = \frac{(3/4)^{k_t} (1/4)^{t-k_t}}{(1/2)^t} = \frac{3^{k_t}}{2^t},$$

where  $k_t$  is the number of 1s in  $x_1, \dots, x_t$ . It is a **test martingale** (nonnegative and starting from 1).

We will use the SLA

$$F(y) := 0.1y^{0.9}.$$

# Testing a simple hypothesis vs a simple alternative





## Legend

We generated  $x_1, \dots, x_{10,000}$  by tossing a coin with bias  $\theta = \ln 2 / \ln 3 \approx 0.63$ . Vertical axis:  $\log$  (base 10) scale.

- The red line is traced by  $X_t$  (the current evidence against  $\theta = 1/2$ ).
- The upper dotted line is  $X_t^*$  (the best evidence so far against  $\theta = 1/2$ ).
- The lower dotted line  $F(X_t^*) = 0.1(X_t^*)^{0.9}$  shrinks this best evidence using our SLA (**calibrates** the exaggerated evidence).
- The blue line is a test martingale  $\mathcal{K}_t$  under the null hypothesis that satisfies  $\mathcal{K}_t \geq F(X_t^*)$ .

## Some values

$$\begin{aligned} X_{10,000} &= 2.2 & X_{10,000}^* &= 7.3 \times 10^{15} \\ F(X_{10,000}^*) &= 1.9 \times 10^{13} & \mathcal{K}_{10,000} &= 2.2 \times 10^{13} \end{aligned}$$

The test martingale (under the null hypothesis)  $\mathcal{K}_t$  legitimately and correctly rejects the null hypothesis at time 10,000 on the basis of  $X_t$ 's high earlier values, even though the likelihood ratio  $X_{10,000}$  is not high.

## Testing $\theta = 3/4$ vs $\theta = 1/2$

The test martingale  $X_t$ 's overwhelming values against  $\theta = 1/2$  are followed, around  $t = 7,000$ , by overwhelming values (order of magnitude  $10^{-15}$ ) against  $\theta = 3/4$ . Had we been testing  $\theta = 3/4$  against  $\theta = 1/2$ , we would have found that it can also be rejected very strongly even after calibration.

The data generating mechanism  $P_\theta$ ,  $\theta = \ln 2 / \ln 3$ , is “midway” between  $P_{1/2}$  and  $P_{3/4}$ , and as  $t \rightarrow \infty$ ,  $\ln X_t$  oscillates between approximately  $\pm 0.75 \sqrt{t \ln \ln t}$ .

A very uncomfortable situation for a Bayesian. If, say, his prior probabilities are 50/50, his posterior probability that  $\theta = 1/2$  will fluctuate wildly (from  $10^{-15}$  to  $1 - 10^{-15}$  in the picture).

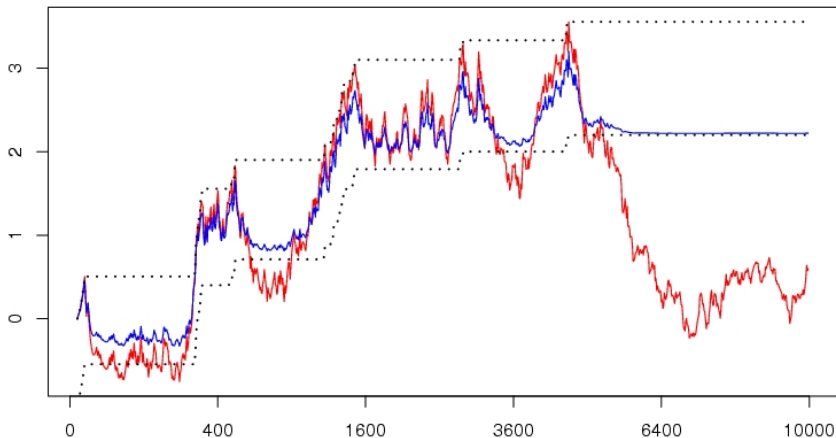
# Testing a simple null hypothesis against a “composite” alternative

Retaining  $\theta = 1/2$  as our null hypothesis, we now take as our alternative hypothesis the probability distribution  $Q$  obtained by averaging  $P_\theta$  with respect to the uniform distribution for  $\theta$ . The likelihood ratio:

$$X_t := \frac{Q(x_1, \dots, x_t)}{P_{1/2}(x_1, \dots, x_t)} = \frac{\int_0^1 \theta^{k_t} (1 - \theta)^{t - k_t} d\theta}{(1/2)^t} = \frac{k_t! (t - k_t)! 2^t}{(t + 1)!}.$$

Let us generate 0s and 1s independently but with a probability for  $x_t = 1$  that slowly converges to  $1/2$ :  $\frac{1}{2} + \frac{1}{4} \sqrt{\ln t/t}$ .

# Testing a simple hypothesis vs a composite alternative

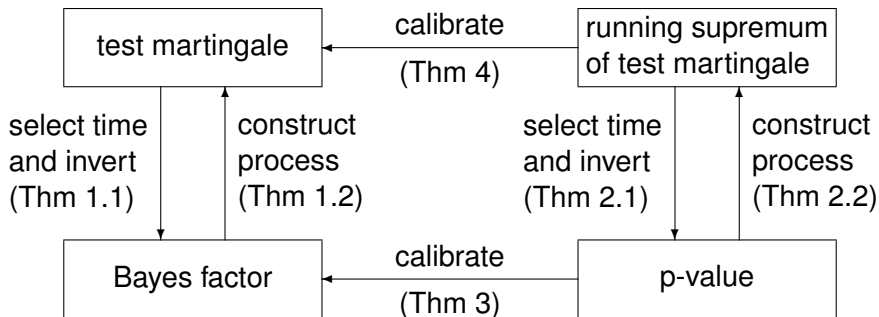


## Final values

$$\begin{aligned} X_{10,000} &= 3.5 & X_{10,000}^* &= 3,599 \\ F(X_{10,000}^*) &= 159 & \mathcal{K}_{10,000} &= 166 \end{aligned}$$

In this case, the evidence against  $\theta = 1/2$  is very substantial but not overwhelming. (When testing composite vs composite, such as  $\theta \leq 1/2$  against  $\theta > 1/2$ , it is hardly possible to find any evidence.)

# Advertisement



Details: in the *Statistical Science* paper (reference at the end of the talk).

## Connection with p-values from the point of view of game-theoretic probability

There is a direct connection simply by the definition of game-theoretic probability.

Fix a game-theoretic martingale (i.e., Sceptic's capital process when he follows a fixed strategy). Take the highest value reached by the martingale (=Sceptic's capital) as the test statistic. By definition, the p-value will be at most  $1/X_{\infty}^*$ .



# Outline

- 1 Simple lookback adjusters
- 2 Lookback adjusters
  - Definition and characterization of LAs
  - Connections
  - Option pricing: Simple American lookbacks
  - Option pricing: American lookbacks
- 3 Down-up adjusters
- 4 References

## What we want to achieve in this section

More generally, we can ask when Investor can guarantee

$$\mathcal{K}_t \geq F(X_t^*, X_t), \quad \forall t.$$

Such  $F$ : **lookback adjusters (LAs)**. They ensure against loss of evidence in a stronger sense than SLAs.

We are interested only in nonnegative SLAs and LAs  $F$ .

# Admissibility

The same notion of admissibility as for SLAs.

An LA  $G$  **dominates** an LA  $F$  if  $G \geq F$ .

$F$  is **admissible** if it is not dominated by any  $G$  different from  $F$ .  
“Admissible LA” is abbreviated to “**ALA**”.

# Lookback adjusters

## Theorem

*Every LA is dominated by an ALA. A positive function  $F(X^*, X)$  with domain  $X^* \in [1, \infty)$  and  $X \in [0, X^*]$  is an ALA if and only if the following two conditions are satisfied:*

- *the function*

$$F^-(X^*) := F(X^*, X^*), \quad X^* \in [1, \infty),$$

*is increasing, concave, and satisfies  $F^-(1) = 1$  and  $F_r^-(1) \leq 1$ ;*

- *for each  $X^* \in [1, \infty)$ , the function  $F(X^*, X)$  is linear in  $X$  and its slope is equal to  $F_r^-(X^*)$ .*

## Notation and terminology

$f_r$  means the right derivative of  $f$ .

The function  $F^= : [1, \infty) \rightarrow [0, \infty)$  defined by

$$F^=(X^*) := F(X^*, X^*), \quad X^* \in [1, \infty),$$

will be called the **spine** of an ALA  $F(X^*, X)$ .

## Trivial part of the theorem

### Lemma

*If a positive function  $F(X^*, X)$ ,  $X^* \in [1, \infty)$ ,  $X \in [0, X^*]$ , satisfies the two conditions in the theorem, it is an LA.*

### Proof.

The following trading strategy witnesses that  $F$  is an LA: at any time  $t$ , take the position  $p_t := F_r^-(X_{t-1}^*)$ . □

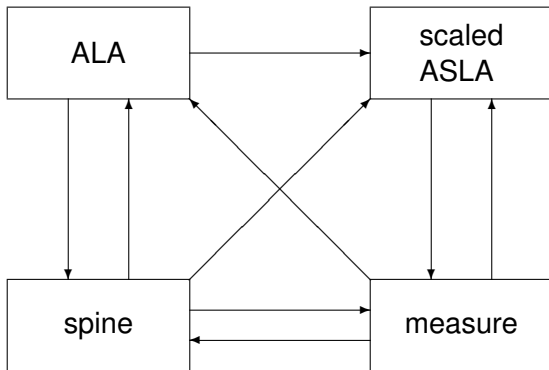
## Connections, I

What is the connection between ASLAs and ALAs? Their definitions (concave vs possibly discontinuous with an integral condition) appear to have nothing in common.

The next slide: the scheme of connections between related notions. An arrow means that there is a simple expression of one via another (sometimes two simple expressions).

**Scaled ASLA** (more fully, **scaled down ASLA**) is an ASLA multiplied by  $c \in [0, 1]$ .

## Visual frame: 3 bijections and 3 shortcuts





## Connections, II: scaled ASLAs from measures

We already know how to get an ASLA from a probability measure  $P$  on  $[0, \infty)$ :

$$F(y) := \int_{[1,y]} uP(du).$$

But in our picture, “measure” means a probability measure on  $[0, \infty]$ , so the formula gives only a scaled ASLA (scaled down by  $P([0, \infty))$ ).

Why does it make sense to consider probability measures on  $[0, \infty]$  (leading to inadmissible ASLAs)? They give

$$\mathcal{K}_t \geq F(X_t^*) + cX_t,$$

where  $c := P(\{\infty\})$ . Double insurance: against performing much worse than  $X_t$  (strong insurance) and against performing much worse than  $X_t^*$  (weaker insurance).

## Connections, III: ALAs from spines

Remember:  $F^=(X) := F(X, X)$ .

A spine = an ALA without the linear bits (informationally redundant). The full ALA can be restored by:

$$F(X^*, X) = F^=(X^*) + F_r^=(X^*)(X - X^*).$$

## Connections, IV: spines and measures

Given a spine  $F^-$ , the corresponding measure is determined by

$$P((X, \infty]) = F_r^-(X), \quad X \in [1, \infty).$$

The spine can be restored by

$$F^-(X) = \int_{[1, X]} uP(du) + XP((X, \infty])$$

(the capital of the experts who cashed in their share plus the capital of the experts still holding it). More generally, the corresponding ALA is

$$F(X^*, X) = \int_{[1, X^*]} uP(du) + XP((X^*, \infty]).$$

## Connections, V: ALAs and scaled ASLAs

A function  $F'(X^*)$  is a scaled ASLA if and only if it can be represented in the form  $F(X^*, 0)$  for some ALA  $F$ . Details:

### Proposition

- Suppose  $F(X^*, X)$  is an ALA. Then  $F'(X^*) := F(X^*, 0)$  is a scaled ASLA. If, furthermore,  $F_r^-(\infty) = 0$ ,  $F(X^*)$  is an ASLA.
- Suppose  $F'(X^*)$  is a scaled ASLA. Then there exists a unique ALA  $F(X^*, X)$  such that  $F'(X^*) = F(X^*, 0)$  for all  $X^*$ . If, furthermore,  $F'(X^*)$  is an ASLA, this ALA  $F(X^*, X)$  will satisfy  $F_r^-(\infty) = 0$ .

## How to use this kind of results for option pricing

We would like to price the following exotic option  $O_G$  (a kind of perpetual American lookback): at the time  $t$  of her choice, the option's owner is entitled to  $G(X_t^*)$ , where  $G$  is a given nonnegative increasing function. The result about ASLAs can be restated as: the **upper price** of this option at time 0 (after learning  $X_0$ ) is  $\int_1^\infty G(y)y^{-2}dy$ .

Formally,  $\int_1^\infty G(y)y^{-2}dy$  is the smallest initial capital  $c$  such that there exists a trading strategy starting with  $c$  and guaranteeing  $\mathcal{K}_t \geq G(X_t^*)$  for all  $t$  (intuitively, the seller can always meet his obligation).

## Risk-neutral probability, I

The formula  $\int_1^\infty G(y)y^{-2}dy$  assumes  $X_0 = 1$ . Without this assumption, the upper price at time 0 is  $\int_1^\infty G(X_0y)y^{-2}dy$  (by re-scaling).

Notice: the upper price of  $O_G$  can be written as  $X_0 \int_{X_0}^\infty G(y)y^{-2}dy$ : the expected value of  $G$  with respect to the probability measure  $P$  on  $[X_0, \infty)$  with density  $X_0/y^2$ . It plays the role of **risk-neutral probability** (but, unusually, emerges in a heavily incomplete market).

## Risk-neutral probability, II

The basic interpretation of risk-neutral probability:  $P$  is the distribution of the maximum of Brownian motion started at  $X_0$  and stopped when it hits 0.

But the argument for the density  $X_0/y^2$  of  $X_\infty^*$  depends only on  $X_t$  being a martingale without awkward (i.e., upward) jumps that converges to  $X_\infty \notin (0, \infty)$ . In particular, we can assume the standard “Black–Scholes model”

$$\frac{dX_t}{X_t} = \sigma dW_t,$$

where  $W_t$  is Brownian motion. The worst-case upper price = the expected value w.r. to the most standard model.

## Pricing $O_G$ at time $t$

This is easy: replace  $X_0$  by  $X_t$  and  $G(y)$  by  $G(X_t^* \vee y)$ .

So the upper price of  $O_G$  at time  $t$  is

$$X_t \int_{X_t}^{\infty} G(X_t^* \vee y) y^{-2} dy.$$

General remark: we will get the same expressions for pricing European options with the given payoff at the time  $\infty$ .



# American lookbacks, I

Suppose the payoff of our American lookback is  $F(X_t^*, X_t)$  (allowed to depend on  $X_t$ ).

For each concave increasing  $G : [X_0, \infty) \rightarrow \mathbb{R}$ , define

$$\bar{G}(X^*, X) := G(X^*) + G_r(X^*)(X - X^*),$$
$$X^* \in [X_0, \infty), \quad X \in [0, X^*].$$

## American lookbacks, II

The upper price  $\bar{\mathbb{E}}(F \mid X_0)$  of the American option paying  $F(X_t^*, X_t)$  can be determined in two steps:

- Let  $H : [X_0, \infty) \rightarrow [0, \infty)$  be the smallest concave increasing function such that  $\bar{H} \geq F$ . **Lemma:** It exists (but maybe  $H := \infty$ ).
- The function  $H$  determines  $\bar{\mathbb{E}}(F \mid X_0)$  via

$$\bar{\mathbb{E}}(F \mid X_0) = H(X_0).$$

Given the initial capital  $H(X_0)$ , the option's seller can meet his obligation by holding  $p_t := H_r(X_{t-1}^*)$  units of  $X$  at time  $t$ .

# Outline

- 1 Simple lookback adjusters
- 2 Lookback adjusters
- 3 Down-up adjusters**
  - Introduction
  - Complication
  - Characterization
  - Examples
- 4 References

## Buy low, sell high 1

The adjusters we considered so far: “sell high”. Now we want to implement both parts of the traders’ adage “buy low, sell high”.

If we know in advance an interval  $(a, b)$  ( $0 \leq a \leq 1 \leq b$ ) such that the price **upcrosses**  $(a, b)$  (there are  $s < t$  such that  $X_s \leq a$  and  $b \leq X_t$ ), we can increase our initial capital  $b/a$ -fold. In practice we do not know which upcrossings are going to occur. . .

## Buy low, sell high 2

We are looking for strategies whose payoff scales nicely with the extremity of the upcrossing present. Suppose a financial advisor claims to have achieved this with a secret strategy and publishes a function  $G$  ( $G(a, b) \approx b/a$  in some sense) promising that her strategy will

*keep our capital above  $G(a, b)$  for each upcrossing  $(a, b)$ .*

We would like to answer the following questions:

- 1 Should we believe her? Is it actually possible to guarantee  $G$ ? (If so, we call  $G$  a **down-up adjuster**.)
- 2 Is she ambitious enough? Or can one guarantee strictly more than  $G$ ? (Is  $G$  **admissible**?)

## New phenomenon

In the case of “up adjusters” (SLAs), we could just combine the basic guarantees  $F(y) := c \mathbf{1}_{\{y \geq c\}}$  achievable by trading strategies of selling when the price reaches a given threshold. Now combinations of the basic guarantees (exploiting a given upcrossing  $(a, b)$ ) are typically not admissible! For example, consider the mixture

$$G(a, b) := \mathbf{1}_{\{a \leq 1 \text{ and } b \geq 2\}} + \mathbf{1}_{\{a \leq \frac{1}{2} \text{ and } b \geq 1\}}.$$

Direct calculation shows: this can be guaranteed from the initial capital  $\frac{11}{12} < 1$ . So  $G$  is not achievable: it is dominated by the adjuster  $\frac{12}{11}G$ .

## Why?

Consider the price path  $(1, 2, \frac{1}{2}, 1, 0, \dots)$ . Starting from 1 our mixture strategy achieves 2 whereas 1 would have been sufficient ( $[\frac{1}{2}, 2]$  is never upcrossed).

This suggests that the strategy wastes part of the initial capital.

## Characterization of down-up adjusters

A function  $G : (0, 1] \times (0, \infty) \rightarrow [0, \infty)$  a **candidate guarantee** if it is upper semi-continuous, decreasing in its first argument, and increasing in its second argument. The **second-argument upper inverse** of  $G$  is

$$G^{-1}(a, h) := \inf\{b \geq a : G(a, b) \geq h\}.$$

### Theorem (characterisation)

*A candidate guarantee  $G$  is an adjuster if and only if*

$$\int_0^\infty 1 - \exp\left(\int_0^1 \frac{da}{a - G^{-1}(a, h)}\right) dh \leq 1.$$

*Moreover,  $G$  is admissible if and only if this holds with equality.*



## Example adjusters 1

- Considering  $G(a, b)$  that do not depend on  $a$  we recover the results about SLAs.
- Candidate guarantees of the form  $G(a, b) = F(b - a)$  have upper price

$$\int_0^\infty F(y) \frac{e^{-1/y}}{y^2} dy.$$

The distribution with density  $\frac{e^{-1/y}}{y^2} dy$  is the risk-neutral measure of the largest upcrossed length. This is analogous to  $y^{-2} dy$  being the risk-neutral measure of the maximum price.

## Example adjusters 2

- Guarantees of the form  $G(a, b) = F(b/a)$  for increasing and unbounded  $F$  have infinite upper price.
- An admissible down-up adjuster that approaches the ideal  $G(a, b) \approx b/a$  is

$$G(a, b) := \frac{(b-a)^p}{a^q} \frac{\left(\frac{p-q}{p}\right)^p}{\Gamma(1-p)},$$

for any  $0 \leq q < p < 1$ .

# Outline

- 1 Simple lookback adjusters
- 2 Lookback adjusters
- 3 Down-up adjusters
- 4 **References**
  - Statistical interpretation
  - Financial interpretation

## Proofs and related results, I

### Statistical interpretation:



Glenn Shafer, Alexander Shen, Nikolai Vereshchagin, and Vladimir Vovk.

Test martingales, Bayes factors and  $p$ -values.  
*Statistical Science* **26**, 84–101 (2011).



A. Philip Dawid, Steven de Rooij, Glenn Shafer, Alexander Shen, Nikolai Vereshchagin, and Vladimir Vovk.

Insuring against loss of evidence in game-theoretic probability.

*Statistics and Probability Letters* **81**, 157–162 (2011).

## Proofs and related results, II

Financial interpretation:



A. Philip Dawid, Steven de Rooij, Peter Grünwald, Wouter Koolen, Glenn Shafer, Alexander Shen, Nikolai Vereshchagin, and Vladimir Vovk.

[Probability-free pricing of adjusted American lookbacks.](#)  
[arXiv:1108.4113 \[q-fin.PR\], August 2011.](#)

This is the most detailed exposition.

## Proofs and related results, III

This paper shows that a continuous price path of a financial security behaves (for the purpose of option pricing) like a time-changed Brownian motion (and so explains the appearance of the density  $1/y^2$ ):



Vladimir Vovk.

Continuous-time trading and the emergence of probability.  
*Finance and Stochastics*,  
**16**, 561–609 (2012).

All these papers are available from

<http://probabilityandfinance.com> (Working Papers  
28, 33, 34, and 37).

## Proofs and related results, IV

Down-up adjusters:



Wouter M. Koolen and Vladimir Vovk.

Buy low, sell high.

In: *Proceedings of the Twenty Third International Conference on Algorithmic Learning Theory* (ed. by N. Bshouty, G. Stoltz, N. Vayatis and T. Zeugmann).

*Lecture Notes in Artificial Intelligence*. Berlin: Springer, 2012.

Thank you for your attention!