An application of the Foster - Vohra method of calibration to stock market games.

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International Workshop on Statistical Learning, June 26-28, Moscow

Assymptotic calibration

- Forecasting a sequence of outcomes from an unknown source.
- Nonstandard measure of performance: calibration tests (Dawid(1984)).
- Known applications: (1) convergence to correlated equilibrium (Foster and Vohra (1997)); (2) Vovk's defensive forecasting (Vovk (2006); (3) constructing aggregating strategies (Vovk (2010)).
- We present applications to algoritmic trading.

Online forecasting task

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FOR n = 1, 2, ...
Forecaster announces a forecast p_n \in [0, 1].
Nature announces an outcome S_n \in [0, 1].
ENDFOR
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Example for binary case $S_n \in \{0,1\}$: p_n is a probability that it will rain $(S_n = 1 \text{ means rain})$.

In general, p_n can be interpreted as the expected value of S_n .

How to evaluate performance of the forecaster?



Dawid's (1984) method of calibration: informal setting

Informally: It should rain about 80% of the days for which $p_n = 0.8$, and so on.

A sequence of forecasts $p_1, p_2, ...$ is "calibrated" for an infinite binary sequence $S_1, S_2...$ if for each $p^* \in [0, 1]$

$$\frac{\sum\limits_{p_i\approx p^*}S_i}{\sum\limits_{p_i\approx p^*}1}\approx p^*$$

as the denominator of this relation tends to infinity when $n \to \infty$.



Formal definition:

A sequence of forecasts $p_1, p_2,...$ is well-calibrated for an infinite sequence $S_1, S_2...$ if for the indicator function I(p) of any subinterval $I \subseteq [0,1]$ the calibration error tends to zero:

$$\frac{\sum_{i=1}^{n} I(p_i)(S_i - p_i)}{\sum_{i=1}^{n} I(p_i)} \longrightarrow 0$$

as the denominator of this relation tends to infinity when $n \to \infty$.

Commonly used the weaker condition: for each checking rule I(p),

$$\frac{1}{n}\sum_{i=1}^{n}I(p_i)(S_i-p_i)\to 0 \text{ as } n\to\infty$$





Adversarial Nature (Oakes (1985))

Any total deterministic forecasting algorithm *f*

$$p_n = f(S_1, S_2, ..., S_{n-1})$$

is not calibrated for the sequence $S_1, S_2...$, where

$$S_i = \left\{ egin{array}{l} 1 & \mbox{if } p_i < 0.5 \\ 0 & \mbox{otherwise.} \end{array}
ight.$$

The condition of calibration fails for I = [0, 0.5) or I = [0.5, 1].



Probability forecasting game

Foster and Vohra (1994) – first positive result

FOR n = 1, 2, ...

Forecaster announces a probability distribution P_n on [0,1]. **Nature** announces an outcome $S_n \in [0,1]$.

Forecaster draws \tilde{p}_n from P_n and observes outcome S_n .

ENDFOR

The forecast \tilde{p}_n is hidden from **Nature** at step *n*. Distributions P_n , n = 1, 2, ... defines the overall probability distribution on infinite trajectories $\tilde{p}_1, \tilde{p}_2, \ldots$ of forecasts.



Kakade and Foster's (2004) calibration theorem:

 P_n can be taken in form of random rounding of a real number.

For any $\Delta > 0$, given binary S_1, \ldots, S_{i-1} some algorithm computes deterministic forecast p_i and randomly rounds it up to Δ to \tilde{p}_i such that:

For the characteristic function I(p) of any subinterval of [0,1]

$$\limsup_{n\to\infty}\left|\frac{1}{n}\sum_{i=1}^n I(\tilde{p}_i)(S_i-\tilde{p}_i)\right|\leq \Delta$$

almost surely.

This result is also valid for real outcomes $S_i \in [0, 1]$.





Probability forecasting game with side information

FOR n = 1, 2, ...

Nature announces a signal $x_n \in [0,1]$.

Forecaster announces a probability distribution P_n on [0,1].

Nature announces an outcome $S_n \in [0,1]$.

Forecaster draws \tilde{p}_n from P_n and observes outcome S_n .

ENDFOR





Side information and history depended checking rules

History at step *n*: $c_n = (\tilde{p}_1, S_1, ..., \tilde{p}_{n-1}, S_{n-1})$.

Extraction of information: $\bar{z}_n = f(x_n, c_n) \in [0, 1]^k$, where x_n – signal, c_n – history, f – extraction function.

Let $R \subseteq [0,1]^{k+1}$ and its indicator function:

where $p \in [0,1]$ – forecast and $\bar{z} \in [0,1]^k$ – extracted information vector.





General calibration theorem:

Theorem

Given $\varepsilon > 0$ and extraction function f with range in \mathscr{R}^k we can compute forecasts p_1, p_2, \ldots and randomize them and extracted vectors such that: for any subset $R \subseteq [0.1]^{k+1}$, n, and for any $\delta > 0$, with probability at least $1 - \delta$,

$$\begin{split} \left| \sum_{i=1}^n I_R(\tilde{p}_i, \tilde{z}_i) (\mathcal{S}_i - \tilde{p}_i) \right| \leq \\ \leq 22 \left(\frac{k+1}{4} \right)^{\frac{2}{k+3}} n^{1 - \frac{1}{k+3} + \varepsilon} + \sqrt{\frac{n}{2} \ln \frac{2}{\delta}}, \end{split}$$

where \tilde{p}_i and \tilde{z}_i are randomizations of p_i and information vector $\bar{z}_i = f(x_i, c_i) \in [0, 1]^k$.

Aplications to Stock Market games

Trading game with side information

FOR
$$n = 1, 2...$$

Stock Market announces side information $x_n \in [0,1]$. **Trader** buys C_n shares of the stock by S_{n-1} each. **Stock Market** announces the price S_n of the stock. **Trader** sells all shares by S_n and updates his capital: $\mathcal{K}_n = \mathcal{K}_{n-1} + C_n(S_n - S_{n-1})$, where $\mathcal{K}_0 = 0$.

Trading strategy is a rule:

$$x_n \Rightarrow C_n$$
 or $c_n, x_1, \dots x_n \Rightarrow C_n$, where c_n – history





Trading strategies

We compete trading strategies of two types:

- Universal trading strategy: $C_n = \tilde{M}_n$ output of randomized algorithm which uses well calibrated forecasts \tilde{p}_n of future price S_n (will be defined below).
- Benchmark class of stationary trading strategies:
 C_n = D(x_n) stationary trading strategy, where
 D: [0,1] → ℛ is a continuous function.
 We approximate continuous functions by functions from RKHS (Reproducing Kernel Hilbert Space).

Benchmark class of stationary trading strategies:

- RKHS is a Hilbert space \mathscr{F} of real-valued functions on a compact metric space X such that the evaluation functional $f \to f(x)$ is continuous for each $x \in X$.
- $\bullet \ f(x) = (f \cdot \Phi(x)).$
- $K_2(x,y) = (\Phi(x) \cdot \Phi(y))$ kernel.
- $\bullet \| \cdot \|_{\mathscr{F}}$ be a norm in \mathscr{F} .
- We consider RKHS \mathscr{F} with finite embedding constant $c_{\mathscr{F}} = \sup_{x} \sup_{\|f\|_{\mathscr{F}} \le 1} |f(x)| = \|\Phi(\bar{x})\|_{\mathscr{F}} < \infty.$
- Universal RKHS: for any continuous f and $\varepsilon > 0$ and $g \in \mathscr{F}$ exists such that $\sup_{0 < x < 1} |f(x) g(x)| < \varepsilon$.
- Sobolev space of absolutely continuous functions $f:[0,1] \to \mathcal{R}$ with $||f||_{\mathscr{F}} \le 1$, where $||f||_{\mathscr{F}} = \sqrt{\int_0^1 (f(t))^2 dt} + \int_0^1 (f'(t))^2 dt}$ is universal.



Calibration theorem:

Theorem

Given an RKHS \mathscr{F} and $\varepsilon > 0$ we can compute forecasts p_1, p_2, \ldots and randomize them and past prices such that for any $\delta > 0$ and for any n, with probability $1 - \delta$,

$$\left|\sum_{i=1}^{n} I(\tilde{p}_{i} > \tilde{S}_{i-1})(S_{i} - \tilde{p}_{i})\right| \leq$$

$$\leq 18(c_{\mathscr{F}}^{2} + 1)^{\frac{1}{4}} n^{3/4 + \varepsilon} + \sqrt{\frac{n}{2} \ln \frac{2}{\delta}},$$

$$\left|\sum_{i=1}^{n} D(x_{i})(S_{i} - p_{i})\right| \leq ||D||_{\mathscr{F}} \sqrt{(c_{\mathscr{F}}^{2} + 1)n}$$

for all $D \in \mathscr{F}$, where I(p > x) is the indicator of the condition p > x.



Universal trading strategy

At each round *n*, **Trader** buys (or sells)

$$\tilde{M}_n = \left\{ \begin{array}{l} 1 \text{ if } \tilde{p}_n > \tilde{S}_{n-1}, \\ -1 \text{ otherwise.} \end{array} \right.$$

shares of the stock by S_{n-1} each, where \tilde{p}_n – randomized well calibrated forecast S_{n-1} – randomized past price



Capitals of traders

 $\mathcal{K}_n^M = \sum_{i=1}^n \tilde{M}_i \Delta S_i$ – capital of universal trading strategy (random quantity)

$$\mathcal{K}_n^D = \sum_{i=1}^n D(x_i) \Delta S_i$$
 – capital of stationary strategy $D(x)$, where $\Delta S_i = S_i - S_{i-1}$

Main result: universality

Theorem

There exists a universal tradimg strategy \tilde{M}_n such that for any continuous function D(x),

$$\liminf_{n\to\infty}\frac{1}{n}\left(\mathscr{K}_n^M-\|D\|_+^{-1}\mathscr{K}_n^D\right)\geq 0$$

almost surely.

$$||D||_+ = \max\{1, \sup_{0 \le x \le 1} |D(x)|\}$$
 – normalization factor.





We can take D(x) = 0 for all x.

Corollary

The universal trading strategy is asymptotically non-risk:

$$\liminf_{n\to\infty}\frac{1}{n}\mathscr{K}_n^M\geq 0$$

almost surely.



Rate of convergence for *D* in RKHS:

Theorem

Given $\varepsilon > 0$, for any n and $\delta > 0$, with probability $1 - \delta$, for all $D \in \mathscr{F}$ (RKHS)

$$\mathscr{K}_{n}^{M} \geq \|D\|_{+}^{-1} \mathscr{K}_{n}^{D} - \\ -38(c_{\mathscr{F}}^{2} + 1)^{\frac{1}{4}} n^{\frac{3}{4} + \varepsilon} - \|D\|_{+}^{-1} \|D\|_{\mathscr{F}} \sqrt{(c_{\mathscr{F}}^{2} + 1)n} - \sqrt{\frac{n}{2} \ln \frac{2}{\delta}}$$



Competing with discontinuous trading strategies

Deterministic signals x_i : counterexample

Theorem

Let \tilde{M}_i be a sequence of independent random variables (randomized trading strategy) such that $|\tilde{M}_i| \le 1$ for all i. Consider the protocol of trading game with signals $x_i = P\{\tilde{M}_i > 0\}$.

Then a binary decision rule D(x) and a sequence $S_1, S_2,...$ of prices can be defined such that with probability one

$$\limsup_{n\to\infty} \left(\frac{1}{n} \sum_{i=1}^{n} \tilde{M}_i \Delta S_i - \frac{1}{2} \frac{1}{n} \sum_{i=1}^{n} D(x_i) \Delta S_i \right) \le 0.$$
 (1)

Competing with discontinuous trading strategies

Randomized signals x_i : positive result

Theorem

An algorithm for computing forecasts and a sequential method of randomization of forecasts \tilde{p}_i and past prices \tilde{S}_{i-1} can be constructed such that for any nontrivial decision rule D for any $\delta > 0$, with probability at least $1 - \delta$,

$$\sum_{i=1}^n \tilde{M}_i \Delta S_i \geq \|D\|_{\infty}^{-1} \sum_{i=1}^n D(\tilde{\mathbf{x}}_i) \Delta S_i - O\left(n^{\frac{4}{5} + \epsilon} + \sqrt{\frac{n}{2} \ln \frac{2m}{\delta}}\right),$$

where \tilde{x}_i – randomized side information.

Numerical experiments (with V.G.Trunov)

Data has been downloaded from FINAM site: www.finam.ru Number of trading points in each game is 88000–116000 min. (From March 26 2010 to March 25 2011) We buy or sell 5 shares at each round Transaction costs are ignored It was found that $\mathcal{K}_n > 0$, i.e., we never incur debt in our experiments.

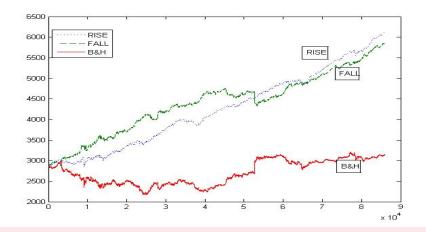


Figure: GOOG



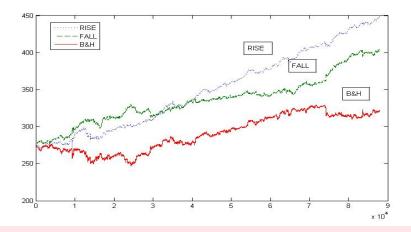


Figure: KOCO



		Buy&	UN	UN	ARMA	ARI
	TICKER	Hold	FOR A RISE	FOR A FALL	FOR A RISE	FOR
		PROFIT %	PROFIT %	Profit %	Profit %	PRC
Ì	TEST	6.85	-1.39	-8.19	9.88	3.08
Ì	AT-T	7.71	137.40	129.70	30.73	23.0
ĺ	KOCO	16.55	62.66	46.15	2.90	-13.
Ì	GOOG	10.25	114.85	104.62	12.85	2.62
ĺ	InBM	24.28	85.38	61.09	29.31	5.02
Ì	INTL	4.29	111.70	107.50	25.86	21.6
Ì	MSD	10.71	58.32	47.60	18.66	7.95
ĺ	US1.AMT	22.01	22.74	0.77	28.46	6.49
Ì	US1.IP	2.40	19.83	17.47	9.36	7.00
Ì	US2.BRCM	25.30	53.62	28.28	20.06	-5.2
Ì	US2.FSLR	40.15	143.92	103.61	-9.86	-50.
Ì	SIBN	-6.54	732.87	739.33	357.74	364
Ì	GAZP	22.75	101.20	78.45	31.75	9.00
Ì	LKOH	19.39	261.84	242.45	87.08	67.6
Ì	MTSI	-1.61	669.16	670.68	326.12	327

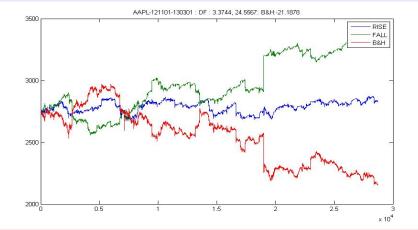


Figure: AAPL



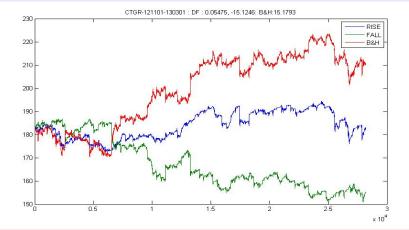


Figure: CTGR



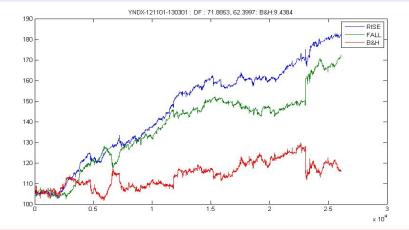


Figure: CTGR



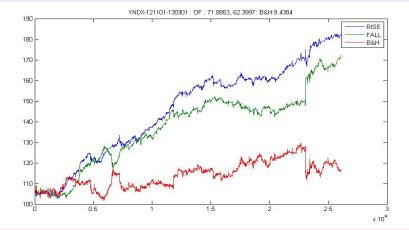


Figure: CTGR

