Probability, Statistics, and Justice

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www.probability.ca

(Canadian Institute for the Administration of Justice,
Annual Conference, October 10, 2013)

About Me . . .

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I'm a Professor of Statistics.

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I'm a Professor of Statistics. A typical day's work:

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I'm a Professor of Statistics. A typical day's work:

Therefore

$$\alpha^-(\beta_i^{(d)}) = \alpha^+(\beta_i^{(d)} - \ell/\sqrt{d})$$

$$\overset{d^{1/2}}{\approx} \alpha^+(\beta_i^{(d)}) - \frac{(\ell(\beta_i^{(d)}) I^{1/2}(\beta_i^{(d)}))'}{2} \left(\frac{-\ell}{\sqrt{d}}\right) \phi\Big(-\frac{I^{1/2}(\beta_i^{(d)})\ell}{2} - \frac{\epsilon \ell K'''(\beta_i^{(d)})}{6 I^{1/2}(\beta_i^{(d)})}\Big)$$

$$-\exp(-\epsilon\ell^2(\beta_i^{(d)})K'''(\beta_i)/6) \frac{(\ell(\beta_i^{(d)}) I^{1/2}(\beta_i^{(d)}))'}{2} \left(\frac{-\ell}{\sqrt{d}}\right) \times$$

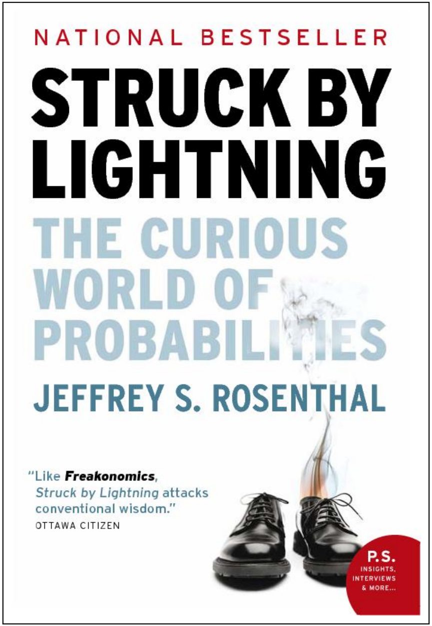
$$\times \phi\Big(-\frac{I^{1/2}(\beta_i^{(d)})\ell}{2} + \frac{\epsilon \ell K'''(\beta_i^{(d)})}{6 I^{1/2}(\beta_i^{(d)})}\Big)$$

Then, since $\underline{\ell} \overset{d^{1/2}}{\approx} \ell + \underline{\epsilon}\ell' \overset{d^{1/2}}{\approx} \ell + \epsilon\ell' = \ell + \frac{\ell\ell'}{d^{1/2}}$, we have that

$$\mu(\beta_i^{(d)}) \overset{d^{1/2}}{\approx} \frac{1}{2d^{1/2}}\Big[-\alpha^+\ell + \left(\ell + \frac{\ell\ell'}{d^{1/2}}\right) \times$$

$$\Big(\alpha^+(\beta_i^{(d)}) - \frac{(\ell(\beta_i^{(d)}) I^{1/2}(\beta_i^{(d)}))'}{2} \left(\frac{-\ell}{\sqrt{d}}\right) \phi\Big(-\frac{I^{1/2}(\beta_i^{(d)})\ell}{2} - \frac{\epsilon \ell K'''(\beta_i^{(d)})}{6 I^{1/2}(\beta_i^{(d)})}\Big) -$$

And then one day I wrote a successful book . . .



Then I was interviewed by the media about:

Then I was interviewed by the media about: Opinion Polls . . .

TORONTO STAR

www.thestar.com

Use caution when approaching polls

Party preference numbers have varied

But differences deceiving, experts say

Jan. 21, 2006. 01:00 AM

ROBERT BENZIE

QUEEN'S PARK BUREAU CHIEF

Not a vote has been counted. The party leaders are still criss-crossing the country in a frantic final bid for support. Campaign volunteers are working the phones, replacing lawn signs and arranging election day transportation for voters who require it.

And yet we already know — or at least we think we know — that on Monday Stephen Harper's Conservatives will defeat Paul Martin's Liberals, and the NDP's Jack Layton will be the federalist leader holding the balance of power in a minority Parliament.

How have we concluded this? Well, the polls tell us so.

But don't different major polls all seem to have differing results?

Yes and no, says Jeffrey Rosenthal, professor of probability theory at the University of Toronto and a leading expert on polling.

Rosenthal, author of the recent bestseller *Struck by Lightning: The Curious World of Probabilities*, says "any one poll should always be taken with a grain of salt.

Crime statistics . . .

You're safer than you think: Statistics expert

Article Photos (4)

Published On Sat Jan 19 2008

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Paola Loriggio
Staff Reporter

As long as there have been cities, there has been fear. Fear of violence, fear of death, fear of anonymous, big-city crime.

High-profile cases of random crime — like the recent shootings of John O'Keefe and Hou Chang Mao, both innocent bystanders killed within a week — feed the public's anxieties.

Police cordon Gerrard St. E. near Broadview Ave. as part of the investigation into a fatal shooting Thursday. A statistics expert says the odds are better of dying in a car accident, than being killed by random crime.

HENRY STANCU/TORONTO STAR FILE PHOTO

But is that fear justified? Random crime isn't going away, but neither is it increasing. Does a spate of random killings put us in greater danger than before? The *Star* asked an expert statistician to assess the risk.

University of Toronto professor Jeffrey S. Rosenthal is the author of *Struck*

Pedestrian death counts . . .

Not so rare for rarities to occur in waves: Professor

TORSTAR NEWS SERVICE
Published: January 29, 2010 5:23 a.m.
Last modified: January 29, 2010 12:40 a.m.

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Scary numbers have dominated Toronto headlines this month: Seven dead in seven days.

Fourteen pedestrians killed across the GTA. The deadliest January for city pedestrians in a decade.

No wonder people are walking scared.

31.9

- Seven isn't that big a number when looked at through a statistician's lens. Jeffrey Rosenthal calculates that between 2000 and 2009, Toronto witnessed an average of 31.9 pedestrian deaths per year and 2.7 deaths per month. Using Poisson distribution, this means there is about a 1.9 per cent chance of there being seven or more pedestrian deaths in a single month.

Playing the odds with everyday life

Toronto professor to lecture on how to make better choices by considering probabilities

By Jessica Prois | February 18th, 2010 - 12:00am

| More

Should people take the beaten path or follow the capricious road-map dots plotted on a whim? Should a khaki-wearing Ivy Leaguer ask out the girl with the full-sleeve tattoo? And should someone give into the lure of the money pot of the Strip, uncertain of his wallet's fate?

For decisions like these, Jeffrey Rosenthal, a statistics professor at the University of Toronto, suggests using probability theory, or mathematical reasoning, to determine the likelihood of a certain outcome. In his book Struck by Lightning: The Curious World of Probabilities, he uses simple math and amusing anecdotes to explain how we might use this tactic to make better sense of seemingly random, everyday events, which he says are actually governed by probability. Rosenthal, a Harvard grad, addresses his theory in a Feb. 18 lecture at UNLV's Marjorie Barrick Museum of Natural History.

Game show strategies . . .

The deal breaker

BY NATIONAL POST MAY 30, 2006

If you should ever be so lucky as to end up on one of the 35 versions of Deal or No Deal that air around the world, it's probably best to leave the parents and their platitudes at home and bring along a mathematician. While the publicity material for Deal or No Deal, the American version of which airs on CH and NBC in Canada, claims it is about "nerves, instincts and raw intuition," the game has just as much to do with probability.

Jeffrey Rosenthal, a professor in the Department of Statistics at the University of Toronto, has been watching Deal or No Deal out of professional interest. (For fun, he likes to watch Jeopardy!) Touring to promote his pop math book Struck by Lightning: The Curious World of Probabilities, he has received a number of requests from readers for tips on how to answer host Howie Mandel's question. His mathematical way of looking at the show clearly gets results: When I tested Rosenthal with situations from the show in his sixth-floor office in U of T's Sidney Smith Hall, he consistently outperformed the actual contestants. (See sidebar on Page B4.)

The Maple Leafs . . .

To: mike.strobel@tor.sunpub.com
From: jeff@math.toronto.edu (Jeffrey Rosenthal)
Date: Wed, 12 Apr 2006 16:11:08 -0400 (EDT)
Subject: my calculations

Hi Mike, good talking to you on the phone just now.

I assumed that in each game, each team has probability 45% of getting two points, 10% of getting one point, and 45% of getting zero points.

Those figures then lead to the following probabilities for Toronto to beat or tie each of the various other teams (in total points at end of season):

Prob that Toronto beats Montreal = 0.17%
Prob that Toronto ties Montreal = 0.30%
Prob that Toronto ties Atlanta = 11.5%
Prob that Toronto beats Atlanta = 30.2%
Prob that Toronto ties Tampa Bay = 3.6%
Prob that Toronto beats Tampa Bay = 2.1%

* This gives a total probability of 5.8% (about one chance in 17) for Toronto to have a chance at the playoffs.

And lotteries ...

TORONTO STAR

www.thestar.com

Advice for lottery winners: Chill out

Apr. 30, 2006. 10:14 AM

ELLEN ROSEMAN

What are your odds of winning the lottery?

Unimaginably small, says University of Toronto statistics professor Jeffrey Rosenthal.

You have one chance in 14 million to score big playing Lotto 6/49. (That's where you have to match all six numbers chosen from 1 to 49.)

"To put it in context, you are over 1,000 times more likely to die in a car crash within the year," Rosenthal says in his book, *Struck by Lightning: The Curious World of Probabilities* (HarperCollins, $34.95).

"In fact, you are more likely to die in a car crash on your way to the store to buy your lottery ticket than you are to win the lottery jackpot.

. . . Lots of lotteries . . .

Lotto 6-49 jackpot could go higher than $41-million

Article

Published On Fri Mar 19 2010 Email | Print | Share

The Canadian Press

University of Toronto statistics professor Jeffrey Rosenthal gives people a jolt of reality when he puts that probability into perspective.

"If you see an adult woman chosen at random, the chance that she will give birth in the next minute and a half is about the same as the chance you'll win the jackpot," he said.

It would be four times more likely for a person chosen at random to become prime minister than for a ticket holder to win the big prize, adds Rosenthal, the author of "Struck by Lightning: The Curious World of Probabilities."

Rosenthal confesses he has never bought a commercial lottery ticket, but jokes that he doesn't want to discourage people from buying more since they bring in revenue for the government _ revenue that pays his salary.

"Scary, scary," laughed Tracy Williams, a secretary for Blake, Cassels and Graydon law firm, when she heard Rosenthal's probabilities.

Williams and her husband have been playing lotteries for 25 years, and said he will never let her stop.

So what is the connection to JUSTICE?

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Auric Goldfinger:

So what is the connection to JUSTICE?

Auric Goldfinger: “Once is happenstance. Twice is coincidence. The third time it’s enemy action.”

Probability, Statistics . . . and Justice?

Statistics and Justice both involve evaluating evidence.

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In this talk, I will try to: (a) explain how statistical reasoning works, and (b) illustrate why it must be used with caution.

How Statisticians Weigh Evidence

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Example: Can your friend distinguish Coke from Pepsi?

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Guesses right the first time. Proof of ability?

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What about twice in a row?

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What about twice in a row? three times? ten times?

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The p-value is the probability of such a result if it's just random.

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- Guess right five times in a row:

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Similarly: Disease with 50% fatality rate.

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Similarly: Disease with 50% fatality rate. New drug:

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If it saves 5 patients in a row,

How Statisticians Weigh Evidence

Example: Can your friend distinguish Coke from Pepsi? Do a test!

Guesses right the first time. Proof of ability? No, could be luck!

What about twice in a row? three times? ten times?

The p-value is the probability of such a result if it's just random.

- Guess right once: p-value $= 1/2 = 50\%$.
- Guess right twice in a row: p-value $= (1/2) \times (1/2) = 25\%$.
- Guess right five times in a row: multiply ("independent"):

p-value $= (1/2) \times (1/2) \times (1/2) \times (1/2) \times (1/2) \doteq 3.1\%$.

The smaller the p-value, the more it seems to "prove" something.

Usual standard: "significant" if p-value less than 5% (i.e., 1 in 20).

For Coke versus Pepsi: two in a row not significant, five in a row is.

Similarly: Disease with 50% fatality rate. New drug: does it work?

If it saves 5 patients in a row, then yes it's "significant"!

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As we will see . . .

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So, no suspicion of fraud/cheating.

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TV Interview: Reunited Half-Brothers

On a beach, brotherhood

Chance meeting in Hawaii brings half siblings together

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By Brian R. Ballou
Globe Staff / April 28, 2011

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One success out of a million is luck, not "meaning".

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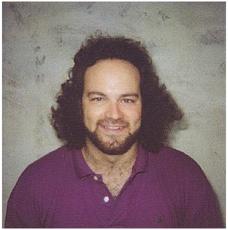

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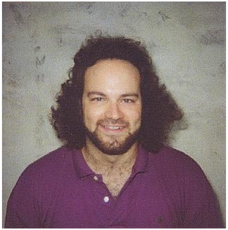

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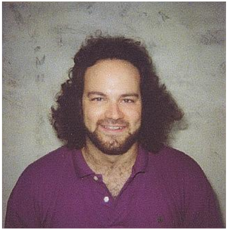

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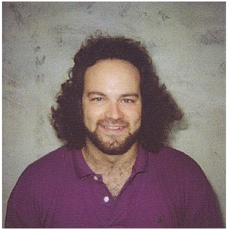

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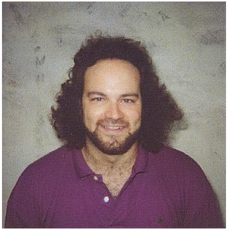

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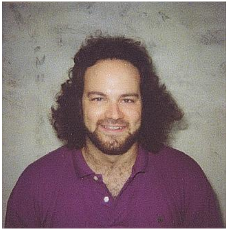

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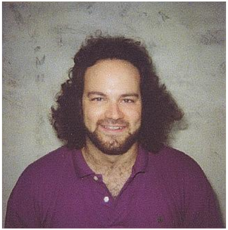

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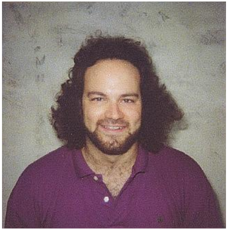

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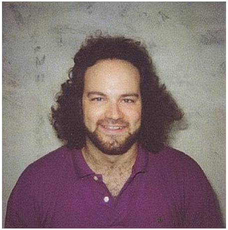

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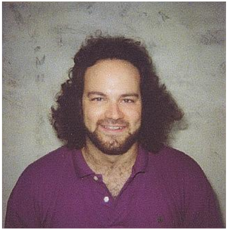

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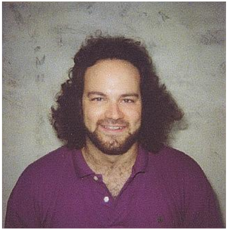

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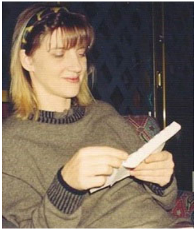

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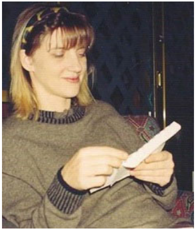

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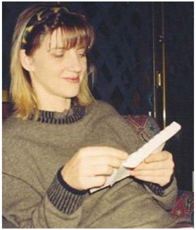

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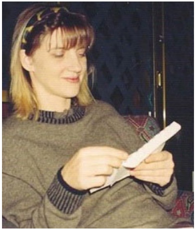

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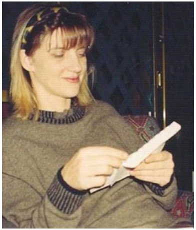

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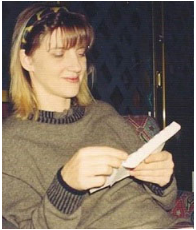

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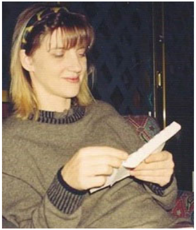

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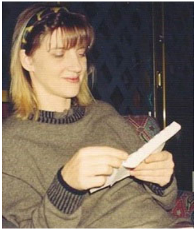

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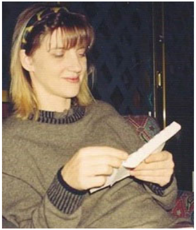

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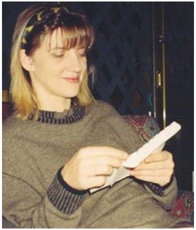

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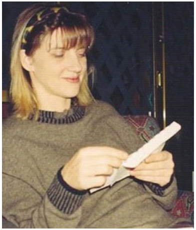

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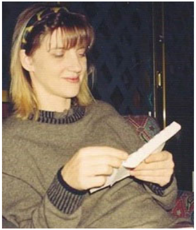

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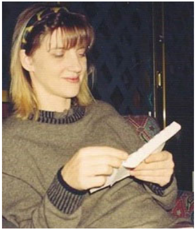

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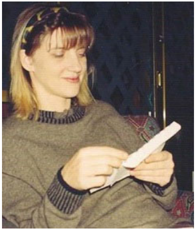

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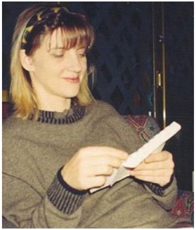

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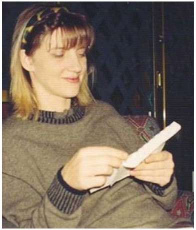

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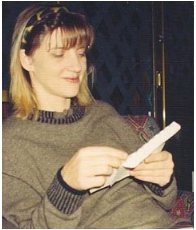

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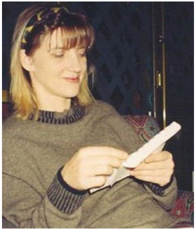

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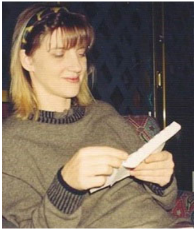

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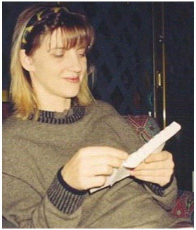

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- Valid calculation? Many statisticians thought no!

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- The convictions were upheld on appeal, June 2004.
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A Statistical Success:

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CBC broadcast scheduled for evening of Wed Oct 25 . . .

Globe & Mail Front Page, Oct. 25, 2006

See IRAQ on page A16

welcoming country. A16

■ Editorial. A26

214 lottery 'insiders' won big bucks

Odds of Ontario results astronomical, investigation by CBC program reports

BY SHANNON KARI

More than two-hundred lottery "insiders" have won prizes of $50,000 or more in Ontario since 1999, and more than two-thirds of these wins may have involved the deception of a customer who bought the ticket.

The allegation is made by the CBC program *the fifth estate*, after an investigation into the number of "insider wins" in the province in the past seven years.

A statistical analysis of the number of insider wins concluded that fewer than 60 insiders, such as ticket retailers or clerks, should have won major prizes during the period that was investigated.

The odds that the 214 insiders who claimed major prizes — $50,000 or more — since 1999 won as a result of pure luck, is one in a trillion, trillion, trillion, trillion, said University of Toronto professor Jeffrey Rosenthal, who conducted the analysis.

The program airing tonight suggests this may be a problem across Canada and the United States.

See LOTTERY on page A10

Toronto Sun

Those big winnings may have been yours

How is it that the people who sell lottery tickets do better than those who buy them?

Joe Warmington

Could it be you?

Is it possible your winning lotto numbers came up and you don't even know it? Is someone else enjoying your cash?

"It is possible more than 100 people since 1999 have won a major jackpot and don't even realize it," said Dr. Jeffrey Rosenthal, of the University of Toronto.

You do the math. That's a

Toronto Star

Province to probe the windfalls of lotter

Opposition wants outside investigator
Statisticians lay bets there was fraud

ROB FERGUSON
AND CURTIS RUSH
STAFF REPORTERS

Queen's Park has ordered a probe of the Ontario Lottery and Gaming Corporation's security measures in the wake of allegations that an astonishing number of inside retailers have won prizes of $50,000 or more since 1999.

"If there is anything we can do to strengthen that we certainly will act," David Caplan, the minister responsible for the corporation, said yesterday.

Caplan said he has ordered

frey Rosenthal's statistical analysis carried out for *the fifth estate*.

Rosenthal's numbers suggest that the real odds of 214 insiders claiming major prizes in those years are one in a trillion, trillion, trillion, trillion – that's a 1 followed by 48 zeroes.

In its Tuesday night report, CBC claimed that two-thirds of wins by so-called insiders may have involved deception by unscrupulous vendors who stole customers' winning tickets.

Rosenthal, a statistician with the University of Toronto, claims the chances of so many vendors winning by chance are so small that "almost anything you can think of is more likely."

The odds that you'll be hit by lightning in the next year are one in 5 million; that you'll be killed in your next vehicle trip one in 7 million, according to Rosenthal, author of *Struck by Lightning: The Curious World of Probability*.

Roncon says the lottery calculations are off.

"We don't know if they've used the correct retailer base," she said, adding that there are more than 140,000 people in the province that sell its products. "In the sit-down interview I did with them (CBC), they presented a very simplistic mathematical equation. It speaks to the fact they don't understand the complexities of our business."

Statistical experts the To *Star* contacted supported senthal's findings.

Fred Hoppe, profess mathematics and statisti McMaster University, cal ed that no more than abo retailers should have won prizes, depending on ass tions made about how ma tailers play the lottery.

Peter Bell, professor of agement science and inf tion systems at the Univer

Another lottery gamble

Imagine that you are trusting enough to give your provincial lottery ticket to a store clerk to learn whether you have won. Imagine that, against astronomical odds, the ticket is worth a lot. The vast majority of retailers and clerks will tell you the truth. But, on the evidence of an episode of CBC's *the fifth estate* scheduled to air last night, a number will lie. They will say you won only a tiny prize and will collect the major one themselves. Yes, there are all sorts of mechanisms to prevent that from happening, including self-serve ticket checkers and machines that play different tunes depending on how much money a ticket has won, but it happens.

One case in Ontario has become public, though the Ontario Lottery and Gaming Corporation (OLGC) has worked hard to keep some details secret. Bob Edmonds, now 82, bought a ticket in 2001 worth $250,000, but a variety-store owner told him he had won only a free ticket. Mr. Edmonds grew suspicious when he later read that the store owner had "won" the big prize. An OLGC investigator had concerns as well, but the corporation paid the retailer the money. It was only when Mr. Edmonds went to the police, and the police began investigating, that an e-mail was sent within the OLGC suggesting that Mr. Edmonds' claim was legitimate.

Even then, nothing happened. The OLGC fought Mr. Edmonds until 2005, settling with him just as a civil jury was about tion incurred $425,000 in legal costs, far exceeding the amount Mr. Edmonds should have won in 2001. And it required that the settlement be covered by a confidentiality clause — a demand that Mr. Edmonds's lawyer plans to contest in court next Monday, on the excellent grounds that an agency of government should not keep such secrets from the public.

The OLGC says the Edmonds case was "isolated" and insists it keeps a tight rein on those who sell its tickets (lottery mechanisms vary across Canada). The math would suggest otherwise. Initially, using an OLGC figure of 60,000 retailers and clerks in Ontario, *the fifth estate* asked Jeffrey Rosenthal, author of *Struck by Lightning: The Curious World of Probabilities*, what the odds were of those clerks winning nearly 200 times in the past seven years with an average prize of $500,000. Dr. Rosenthal's answer: "one chance in a trillion, trillion, trillion, trillion." According to the CBC, the OLGC last week said it really had closer to 140,000 retailers and clerks; even at that, Dr. Rosenthal said, the chance of so many winning so much was "extremely unlikely."

Mr. Edmonds's case would appear not so "isolated" after all. The Ontario government has ordered an internal review of its lottery system. For its part, the lottery corporation should remove the muzzle from Mr. Edmonds and let the public know the details of the settlement it reached. And,

Toronto Sun (p. 4)

MARK O'NEILL

University of Toronto statistician Prof. Jeffrey Rosenthal holds up a 6/49 ticket. He says so many retailers have won prizes it raises suspicions.

Storekeepers lucky?

Lottery officials dismiss statistician's claim that retailers' wins defy odds

Ombudsman:

Ombudsman: “$100 million to lottery insiders”

Lottery agency's close ties to retailers 'fatal flaw': report

Last Updated: Monday, March 26, 2007 | 2:00 PM ET

CBC News

The organization that runs Ontario's lottery system is fixated on profits rather than customer service and needs an independent regulator, the province's ombudsman said Monday.

André Marin spoke at a Toronto news conference to announce the results of an investigation into the Ontario Lottery and Gaming Corp., which has also been ordered to turn over all relevant files to the Ontario Provincial Police so the force can determine whether to launch a criminal investigation.

"The OLG is fixated on profits rather than customer service. It's lost sight that it is supposed to be the guardian of public trust," Marin said.

The government-owned corporation is "too cozy" with its retailers and paid out $100 million to "lottery insiders" from 1999 to 2006, he said.

Heads Roll!

Ontario Lottery chief fired

Mar. 24, 2007, 6:12 a.m. 5 comments

LOTTERY POST

OLG

Ontario Lottery and Gaming Corporation: Ontario Lottery chief fired

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The head of the Ontario Lottery and Gaming Corporation was dismissed from the scandal-plagued organization on Friday, according to CBC News.

CEO Duncan Brown was escorted out of the lottery corporation's offices in Toronto, two sources told the CBC, speaking on condition of anonymity.

New Rules For Signing and Checking Tickets

Ontario Lottery Introduces New Rules To Protect You From Fraud

2006/11/09 | CityNews.ca Staff

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The controversy started when a math professor compared the number of lottery kiosk clerks who've claimed big prizes with the chances of so many of those people actually winning that much money. When he calculated the odds in the multi-trillions, alarm bells went off.

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The Police Investigate

Police open probe of fraudulent Ontario lottery wins

Last Updated: Tuesday, March 27, 2007 | 10:17 AM ET

CBC News

Ontario Provincial Police have been called in to investigate tens of millions of dollars in suspicious lottery wins — prizes paid out to ticket retailers and lottery corporation insiders — following a damning report by the Ontario ombudsman Monday.

The minister responsible for the Ontario Lottery and Gaming Corporation, David Caplan, announced late Monday that he's ordered the corporation to hand over all relevant files on insider wins to the police.

And Make Arrests!

Man jailed for stealing $5.7M lottery win

Last Updated: Tuesday, June 15, 2010 | 1:34 PM ET CBC News

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- Police probe in lottery scandal not over yet

A former convenience store owner in Toronto who stole a winning lottery ticket worth $5.7 million has been sentenced to one year in jail.

An Ontario provincial court judge sentenced Hafiz Malik, 62, on Tuesday, six years after he bilked four people out of the Lotto 6/49 jackpot prize, and six months after he pleaded guilty to fraud.

Lorraine Teicht had taken the ticket to Malik's store on Dupont Street near Lansdowne Avenue in June 2004 to check it. She and three of her Toronto co-workers had been pooling their money and playing Lotto 6/49 on the same numbers for years. The ticket was purchased in Orillia, Ont.

Malik told Teicht she won, but only $10, and he ended up keeping the ticket.

When her colleagues later realized they should have won big they hired a private investigator, who eventually confronted Teicht with suspicions that she herself decided to pocket the winnings.

Provincial police and the Ontario Lottery and Gaming Corp. finally sorted out the mystery and Malik was arrested in

$5.7 Million Repaid to Rightful Winner!

True lottery winners get $5.7M from OLG

Four school board employees, allegedly cheated out of their winning lottery ticket by a retailer who claimed the prize money as his own, received a cheque for $5.7 million -- plus interest -- Wednesday from the Ontario Lottery and Gaming Corporation.

BY THE NATIONAL POST DECEMBER 20, 2007

TORONTO

Four school board employees, allegedly cheated out of their winning lottery ticket by a retailer who claimed the prize money as his own, received a

Another $80,000 Repaid!

Lotto winner paid four years later

The Ontario Lottery and Gaming Corp., which was slammed in a 2007 Ontario ombudsman's report for not cracking down on retailers over lottery fraud, has paid out $80,000 plus interest to a Burlington woman allegedly victimized by a lottery retailer.

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ONTARIO LOTTERY AND GAMING / CNW GROUP

"Special" holiday for Jamie Antinori.

By: Dale Anne Freed STAFF REPORTER, Published on Wed Dec 17 2008

Later, Three More Retailers Charged . . .

$12.5M lottery prize theft leads to 3 arrests

Last Updated: Wednesday, September 29, 2010 | 10:25 PM ET

Comments 462 Recommend 322

CBC News

The case of Kathleen Chung, who allegedly cashed the winning ticket at her brother's convenience store in Burlington in early 2004, was profiled by the CBC's Fifth Estate, triggering a report by the Ontario ombudsman. (CBC)

Three family members in the Toronto area have been charged in the theft of a $12.5-million lottery prize, while police seek the rightful owner of the Lotto Super 7 ticket bought in 2003.

Two of the accused are a father and son who worked at a Burlington lottery outlet and were actively stealing tickets from customers, Ontario Provincial Police Commissioner Chris Lewis

Could the True Winners be Found?

$12.5M lottery ticket stolen; police seeking rightful winner

Article | Photos (5)

Published On Thu Sep 30 2010 | Email | Print | Share | 51

Curtis Rush and Jayme Poisson

Staff Reporters

Found them! (January 2011)

Lottery fraud victims claim $12.5M prize – plus interest

Seven men with wraparound smiles claimed their seven-year-old $12.5 million lottery win Thursday, which stands now at $14.85 million.

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TANNIS TOOHEY / TORONTO STAR

And It All Followed From Statistics!

Solving equations and solving crime

Toronto math prof proves his point when it comes to insiders winning lottery prizes

By THANE BURNETT, NATIONAL BUREAU

Last Updated: 21st February 2009, 2:36am

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For a guy who's never bought a lottery ticket at a corner store, Jeff Rosenthal has sure hit it big.

And lottery corporations across Canada would likely wish he would just stop playing their numbers so well.

Since 2006, the Toronto math professor has been the brain behind uncovering a suspected massive theft of lottery winnings by sticky fingered store clerks.

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Before his sleuthing into insider wins, Rosenthal already defied convention, or at least the image of a math professor who's married to a librarian.