Quantitative Security

Colorado State University

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L13

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Computer Science Dept

Today’s Outline

- Some thoughts
- Review
- Seasonality
- Multi-version software
- Long term effects

Is hacking legal?

- That depends on what you mean by hacking.
  - Original meaning (MIT, 1960): informal programming
  - Unauthorized access of computing systems is illegal.
    - Can be done by people with limited expertise.
  - Discovering vulnerabilities in software/systems one owns is not illegal.
    - May take significant skill.
  - Scanning for security holes in systems you don’t own, is not legal.
  - Paying ransom for data (ransomware) is not legal in USA.
  - Disclosure/selling of zero-day vulnerabilities may be controlled by governments.

Dimensions and Approximations

- For real problems, proper approximations are essential.
  - Jeff Bezos net worth is $194.43 Billion Oct 2, 2020. Can be approximated as 200 Billion.
  - (1,000,001 - 1,000,000) may not be approximated as 0.
- Note the distinction between K (10^3) and M (10^6). You must convert numbers appropriately.
- You need to keep dimensions in mind.
  - Fort Collins to Denver is _______ miles.
  - Windows 10 is about 50 Million lines of code.
  - Documented smallest software defect density is 0.1/KLOC (space shuttle software).
  - In OS, the vulnerabilities are about 1% of the defects.

What you should question

- A claim should probably be tentatively accepted if
  - It is consistent with well established, carefully researched observations
  - Credibility of the researchers and publication
- Question a claim if
  - You think you can come up with a better idea
- Researchers (unlike managers) do not claim they know everything.

I PUT TOGETHER A TIME LINE FOR YOUR PROJECT.
I STARTED BY REASONING THAT ANYTHING I DON'T UNDERSTAND IS EASY TO DO.
PHASE ONE: DESIGN A CLIENT-SERVER ARCHITECTURE FOR OUR WORLD-WIDE OPERATIONS. TIME: SIX MINUTES.
S.Adams
E-Mail: SCOTTADAMS@AOL.COM
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10-17

Term Research Project

- Select your topic idea asap.
- Project Proposal & Sources: due Oct 10
  - See requirements.
- Semi-final report: due Nov 7
  - Lit review done, some preliminary results
- Slides/Presentation: Nov 18, Nov 19-Dec 8
  - interactive
- Final report: due Dec 9
  - Possible publication
- Critical Peer reviews: due Dec 10

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Vulnerability Discovery Models

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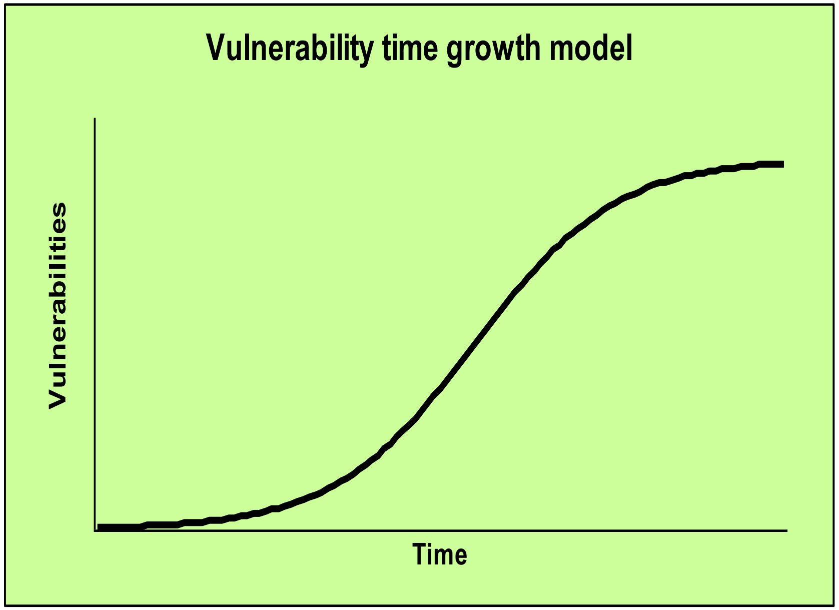
Time–vulnerability Discovery model

$$\frac{dy}{dt} = Ay(B - y)$$

$$y = \frac{B}{BCe^{-ABt} + 1}$$

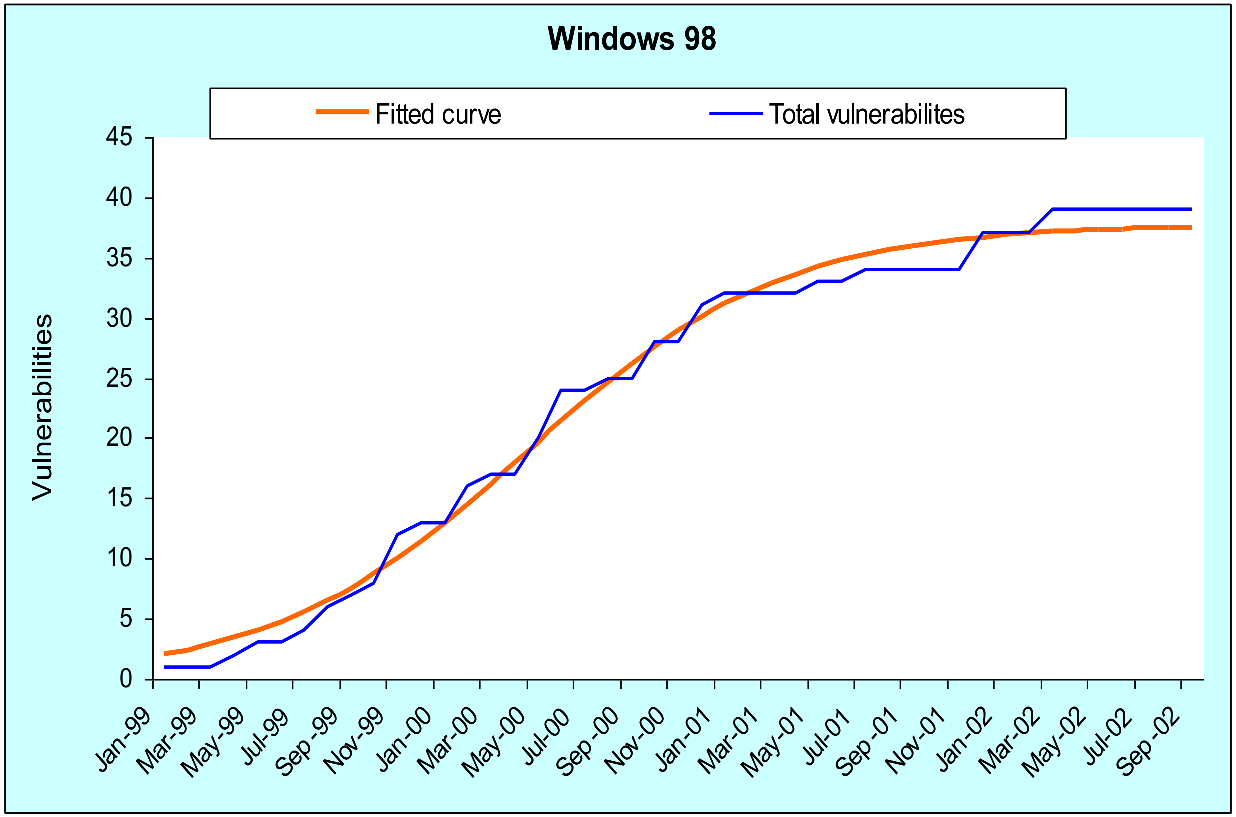
3 phase model S-shaped model.

- Phase 1:
  - •Installed base –low.
- Phase 2:
  - •Installed base–higher and growing/stable.
- Phase 3:
  - •Installed base–dropping.



O. H. Alhazmi and Y. K. Malaiya, "Quantitative Vulnerability Assessment of Systems Software Proc. Ann. IEEE Reliability and Maintainability Symp., 2005, pp. 615-620

Time–based model: Windows 98



	Windows 98
A	0.004873
B	37.7328
C	0.5543
X^2	7.365
$X^2_{critial}$	60.481
P-value	$1- 7.6x10^{-11}$

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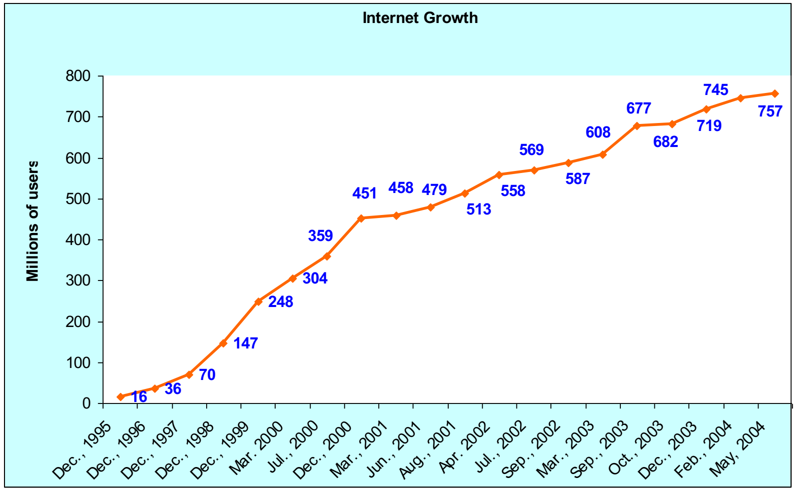
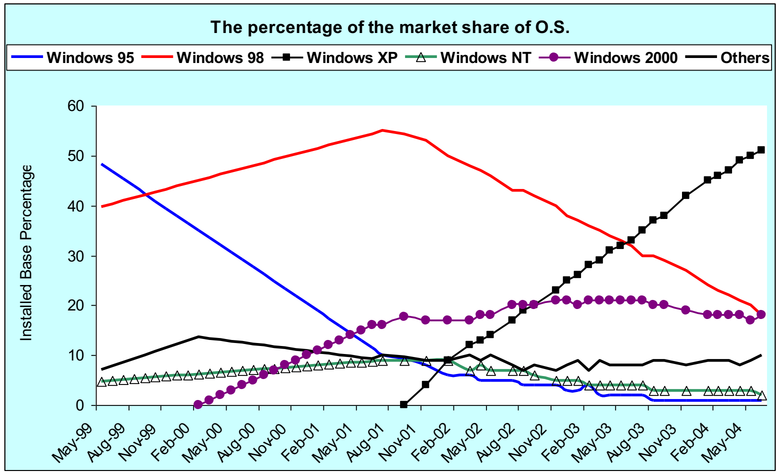
Usage –vulnerability Discovery model

- The data:
  - The global internet population.
  - The market share of the system during a period of time.
- *Equivalent effort*
  - The real environment performs an intensive testing.
  - Malicious activities is relevant to overall activities.
  - Defined as

$$E = \sum_{i=0}^{n} (U_i \times P_i)$$





Software Reliability Modeling

- Applicable to general software bugs
- Key Static software metrics
  - Software size (without comments, KLOC)
  - Defect density (total defects/size)
    - Typical range Range 16 -0.1 /KLOC
    - Software evolution/reuse, requirement volatility
    - Team capabilities, extent of testing
  - Defect finding efficiency

0.1/KLOC	Space Shuttle

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Exponential SRGM

Exponential Reliability Growth Model

- Assumption: rate of finding and removing bugs proportional to the number of bugs present at time t.

$$-\frac{dN(t)}{dt} = \beta_1 N(t)$$

Which yields

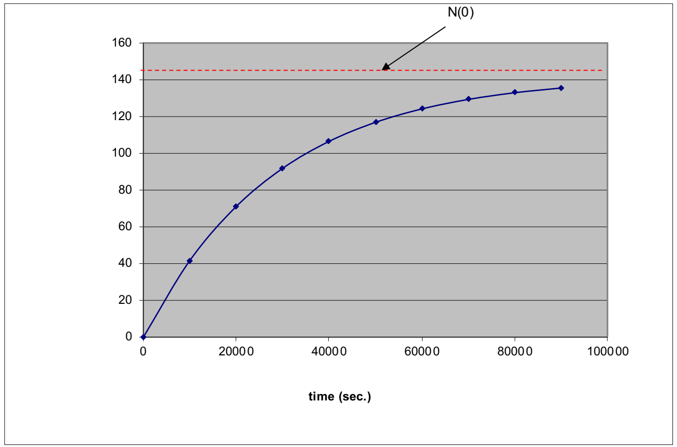
$$N(t) = N(0)e^{-\beta_1 t}$$

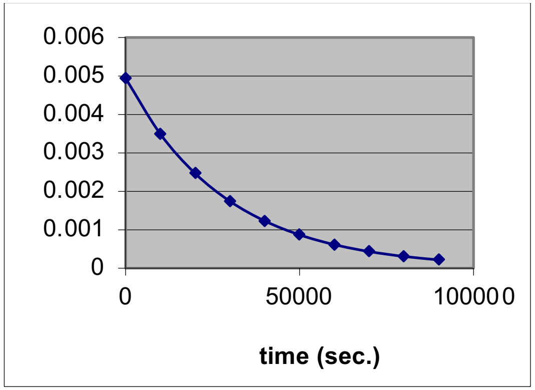
- Cumulative number of defects found is

$$N(0)(1 - e^{-\beta_1 t})$$

- Defect finding rate is

$$N(0)e^{-\beta_1 t}$$





- N(0) may be estimated using defect density and size
- β_1 depends to defect finding efficiency

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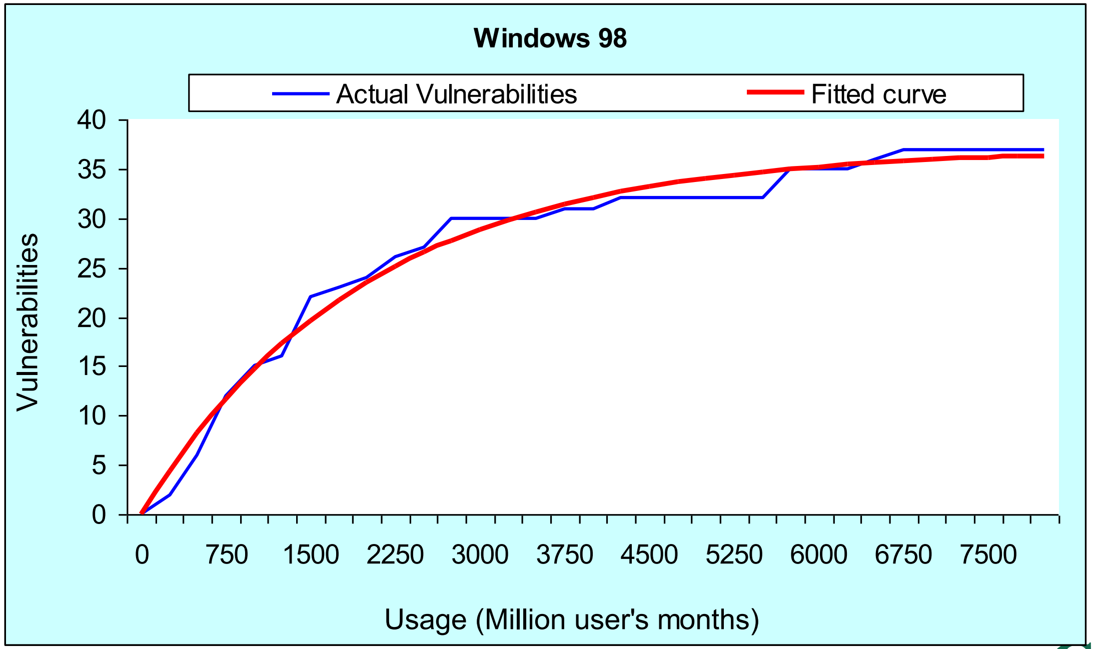
Usage –vulnerability Discovery model

- The model: growth with effort.
- Growth model based on the exponential SRGM
- Time is eliminated.
- $y = N(0)(1 - e^{-\beta_1 E})$



	Windows 98
B	37
λ_{vu}	0.000505
X^2	3.510
$X^2_{critial}$	44.9853
P-value	1- $3.3\text{x}10^{-11}$

Vulnerability density and defect density

- Defect density
  - Valuable metric for planning test effort
  - Used for setting release quality target
  - Some data is available
  - Depends on various factors, may be stable for a team/process
- Vulnerabilities are a class of defects
  - Vulnerability data is in the public domain.
  - Is vulnerability density a useful measure?
  - Is it related to defect density?
    - Vulnerabilities = 5% of defects [Longstaff]?
    - Vulnerabilities = 1% of defects [Anderson]?
- Can be a major step in measuring security.

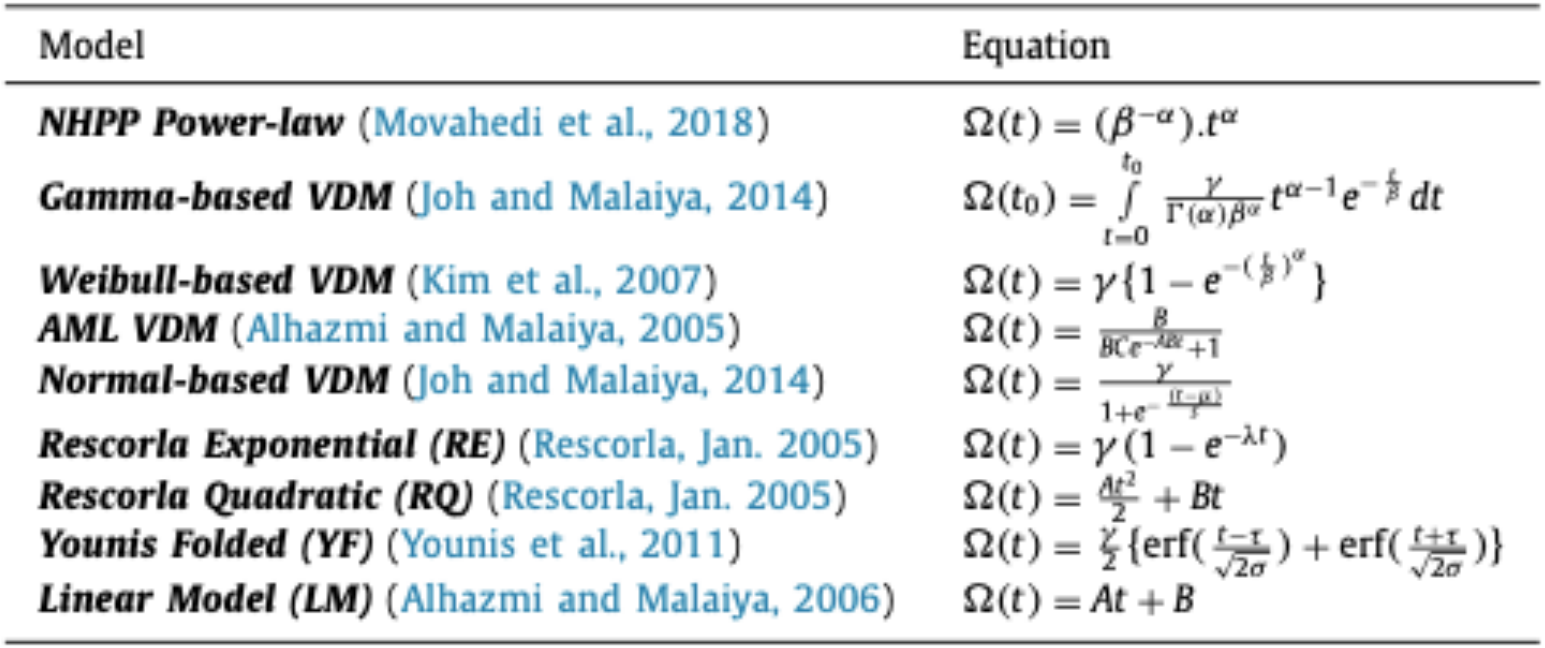
Vulnerability density and defect density

- **Vul dens**: 95/98: 0.003-0.004, NT/2000/XP: 0.01-0.02, Apache 0.04
- **V_{KD}/D_{KD}.** about 1% for client OSs, Higher for HTTP servers, server OSs

System	MSLOC	Known Defects (1000s)	D_{KD} (/Kloc)	Known Vulner - abilies	V_{KD} (/Kloc)	Ratio V_{KD}/D_{KD}
Win 95	15	5	0.33	46	0.0031	0.92%
NT 4.0 server	16	10	0.625	162	0.0101	1.62%
Win 98	18	10	0.556	84	0.0047	0.84%
Win2000	35	63	1.8	508	0.0145	0.81%
Win XP	40	106.5*	2.66*	728	0.0182	0.68%*
Apache HTTP 2006	227 (Unix)	4148	18.27	96	0.423	2.32%
Firefox	2.5	24,027	9.61	134	0.0536	0. 557%

MS Thesis Woo, 2006

Vulnerability Discovery Models



Model	Equation
NHPP Power-law (Movahedi et al., 2018)	$\Omega(t) = (\beta^{-\alpha}).t^{\alpha}$
Gamma-based VDM (Joh and Malaiya, 2014)	$\Omega(t_0) = \int\limits_{t=0}^{t_0} \frac{\gamma}{\Gamma(\alpha)\beta^{\alpha}} t^{\alpha-1} e^{-\frac{t}{\beta}} dt$
Weibull-based VDM (Kim et al., 2007)	$\Omega(t) = \gamma\{1 - e^{-(\frac{t}{\beta})^{\alpha}}\}$
AML VDM (Alhazmi and Malaiya, 2005)	$\Omega(t) = \frac{B}{BCe^{-ABt}+1}$
Normal-based VDM (Joh and Malaiya, 2014)	$\Omega(t) = \frac{\gamma}{1+e^{-\frac{(t-\mu)}{\sigma}}}$
Rescorla Exponential (RE) (Rescorla, Jan. 2005)	$\Omega(t) = \gamma(1 - e^{-\lambda t})$
Rescorla Quadratic (RQ) (Rescorla, Jan. 2005)	$\Omega(t) = \frac{At^2}{2} + Bt$
Younis Folded (YF) (Younis et al., 2011)	$\Omega(t) = \frac{\gamma}{2}\{\mathrm{erf}(\frac{t-\tau}{\sqrt{2}\sigma}) + \mathrm{erf}(\frac{t+\tau}{\sqrt{2}\sigma})\}$
Linear Model (LM) (Alhazmi and Malaiya, 2006)	$\Omega(t) = At + B$

Table of models and their equations

Yazdan Movahedi, Michel Cukier, Ilir Gashi, Vulnerability prediction capability: A comparison between vulnerability discovery models and neural network models, Computers & Security,, Volume 87, 2019.

Seasonality in Vulnerability Discovery

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Seasonality in Vulnerability Discovery

- Vulnerability Discovery Model (VDM):
  - a probabilistic methods for modeling the discovery of software vulnerabilities [Ozment]
  - Spans a few years: introduction to replacement
- Seasonality: periodic variation
  - well known statistical approach
  - quite common in economic time series
    - Biological systems, stock markets etc.

Halloween indicator:
Low returns in May-Oct.

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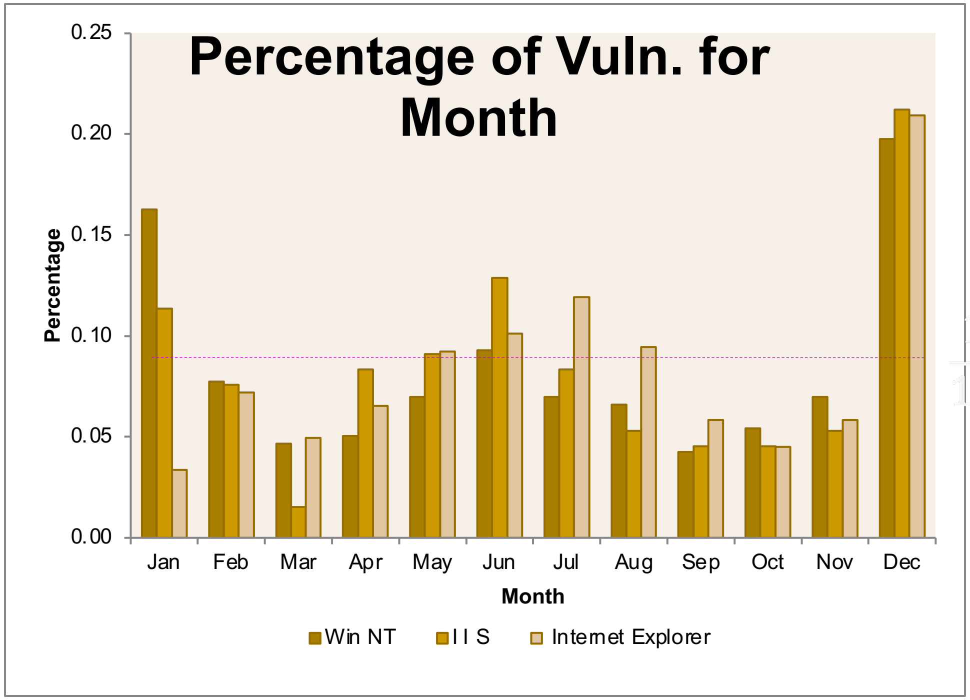
Examining Seasonality

- Is the seasonal pattern statistically significant?
- Periodicity of the pattern
- Analysis:
  - Seasonal index analysis with test
  - Autocorrelation Function analysis χ^2
- Significance
  - Enhance VDMs’ predicting ability
- Annual and Weekly seasonality

Annual: Prevalence in Month

Vulnerabilities Disclosed

	WinNT '95~'07	IIS '96~'07	IE '97~'07
Jan	42	15	15
Feb	20	10	32
Mar	12	2	22
Apr	13	11	29
May	18	12	41
Jun	24	17	45
Jul	18	11	53
Aug	17	7	42
Sep	11	6	26
Oct	14	6	20
Nov	18	7	26
Dec	51	28	93
Total	258	132	444
Mean	21.5	11	37
s.d.	12.37	6.78	20.94



$\frac{1}{12}$

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Seasonal Index

Seasonal Index Values

	WinNT	IIS	IE
Jan	1.95	1.36	0.41
Feb	0.93	0.91	0.86
Mar	0.56	0.81	0.59
Apr	0.60	1.00	0.78
May	0.84	1.09	1.11
Jun	1.12	1.55	1.22
Jul	0.84	1.00	1.43
Aug	0.79	0.64	1.14
Sep	0.51	0.55	0.70
Oct	0.65	0.55	0.54
Nov	0.84	0.64	0.70
Dec	2.37	2.55	2.51
χ_c^2	19.68	19.68	19.68
χ_s^2	78.37	46	130.43
p-value	3.04e-12	3.23e-6	1.42e-6

- Seasonal index: measures how much the average for a particular period tends to be above (or below) the expected value
- H_0: no seasonality is present. We will evaluate it using the monthly seasonal index values given by [4]:

$$s_i = \frac{d_i}{d}$$

where, s_i is the seasonal index for i^{th} month, d_i is the mean value of i^{th} month, d is a grand average

[4] Hossein Arsham. Time-Critical Decision Making for Business Administration. Available: http://home.ubalt. edu/ntsbarsh/Business-stat/stat-data/Forecast.htm#rseasonindx

Autocorrelation function (ACF)

- Plot of autocorrelations function values
- With time series values of $z_b, z_{b+1}, \ldots, z_n$, the ACF at lag k, denoted by r_k, is [5]:

$$r_k = \frac{\sum_{t=b}^{n-k}(z_t - \bar{z})(z_{t+k} - \bar{z})}{\sum_{t=b}^{n}(z_t - \bar{z})^2}$$

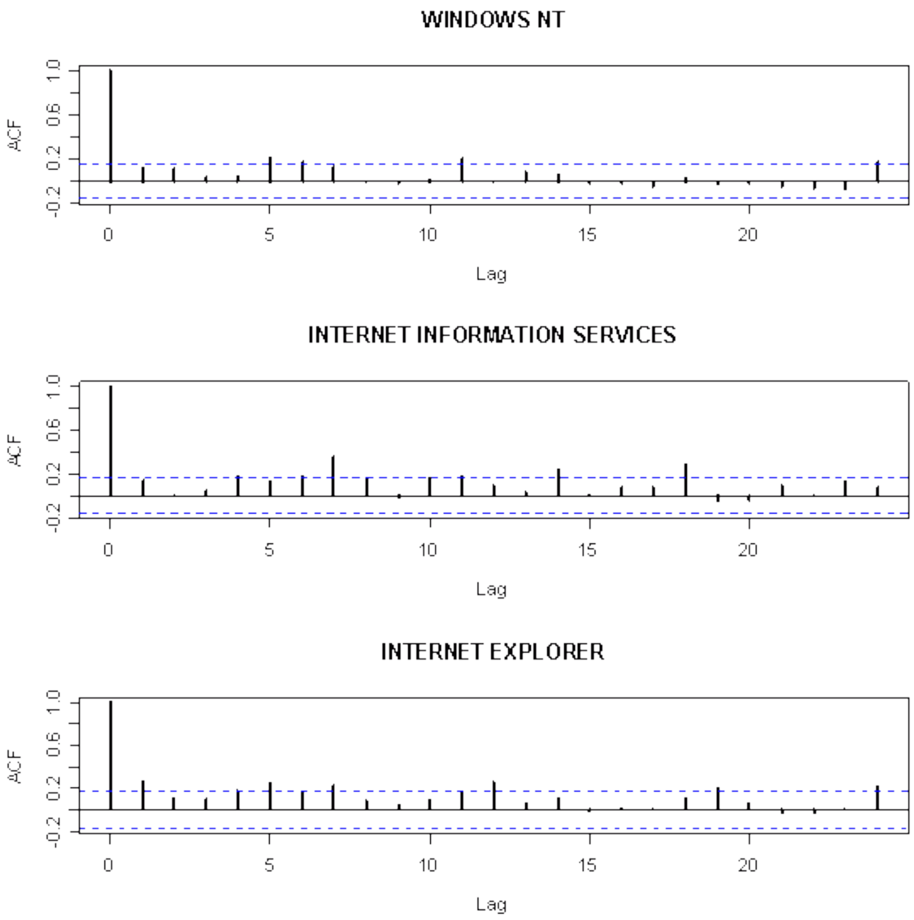
, where

$$\bar{z} = \frac{\sum_{t=b}^{n} z_t}{(n - b + 1)}$$

- Measures the linear relationship between time series observations separated by a lag of time units
- Hence, when an ACF value is located outside of confidence intervals at a lag t, it can be thought that every lag t, there is a relationships along with the time line

[5] B. L. Bowerman and R. T. O'connell, Time Series Forecsting: Unified concepts and computer implementation. 2nd Ed., Boston: Duxbury Press, 1987

Autocorrelation (ACF):Results



- Expected lags corresponding to 6 months or its multiple would have their ACF values outside confidence interval
- Upper/lower dotted lines: 95% confidence intervals.
- An event occurring at time t + k (k > 0) lags behind an event occurring at time t.
- Lags are in month.

Why seasonality?

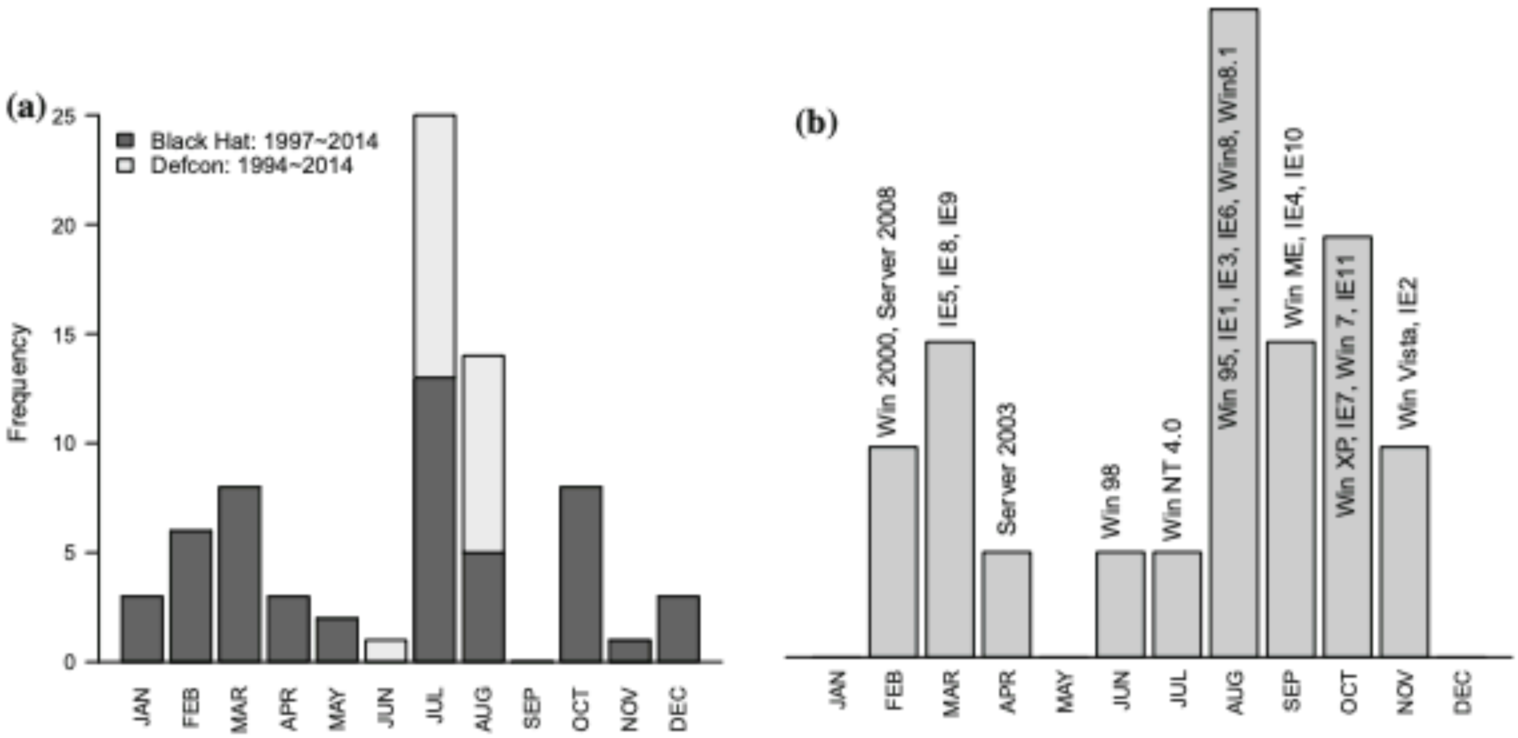
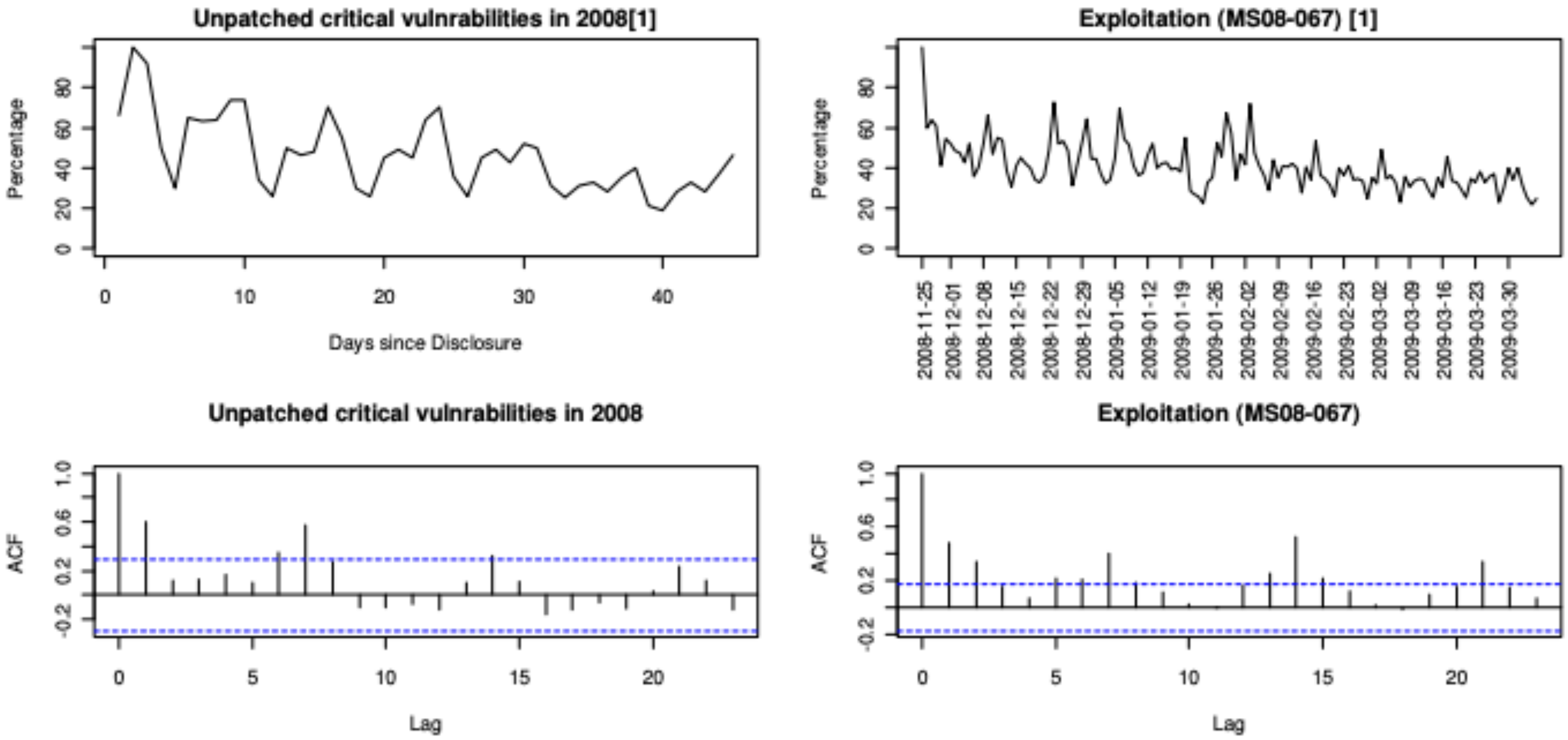


Fig. 6 Frequency of Black Hat and Defcon by month, and major Microsoft software system release time by month. **a** Black Hat and Defcon by month. **b** MS release by month

H. Joh and Y.K. Malaiya, "Periodicity in Software Vulnerability Discovery, Patching and Exploitation", International Journal of Information Security, July 2016, pp 1-18.

Weekly Seasonality



Unpatched critical vulnrabilities in 2008[1]

Exploitation (MS08-067) [1]

Unpatched critical vulnrabilities in 2008

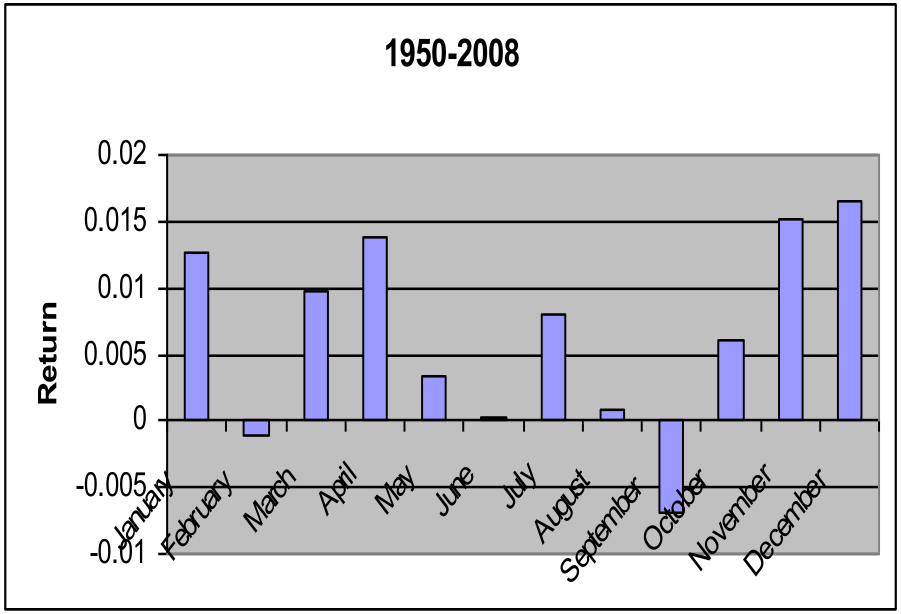
Exploitation (MS08-067)

Figure 1. Run charts for unpatched critical vulnerabilities in 2008 and Exploitation with their corresponding ACFs. The upper two plots are normalized using the maximum value as 100%. In the bottom two plots, legs are in day.

H. Joh, S. Chaichana and Y. K. Malaiya, "Short-term Periodicity in Security Vulnerability Activity" Proc. Int. Symp. Software Reliability Eng. (ISSRE), FA, November 2010, pp. 408-409

Halloween Indicator

- “Also known as “Sell in May and go away”
- Global (1973-1996):
  - Nov.-April: 12.47% ann., st dev 12.58%
  - 12-months:10.92%, st. dev. 17.76%
- 36 of 37 developing/developed nations
- Data going back to 1694
- “No convincing explanation”



Jacobsen, Ben and Bouman, Sven,The Halloween Indicator, 'Sell in May and Go Away': Another Puzzle(July 2001). Available at SSRN: http://ssrn.com/abstract=76248

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Multi-version Systems

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Vulnerability Discovery in Multi-Version Software Systems

- Motivation
- Software Evolution
- Multi-version Software Discovery Model
  - Apache, Mysql and Win XP data

Motivation for Multi-version VDMs

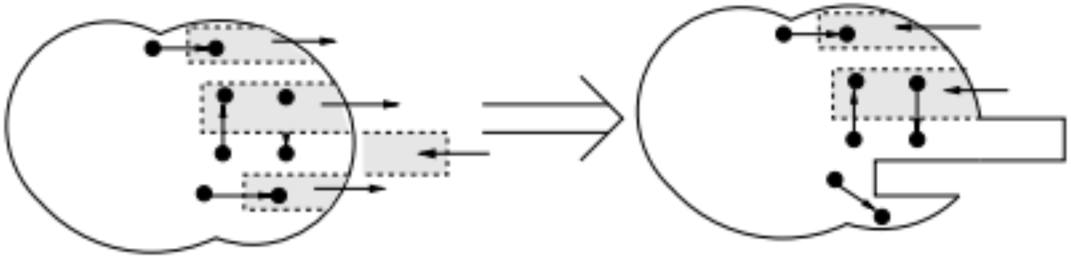
- Superposition effect on vulnerability discovery process due to shared code in successive versions.
- Examination of software evolution: impact on vulnerability introduction and discovery
- Other factors impacting vulnerability discovery process not considered before

Software Reuse

- New software projects use both new and reused blocks.
  - New blocks have a higher defect density because they have undergone less testing.
  - Reused blocks are more reliable.
  - Some defects may be introduced at the new/reused block interface.
  - Overall defect density is weighted average of the two.
  - Encounter rate during execution depends on weighted usage

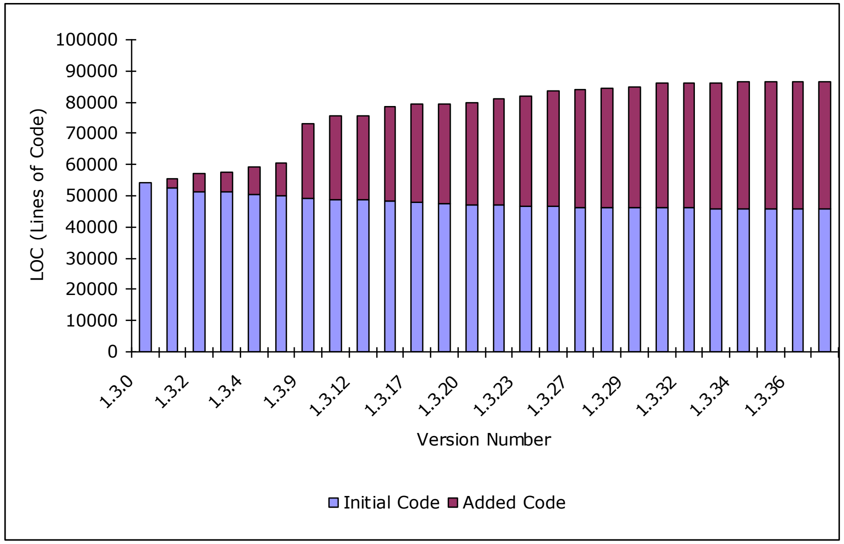
Software Evolution

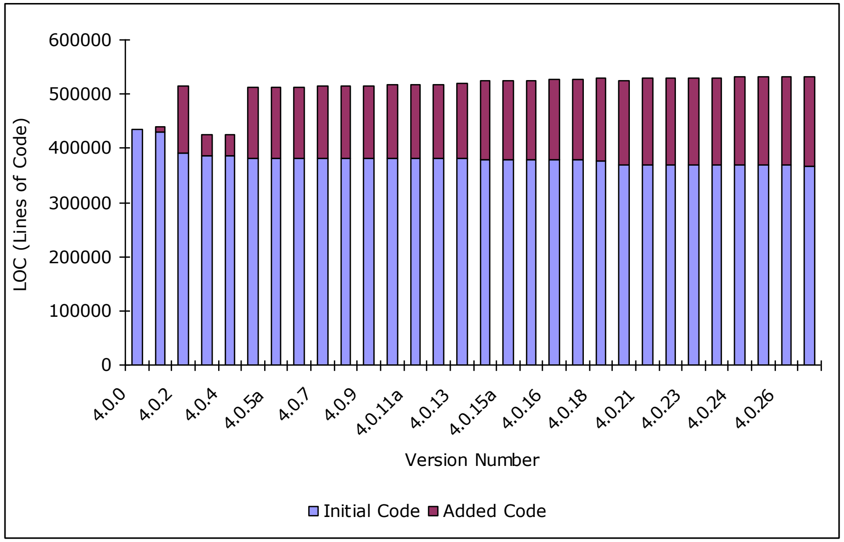
- The modification of software during maintenance or development:
  - fixes and feature additions.
  - Influenced by competition
- Code decay and code addition introduce new vulnerabilities
- Successive version of a software can share a significant fraction of code.



Y. K. Malaiya and J. Denton "Requirement Volatility and Defect Density,"
Proc. IEEE Int. Symp. Software Reliability Engineering, Nov. 1999, pp. 285-294.

Software Evolution: Apache & Mysql

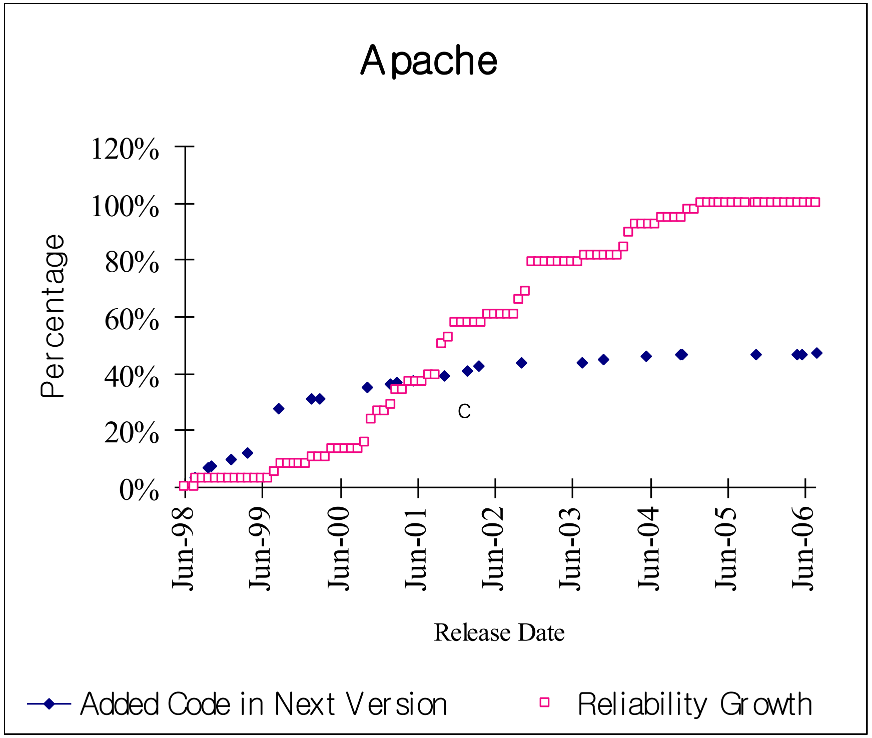


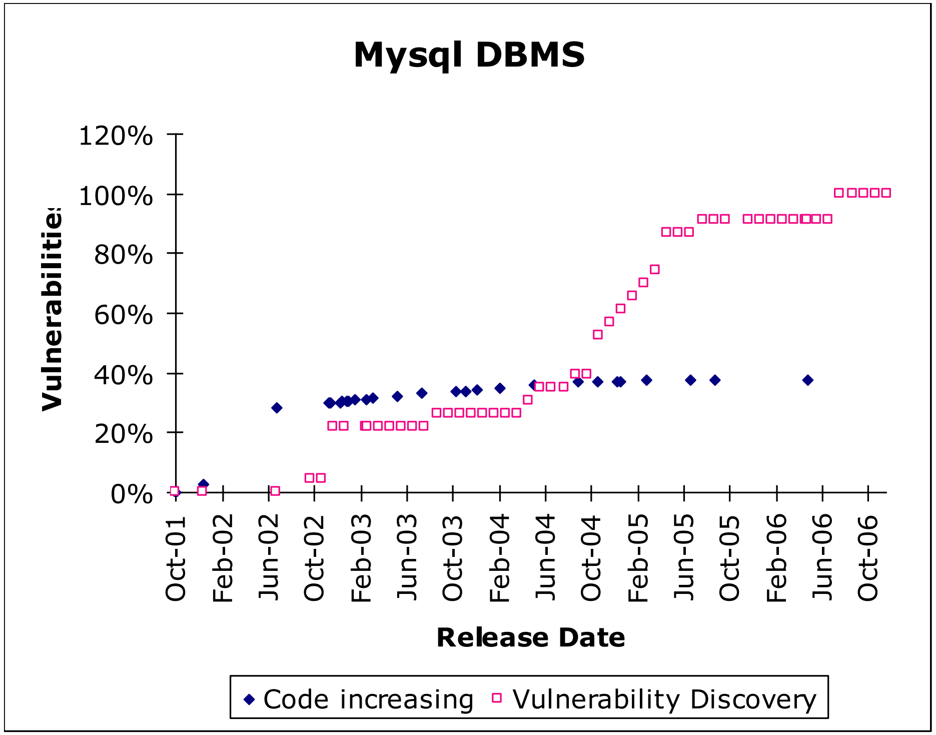


Modification: Apache 43%, Mysql 31%

J. Kim, Y. K. Malaiya and I. Ray, "Vulnerability Discovery in Multi-Version Software Systems," Proc. 10th IEEE Int. Symp. on High Assurance System Engineering (HASE), Dallas, Nov. 2007, pp. 141-148

Vulnerability Discovery & Evolution:



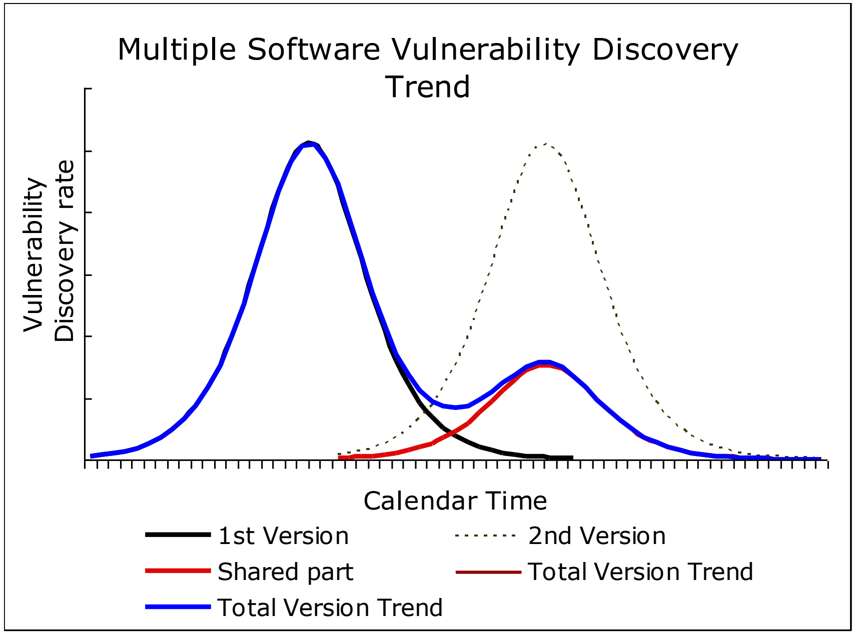


Some vulnerabilities are in added code, many are inherited from precious versions.

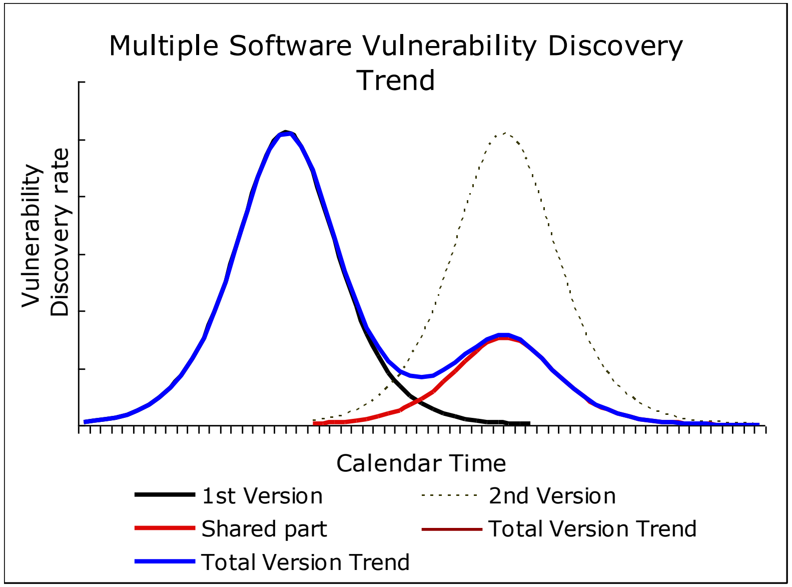
Code Sharing & Vulnerabilities

- Observation
  - Vulnerability increases after saturation in AML modeling

- Accounting for Superposition Effect
  - Shared components between several versions of software



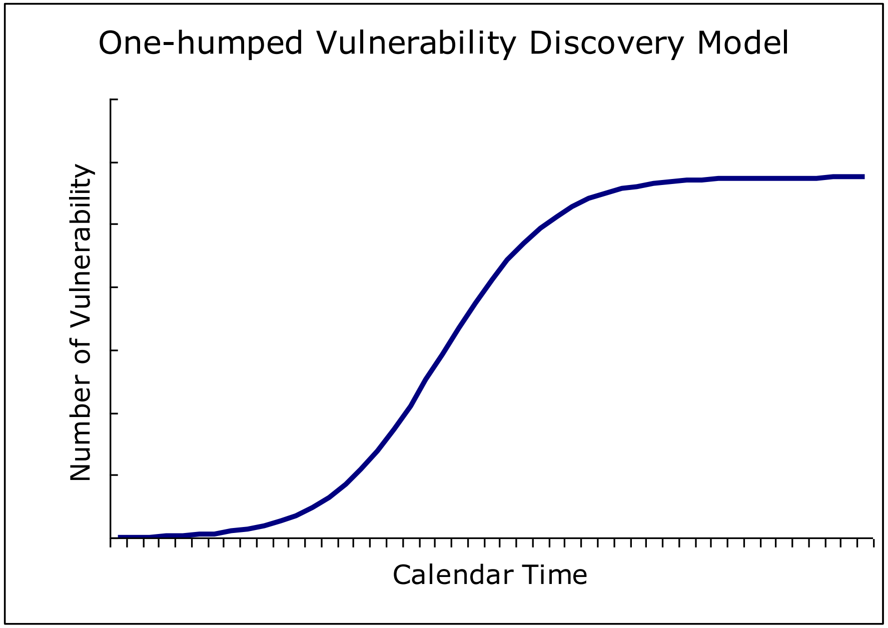
Multi-version Vulnerability Discovery

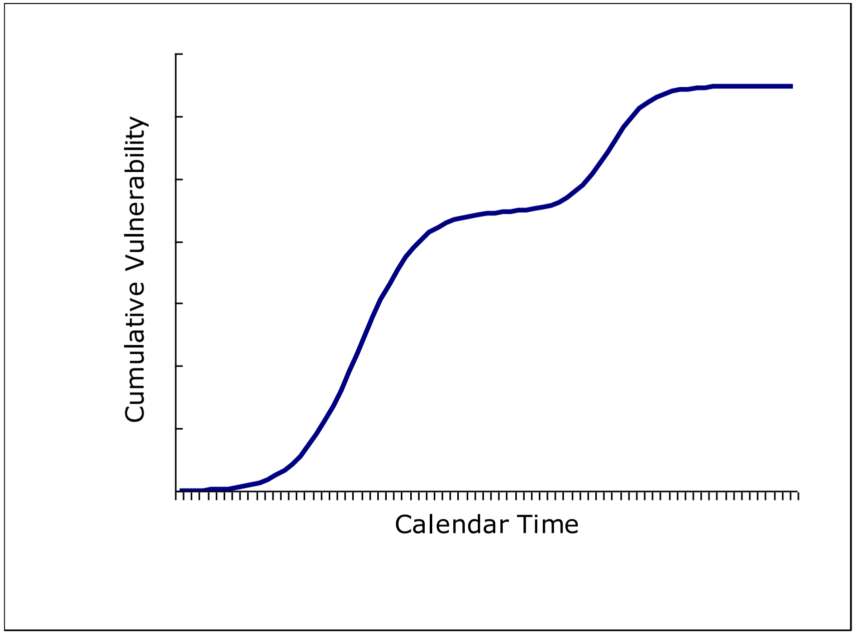


$$\Omega(t) = \frac{B}{BCe^{-ABt}+1} + \alpha\frac{B'}{B'C'e^{-A'B'(t-\varepsilon)}+1}$$

	Previous Version	Next Version	Shared Code Ratio α
Apache	1.3.24 (3-21-2002)	2.0.35 (4-6-2002)	20.16%
Mysql	4.1.1 (12-1-2003)	5.0.0 (12-22-2003)	83.52%

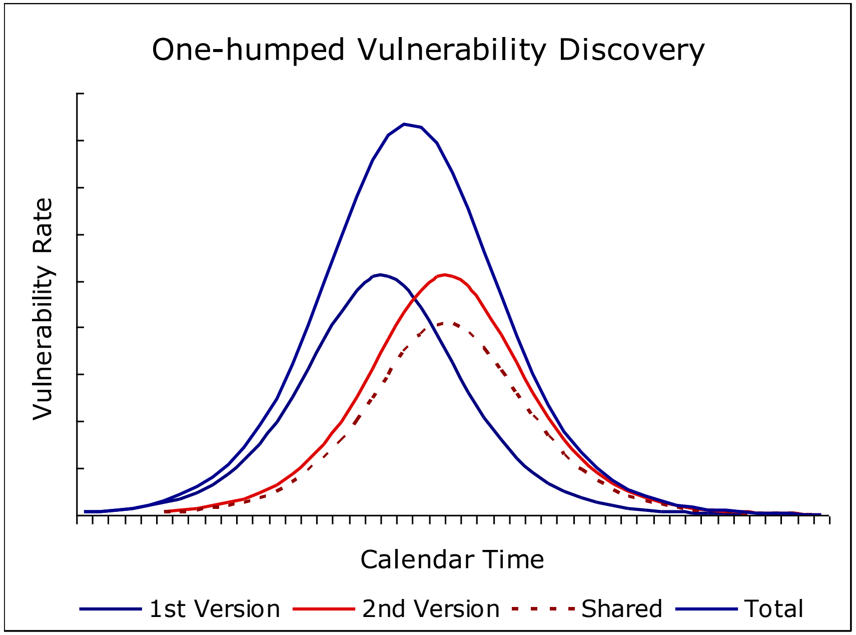
One vs Two Humps

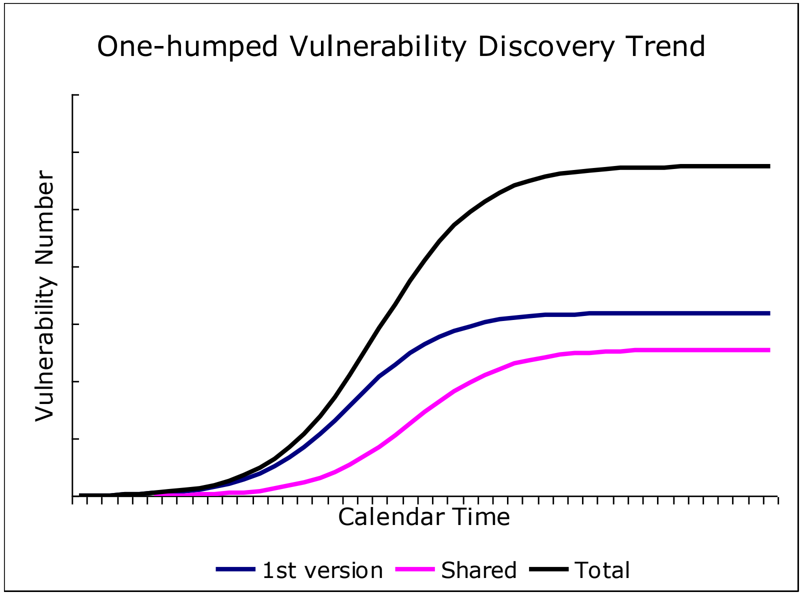




Superposition affect

Multi-version Vulnerability Discovery





- May result in a single hump with prolonged linear period

Evolving Programs

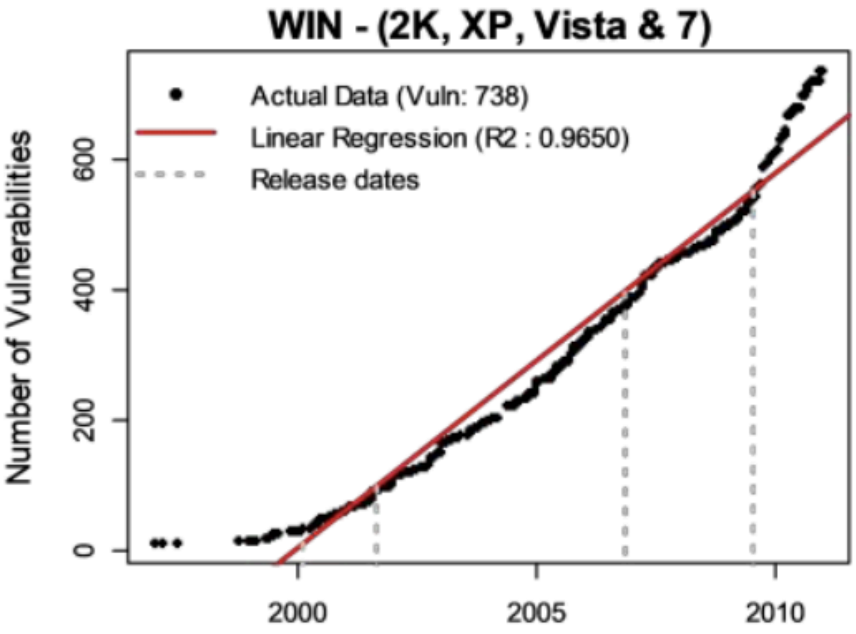
Gradually evolving software

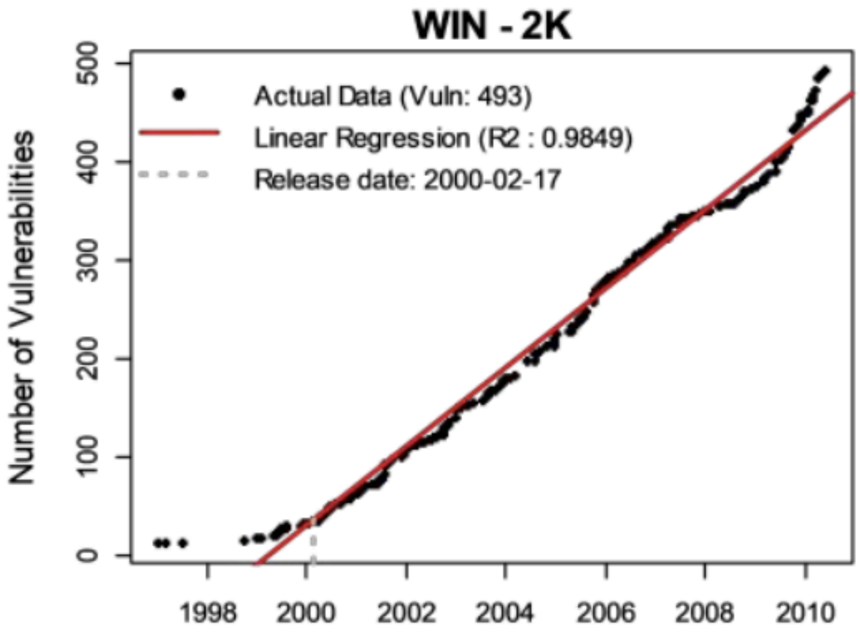
Software evolves in each version.

- Existing code fixed
  - some vulnerabilities found and patched
- Code added for increasing functionality
  - New vulnerabilities injected
  - Total number of vulnerabilities may remain about the same
- Overall code size keeps increasing
  - Vulnerability discovery rate may remain stable

Linear model

- Because of nearly continuous evolution, the linear phase may get stretched.

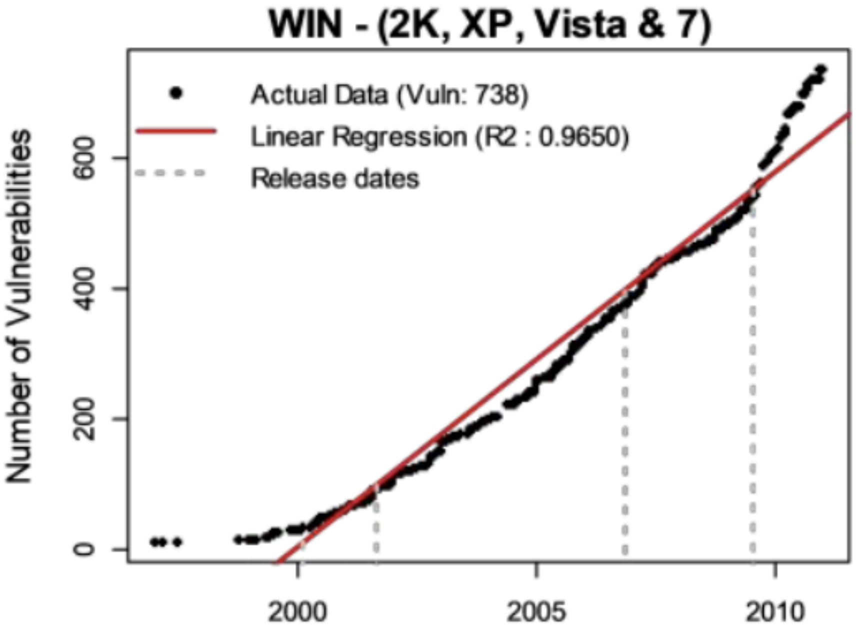


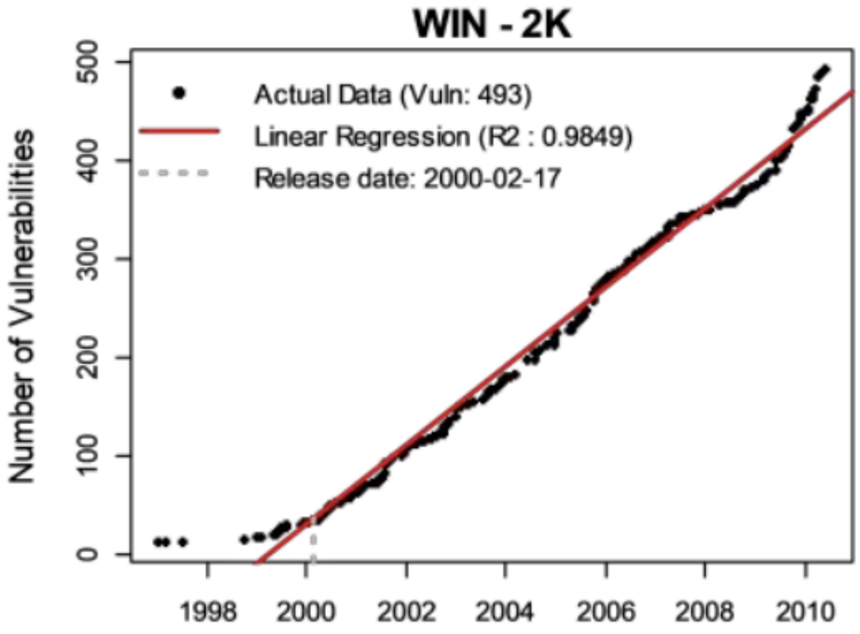


- If the evolution rate is steady, the size of the pool of undiscovered vulnerabilities stays the same (vulnerabilities removal rate = injection rate)
- If the market share is steady, the number of vulnerability finders remains steady.

Joh's thesis

Linear model

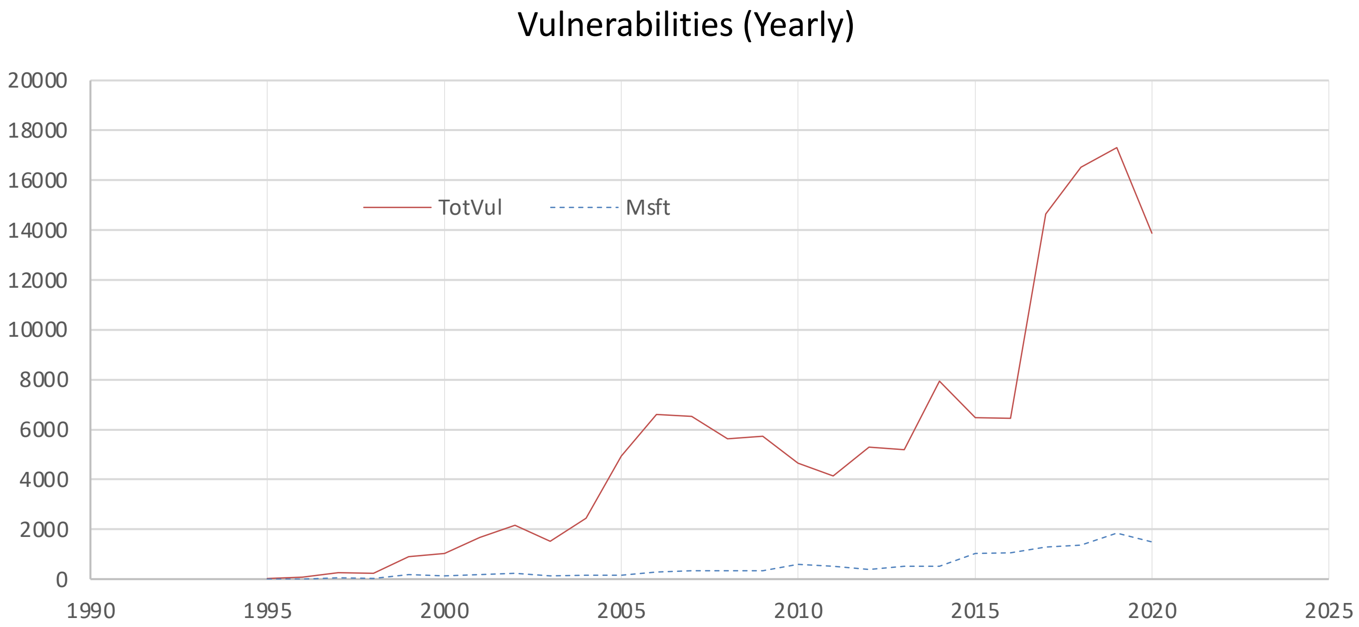




- Four Windows releases: 500 vulnerabilities during July 1998-July 2009
- Size: 35-50 M LOC
- Slope = about 45 vulnerabilities/year
- Further investigation is needed.

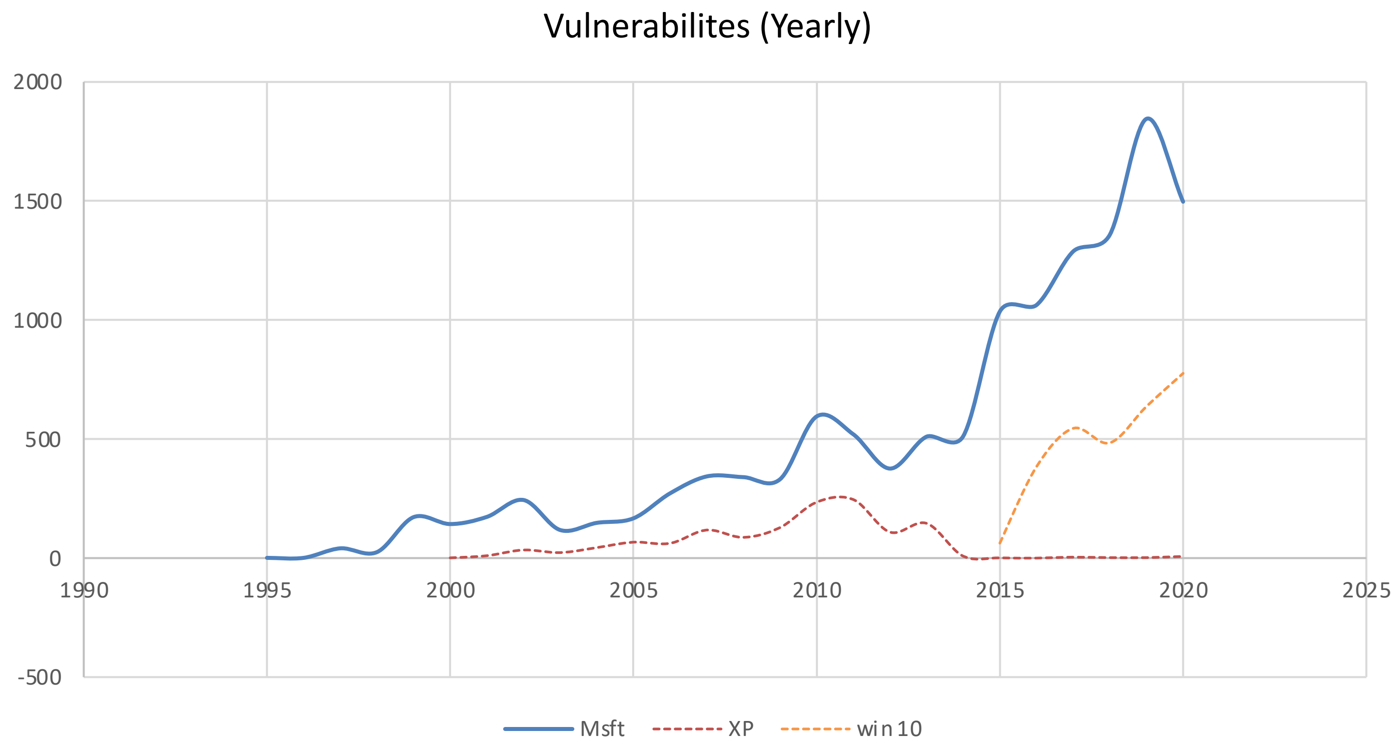
Data from Joh’s thesis

Long Term Trends



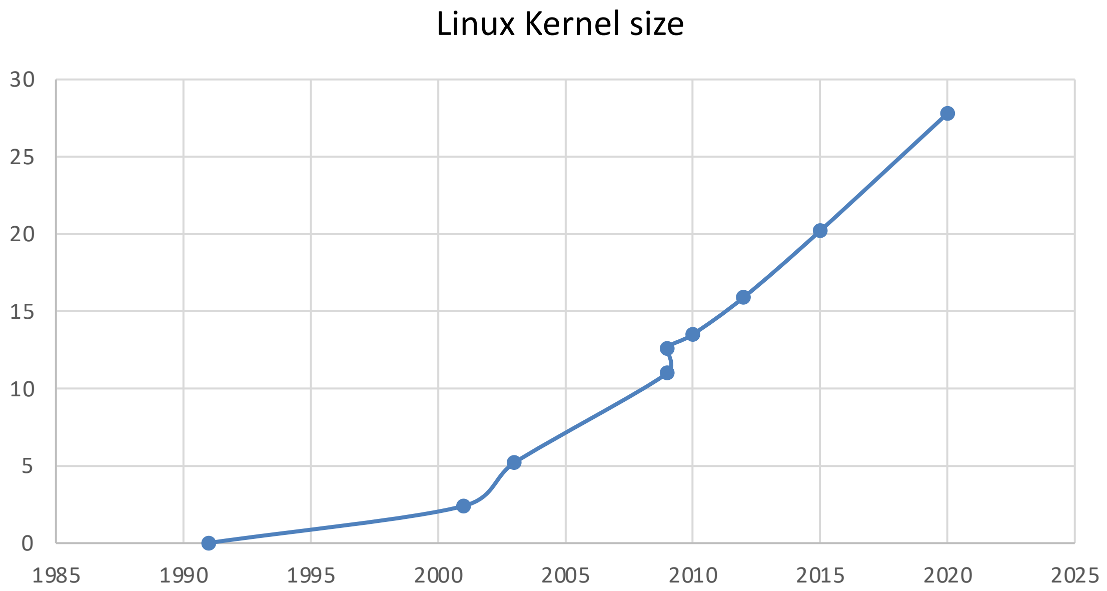
- Long term Trends: Total vulnerabilities, Microsoft products

Long Term Trends



- Long term Trends: Microsoft products, Win XP, Win 10

Long Term Trends



- Size evolution: Linus kernel

Long term trends

Likely factors that affect long-term trends

- Better understanding of safer coding practices
  - Fewer vulnerabilities injected?
- Better vulnerability discovery tools (fuzzers) and more finders
  - Higher vulnerability discovery rates
- More software products
  - More vulnerabilities to be found

Vulnerability Discovery and Risks

What factors impact risk?

- Not the vulnerabilities that have been found and patched
- Vulnerabilities that have been discovered but not patched
  - Before disclosure: black hat people/organizations
  - after disclosure: when patch development is taking time
  - Vulnerabilities with patches, but patches not applied
- Statistical modeling may be needed for assessing probability of breaches