2019

APIC Applied Learning Conference

APIC EDUCATION

Emerging Technologies

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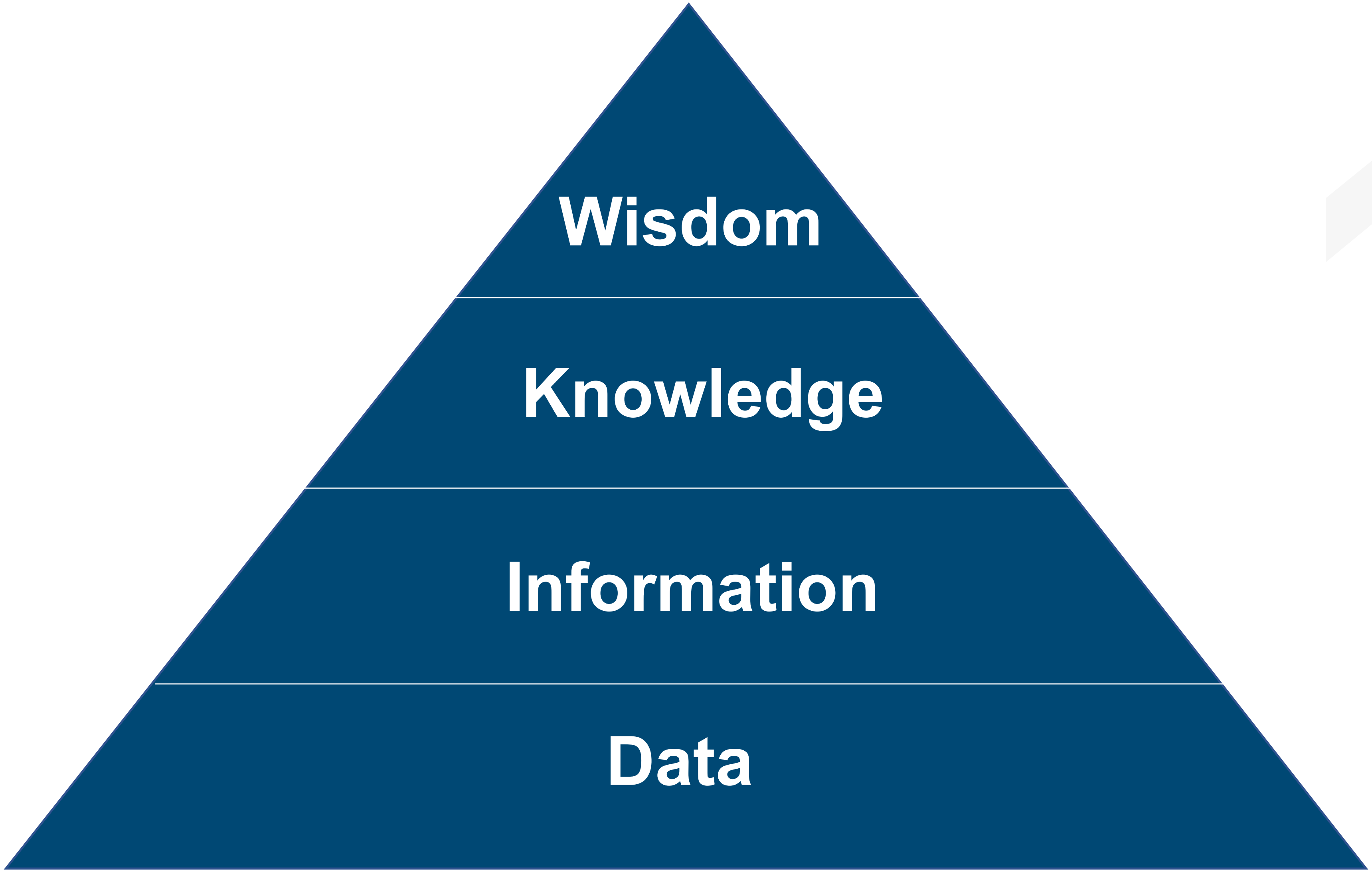
APIC Association for Professionals in Infection Control and Epidemiology

Disclosures

- Faculty: Tim Weimken
- Relationships with commercial interests:
    - Consultant: Medline Industries, Avadim Health

We are only talking about one thing today.

Why data?



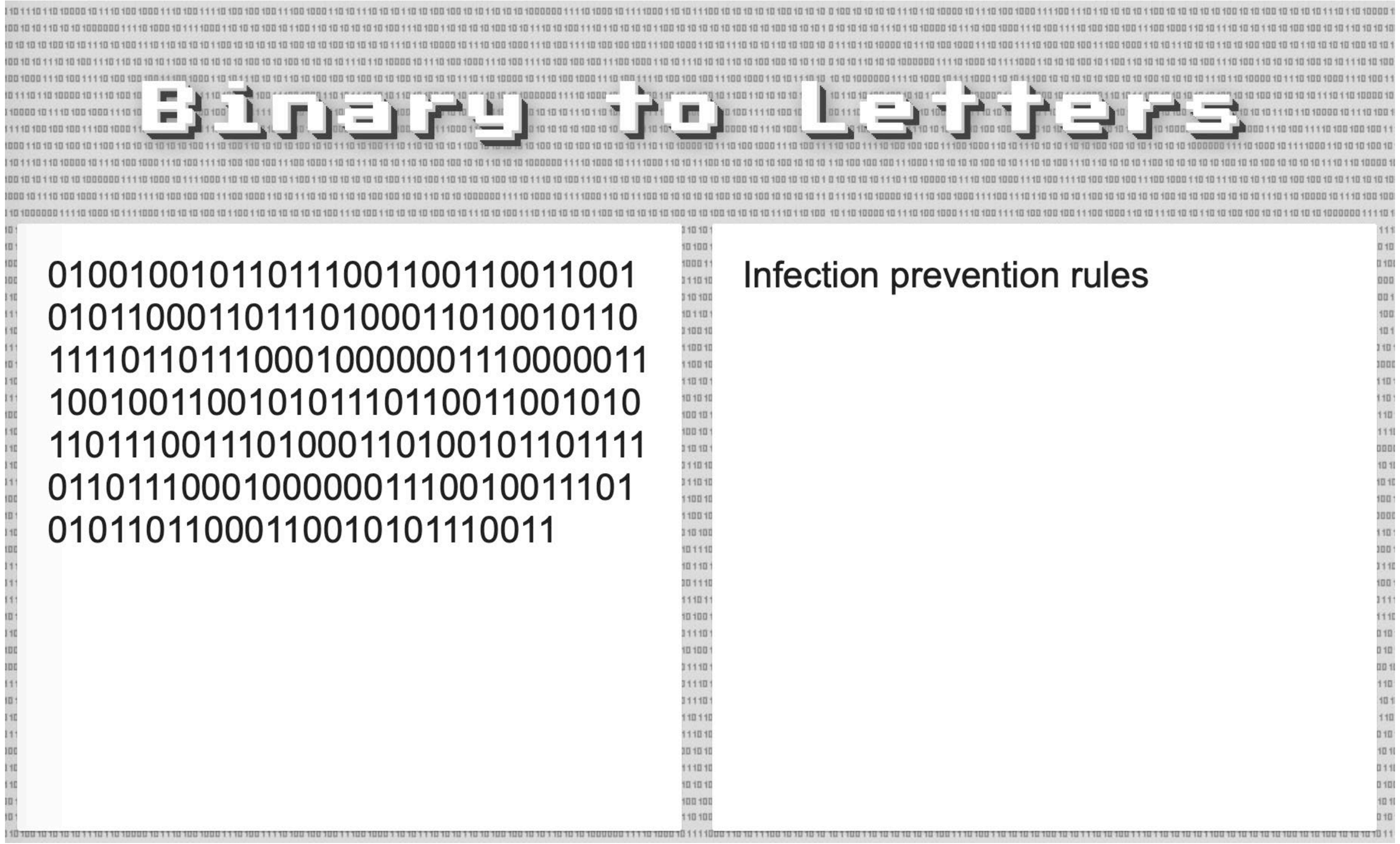
Data

Data are useless values.

0100100101101110011001100110010101100011011101000110100101101111011011100010000000111000001110
0100110010101110110011001010110111001110100011010010110111101101110001000000011100100111010101
1011000110010101110011

Information

Information is translated data into something understandable



Knowledge

<u>Knowledge</u> is relevant, objective information gained through experience and study

Impact of infection prevention and control

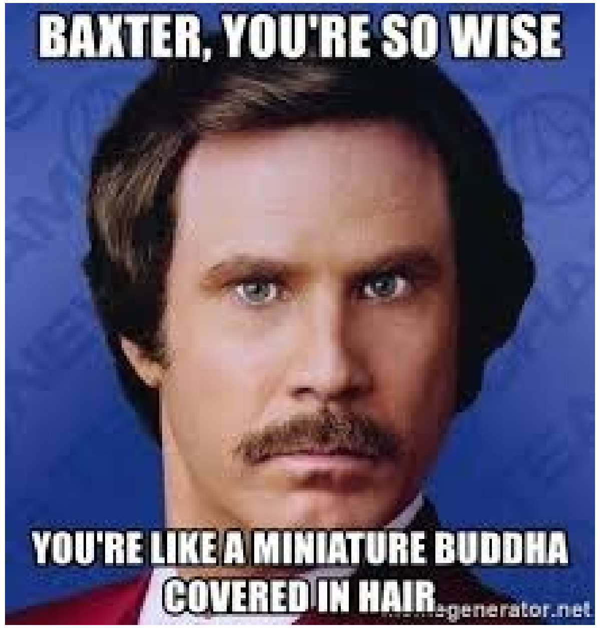
30%

Effective infection prevention and control reduces health care-associated infections by at least 30%.

https://www.who.int/infection-prevention/en/

Wisdom

Wisdom is our ability to take knowledge and translate it to diverse areas – also our ability to judge which knowledge is applicable or correct.



Goals

"Translating data to wisdom for the elimination of healthcare-associated infection"

™ 2019, Tim Wiemken

Where is this going, Tim?

We have data. Lots of it.

Where is this going, Tim?

We have data. Lots of it.

~ 1 billion in/outpatient interactions in the USA each year.

Where is this going, Tim?

We have data. Lots of it.

~ 1 billion in/outpatient interactions in the USA each year.

The population of the USA is ~ 330 million

China and India: 1.4 Billion people each.

Where is this going, Tim?

This means maybe ~10 billion in/outpatient interactions in those areas

Where is this going, Tim?

There is a big difference between a million and a billion. Now think 10 times that.

Unit	Million	Billion
Dollars	Buys a nice house	Buys a 100-story skyscraper
People	Population of San Jose, CA	Population of Western Hemisphere
Feet	Distance from NYC to Boston	Distance from NYC to the Moon
Seconds	About 12 days	About 32 years

Just call me big data

Traditional analytics (statistics) cannot handle these ‘big data’.

But generally, more data = better predictions

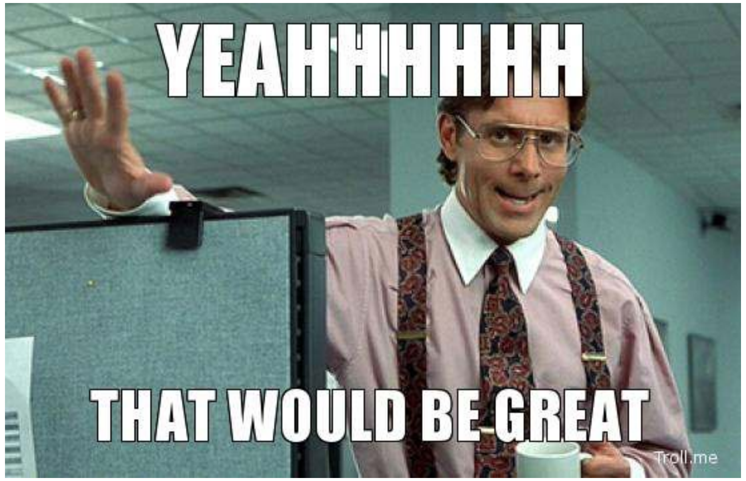
Machine Learning to the Rescue

Machine learning is a set of analytical tools and algorithms that allow for predictive modeling.

Machine learning is a way to achieve "artificial intelligence".

Big Data in Infection Prevention

Wouldn't it be great to have an automated prediction of healthcare-associated infections instead of spending all day (or week) going through the NHSN definitions?



Why not? Even rudimentary approaches are pretty good

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Research article | OPEN Open Peer Review | Published: 13 March 2019

Predicting hospital-acquired pneumonia among schizophrenic patients: a machine learning approach

Kuang Ming Kuo, Paul C. Talley, Chi Hsien Huang & Liang Chih Cheng

BMC Medical Informatics and Decision Making **19**, Article number: 42 (2019) | Download Citation

Sample	Method	Accuracy(SD)	AUC(SD)	Sensitivity(SD)	Specificity(SD)	Kappa(SD)
Train	CART	0.804(0.089)	0.851(0.074)	0.739(0.094)	0.851(0.106)	0.597(0.180)
	C5.0	0.912(0.033)	0.971(0.018)	0.868(0.047)	0.942(0.030)	0.819(0.068)
	KNN	0.645(0.083)	0.696(0.066)	0.628(0.127)	0.657(0.130)	0.282(0.162)
	NB	0.675(0.095)	0.798(0.094)	0.868(0.096)	0.544(0.098)	0.376(0.178)
	RF	0.917(0.017)	0.971(0.016)	0.891(0.048)	0.937(0.032)	0.831(0.035)
	SVM	0.871(0.030)	0.936(0.030)	0.832(0.077)	0.923(0.043)	0.733(0.062)
	LGR	0.670(0.084)	0.762(0.083)	0.621(0.076)	0.706(0.139)	0.330(0.160)
Test	CART	0.830	0.880	0.904	0.732	0.648
	C5.0	0.945	0.993	0.989	0.887	0.887
	KNN	0.667	0.701	0.745	0.563	0.312
	NB	0.733	0.831	0.628	0.873	0.479
	RF	0.927	0.994	1.000	0.831	0.849
	SVM	0.897	0.953	0.968	0.803	0.786
	LGR	0.739	0.823	0.798	0.662	0.464

Why not? Even rudimentary approaches are pretty good

Applying deep learning on electronic health records in Swedish to predict healthcare-associated infections

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Proceedings of the 15th Workshop on Biomedical Natural Language Processing, pages 191–195,
Berlin, Germany, August 12, 2016. ©2016 Association for Computational Linguistics

Abstract

Detecting healthcare-associated infections pose a major challenge in healthcare. Using natural language processing and machine learning applied on electronic patient records is one approach that has been shown to work. However the results indicate that there was room for improvement and therefore we have applied deep learning methods. Specifically we implemented a network of stacked sparse auto encoders and a network of stacked restricted Boltzmann machines. Our best results were obtained using the stacked restricted Boltzmann machines with a precision of 0.79 and a recall of 0.88.

Why not? Nothing agrees with clinical definitions

Major article

Surveillance versus clinical adjudication: Differences persist with new ventilator-associated event definition

Kathleen M. McMullen MPH, CIC [a,*], Anthony F. Boyer MD [b], Noah Schoenberg MD [b], Hilary M. Babcock MD, MPH [c], Scott T. Micek PharmD [d], Marin H. Kollef MD [b]

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Key Words:
Pneumonia
Ventilator-associated
Surveillance
Infections
Nosocomial

Background: The National Healthcare Safety Network (NHSN) has recently supported efforts to shift surveillance away from ventilator-associated pneumonia to ventilator-associated events (VAEs) to decrease subjectivity in surveillance and minimize concerns over clinical correlation. The goals of this study were to compare the results of an automated surveillance strategy using the new VAE definition with a prospectively performed clinical application of the definition.

Methods: All patients ventilated for ≥2 days in a medical and surgical intensive care unit were evaluated by 2 methods: retrospective surveillance using an automated algorithm combined with manual chart review after the NHSN's VAE methodology and prospective surveillance by pulmonary physicians in collaboration with the clinical team administering care to the patient at the bedside.

Results: Overall, a similar number of events were called by each method (69 vs 67). Of the 1,209 patients, 56 were determined to have VAEs by both methods ($\kappa = .81$, $P = .04$). There were 24 patients considered to be a VAE by only 1 of the methods. Most discrepancies were the result of clinical disagreement with the NHSN's VAE methodology.

Conclusions: There was good agreement between the study teams. Awareness of the limitations of the surveillance definition for VAE can help infection prevention personnel in discussions with critical care partners about optimal use of these data.

Why not? We only kind of agree with other countries

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Antimicrobial Resistance & Infection Control

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Research | OPEN | Published: 02 August 2012

Concordance between European and US case definitions of healthcare-associated infections

Sonja Hansen, Dorit Sohr, Christine Geffers, Pascal Astagneau, Alexander Blacky, Walter Koller, Ingrid Morales, Maria Luisa Moro, Mercedes Palomar, Emese Szilagyi, Carl Suetens & Petra Gastmeier

Antimicrobial Resistance and Infection Control 1, Article number: 28 (2012) | Download Citation

Results

Differences in HAI definitions were found for bloodstream infection (BSI), pneumonia (PN), urinary tract infection (UTI) and the two key terms "intensive care unit (ICU)-acquired infection" and "mechanical ventilation". Concordance was analyzed for these definitions and key terms with the exception of UTI. Surveillance was performed in 47 ICUs and 6,506 patients were assessed. One hundred and eighty PN and 123 BSI cases were identified. When all PN cases were considered, concordance for PN was $\kappa = 0.99$ [CI 95%: 0.98-1.00]. When PN cases were divided into subgroups, concordance was $\kappa = 0.90$ (CI 95%: 0.86-0.94) for clinically defined PN and $\kappa = 0.72$ (CI 95%: 0.63-0.82) for microbiologically defined PN. Concordance for BSI was $\kappa = 0.73$ [CI 95%: 0.66-0.80]. However, BSI cases secondary to another infection site (42% of all BSI cases) are excluded when using US definitions and concordance for BSI was $\kappa = 1.00$ when only primary BSI cases, i.e. Europe-defined BSI with "catheter" or "unknown" origin and US-defined laboratory-confirmed BSI (LCBI), were considered.

Why not? We can’t even agree with ourselves

Agreement in Classifying Bloodstream Infections Among Multiple Reviewers Conducting Surveillance

Jeanmarie Mayer,[1] Tom Greene,[1] Janelle Howell,[2] Jian Ying,[1] Michael A. Rubin,[1,2] William E. Trick,[3] and Matthew H. Samore,[1,2] for the CDC Prevention Epicenters Program[4]

[1]University of Utah School of Medicine, and [2]Salt Lake City Veterans Affairs Medical Center IDEAS Center, Salt Lake City, Utah; [3]Stroger Hospital of Cook County, Chicago, Illinois; and [4]Centers for Disease Control and Prevention, Atlanta, Georgia

Clinical Infectious Diseases 2012;55(3):364–70

Results. Overall, 114 patient records were reviewed by 18 IPs, the majority of whom specified they followed National Healthcare Safety Network criteria. The overall agreement among IPs by κ statistic was 0.42 (standard error [SE], 0.06). IPs had better agreement with a simple laboratory-based definition with an average κ of 0.55 (SE, 0.05). The proportion of patient records that 18 IPs reported with CLABSI ranged from 14% to 39% (overall mean, 28% with a coefficient of variation of 25%). When simple laboratory-based methods were applied to different sets of patient records, classification was more consistent with CLABSI assigned in a proportion ranging from 36% to 42% (overall mean, 39%).

Conclusions. Reliability of IP-conducted surveillance to identify HAI may not be ideal for public reporting goals of interhospital comparisons.

Machine learning in action

- Predicting ‘no shows’ in a clinic visit.
- Data from our local EPIC instance
- Lots of tinkering with variables, imputing missing values, adding in external data by linking geospatially.
- Sound fancy? Its not really that fancy.

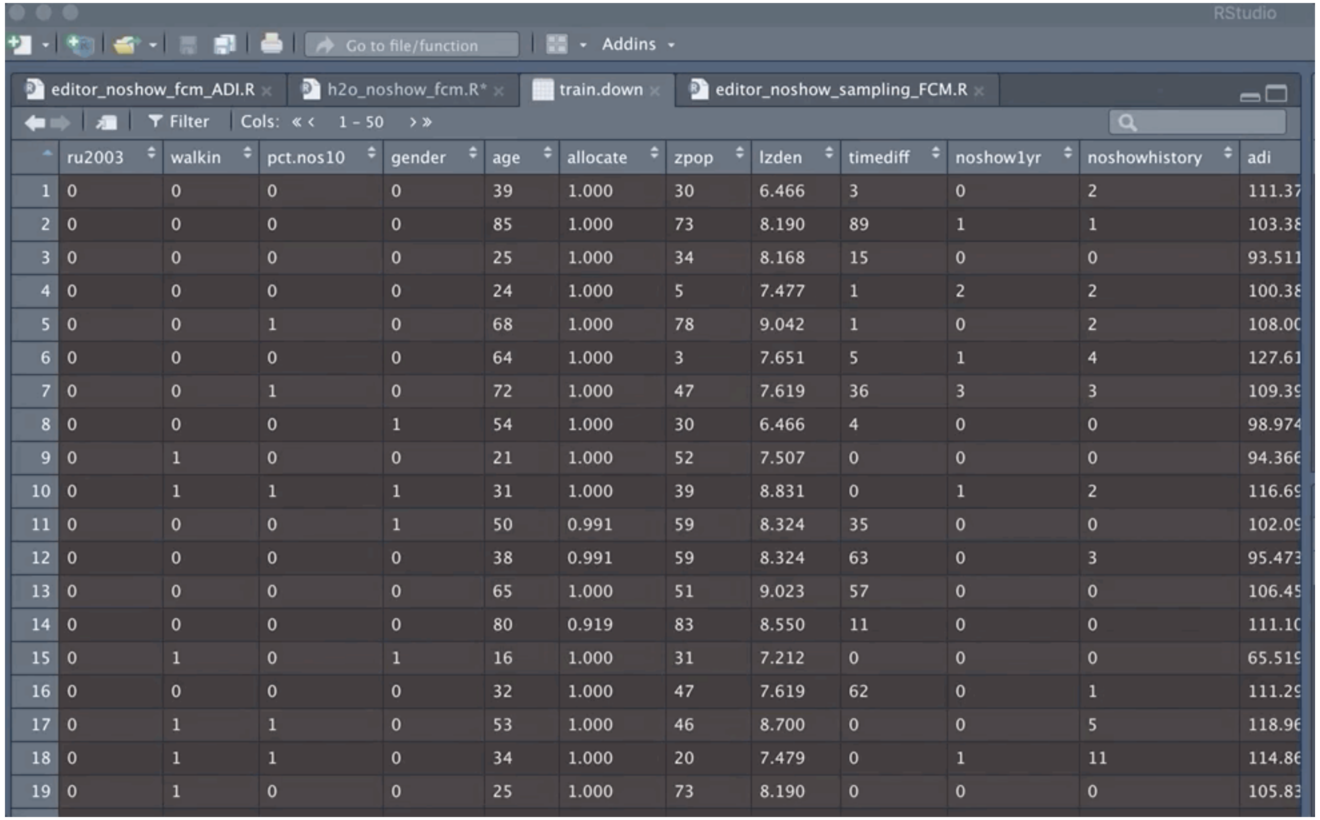
Why not? If you know what you are doing, its not that hard.

Data from the EHR

Variables modified and created…

No show history, population of zip code, age, sex…

102 variables in total


RStudio
Go to file/function
Addins
editor_noshow_fcm_ADI.R
h2o_noshow_fcm.R*
train.down
editor_noshow_sampling_FCM.R
Filter
Cols: « ‹ 1 - 50 › »

	ru2003	walkin	pct.nos10	gender	age	allocate	zpop	lzden	timediff	noshow1yr	noshowhistory	adi
1	0	0	0	0	39	1.000	30	6.466	3	0	2	111.37
2	0	0	0	0	85	1.000	73	8.190	89	1	1	103.38
3	0	0	0	0	25	1.000	34	8.168	15	0	0	93.511
4	0	0	0	0	24	1.000	5	7.477	1	2	2	100.38
5	0	0	1	0	68	1.000	78	9.042	1	0	2	108.00
6	0	0	0	0	64	1.000	3	7.651	5	1	4	127.61
7	0	0	1	0	72	1.000	47	7.619	36	3	3	109.39
8	0	0	0	1	54	1.000	30	6.466	4	0	0	98.974
9	0	1	0	0	21	1.000	52	7.507	0	0	0	94.366
10	0	1	1	1	31	1.000	39	8.831	0	1	2	116.69
11	0	0	0	1	50	0.991	59	8.324	35	0	0	102.09
12	0	0	0	0	38	0.991	59	8.324	63	0	3	95.473
13	0	0	0	0	65	1.000	51	9.023	57	0	0	106.45
14	0	0	0	0	80	0.919	83	8.550	11	0	0	111.10
15	0	1	0	1	16	1.000	31	7.212	0	0	0	65.519
16	0	0	0	0	32	1.000	47	7.619	62	0	1	111.29
17	0	1	1	0	53	1.000	46	8.700	0	0	5	118.96
18	0	1	1	0	34	1.000	20	7.479	0	1	11	114.86
19	0	1	0	0	25	1.000	73	8.190	0	0	0	105.83

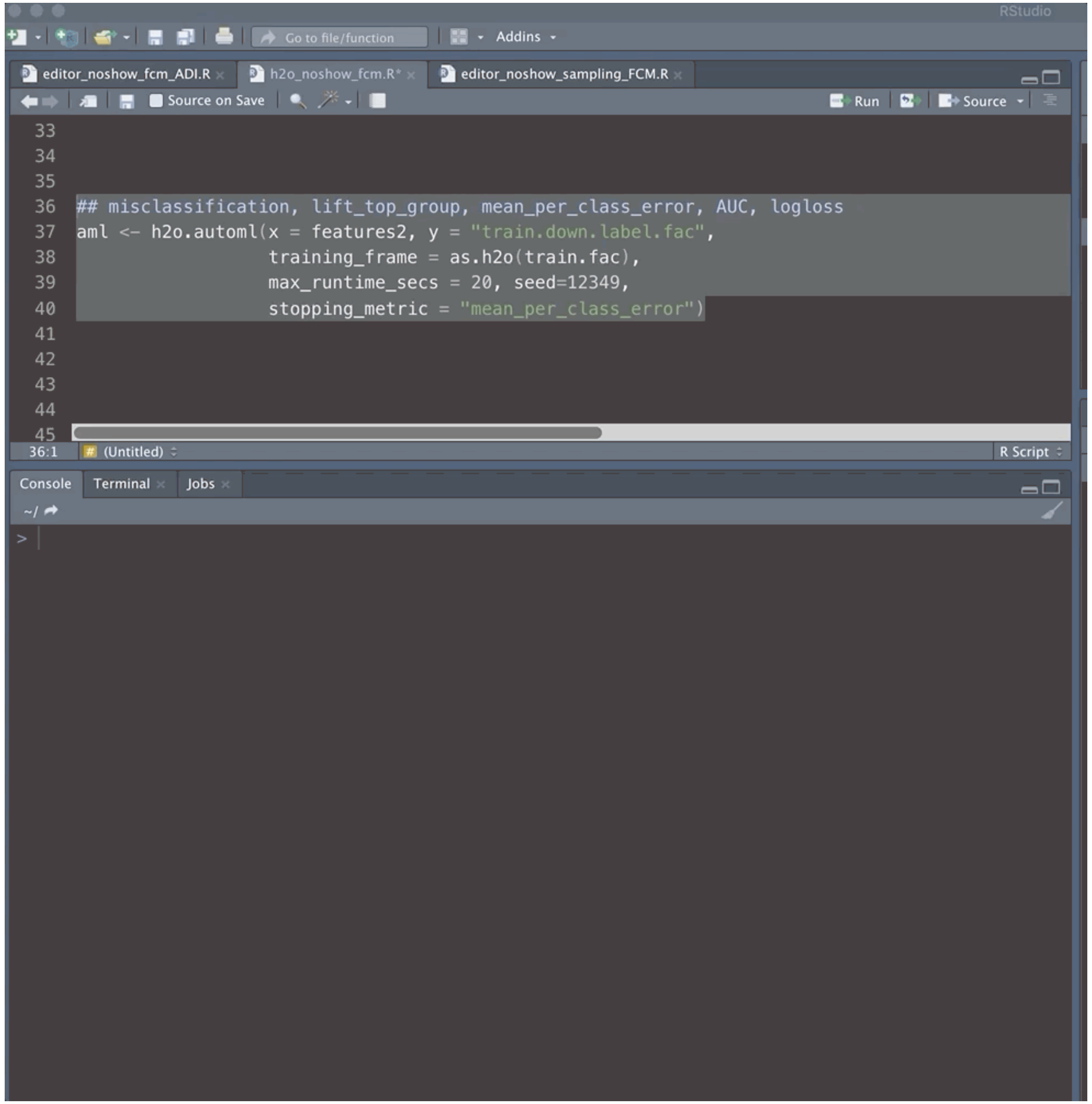
One at the end “class” is 0 for show, and 1 for no show

"Training" a machine to learn

Using a FREE program
to automate this model, H2O

Takes out most of the legwork.

The model learns the patterns
associated with showing or not



Testing the performance

- Throw similar data at the model and see how well the prediction matches with the actual show/no show status

```
#### extract best model
championModel = aml@leader
#### get accuracy in test set
preds<-predict(championModel, as.h2o(test.features.fac))
#### extract actual predictions
out<-as.vector(preds$predict$predict)
#### create confusion matrix
cm<-confusionMatrix(factor(out), test.label.fac, positive="noshow")

#### get row percentages for predictions vs actual in test set
round(prop.table(cm$table,1)*100,1)
round(prop.table(cm$table,2)*100,1)

#### view full confusion matrix
cm
h2o.saveModel(championModel, "/Users/timothywiemken/Library/Mobile Documents/com~apple~CloudD



##### END
```

65:1 (Untitled) R Script

Console Terminal Jobs

~/

>

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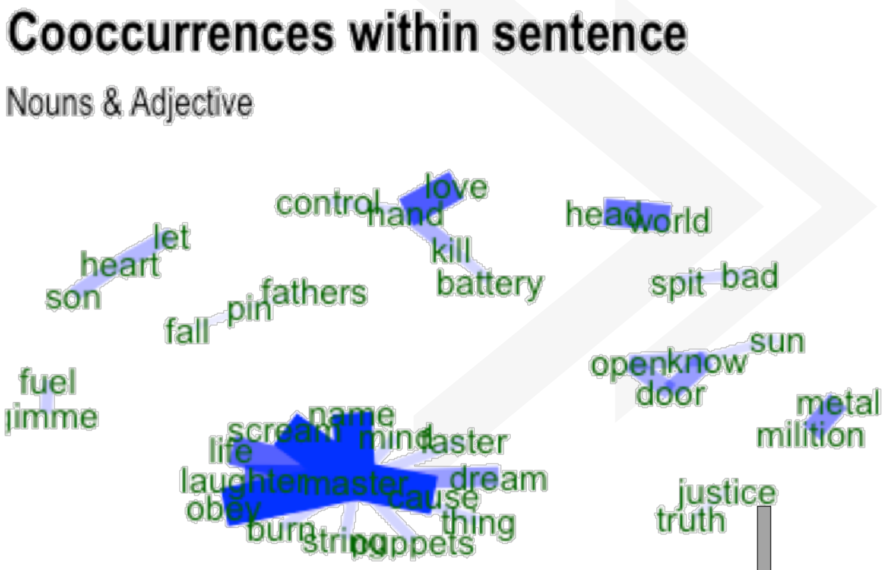
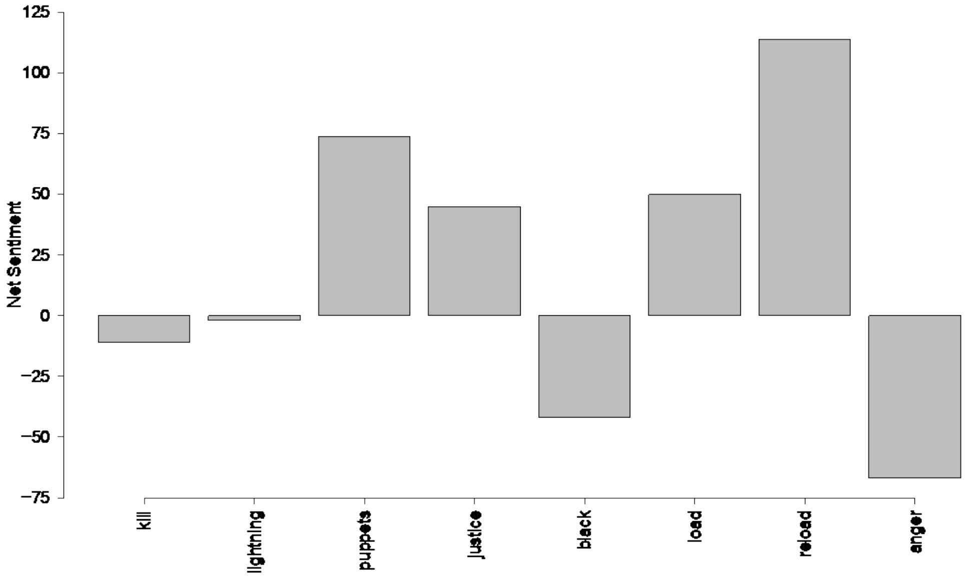
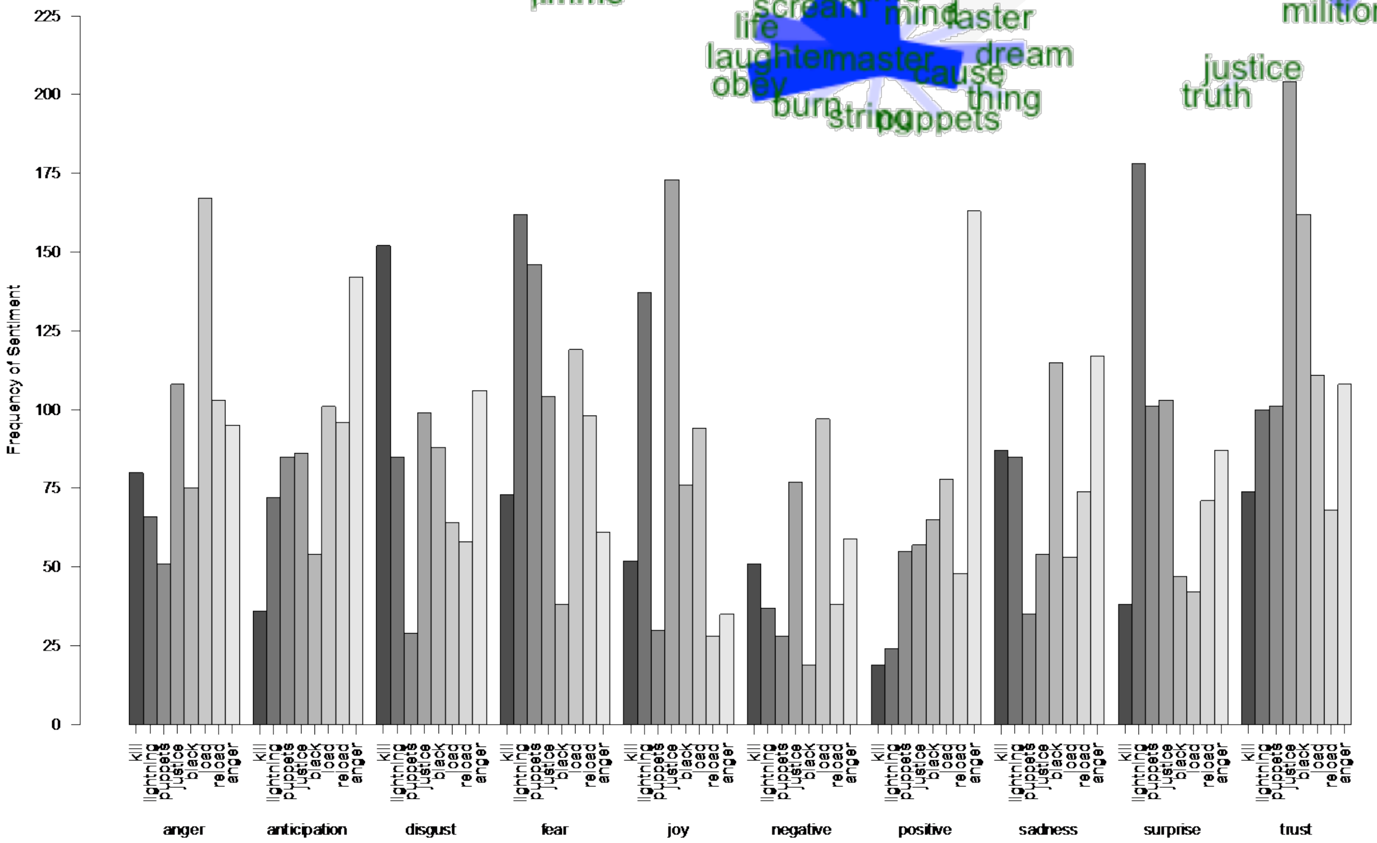
Natural Language Processing

- NLP is a set of methods to evaluate and utilize qualitative data (text)







Natural Language Processing and Qualitative Data

Methods Inf Med. 2019 Jun;58(1):31-41. doi: 10.1055/s-0039-1677692. Epub 2019 Mar 15.

Deep Learning versus Conventional Machine Learning for Detection of Healthcare-Associated Infections in French Clinical Narratives.

Rabhi S[1], Jakubowicz J[1], Metzger MH[2,3,4].

Author information

Abstract

OBJECTIVE: The objective of this article was to compare the performances of health care-associated infection (HAI) detection between deep learning and conventional machine learning (ML) methods in French medical reports.

METHODS: The corpus consisted in different types of medical reports (discharge summaries, surgery reports, consultation reports, etc.). A total of 1,531 medical text documents were extracted and deidentified in three French university hospitals. Each of them was labeled as presence (1) or absence (0) of HAI. We started by normalizing the records using a list of preprocessing techniques. We calculated an overall performance metric, the F1 Score, to compare a deep learning method (convolutional neural network [CNN]) with the most popular conventional ML models (Bernoulli and multi-naïve Bayes, k-nearest neighbors, logistic regression, random forests, extra-trees, gradient boosting, support vector machines). We applied the hyperparameter Bayesian optimization for each model based on its HAI identification performances. We included the set of text representation as an additional hyperparameter for each model, using four different text representations (bag of words, term frequency-inverse document frequency, word2vec, and Glove).

RESULTS: CNN outperforms all other conventional ML algorithms for HAI classification. The best F1 Score of 97.7% ± 3.6% and best area under the curve score of 99.8% ± 0.41% were achieved when CNN was directly applied to the processed clinical notes without a pretrained word2vec embedding. Through receiver operating characteristic curve analysis, we could achieve a good balance between false notifications (with a specificity equal to 0.937) and system detection capability (with a sensitivity equal to 0.962) using the Youden's index reference.

CONCLUSIONS: The main drawback of CNNs is their opacity. To address this issue, we investigated CNN inner layers' activation values to visualize the most meaningful phrases in a document. This method could be used to build a phrase-based medical assistant algorithm to help the infection control practitioner to select relevant medical records. Our study demonstrated that deep learning approach outperforms other classification learning algorithms for automatically identifying HAIs in medical reports.

Natural Language Processing

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

Accuracy of using natural language processing methods for identifying healthcare-associated infections

Nastassia Tvardik[a], Ivan Kergourlay[b], André Bittar[c], Frédérique Segond[d,e], Stefan Darmoni[b,f,g], Marie-Hélène Metzger[a,h,*]

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[b] University Hospital of Rouen, Department of Biomedical Informatics, CISMeF, Rouen, France
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ARTICLE INFO

Keywords:
Epidemiology
Healthcare-associated infections
Decision support systems, Clinical
Medical records systems, computerized
Natural language processing

ABSTRACT

Objective: There is a growing interest in using natural language processing (NLP) for healthcare-associated infections (HAIs) monitoring. A French project consortium, SYNODOS, developed a NLP solution for detecting medical events in electronic medical records for epidemiological purposes. The objective of this study was to evaluate the performance of the SYNODOS data processing chain for detecting HAIs in clinical documents.

Materials and methods: The collection of textual records in these hospitals was carried out between October 2009 and December 2010 in three French University hospitals (Lyon, Rouen and Nice). The following medical specialties were included in the study: digestive surgery, neurosurgery, orthopedic surgery, adult intensive-care units. Reference Standard surveillance was compared with the results of automatic detection using NLP. Sensitivity on 56 HAI cases and specificity on 57 non-HAI cases were calculated.

Results: The accuracy rate was 84% (n = 95/113). The overall sensitivity of automatic detection of HAIs was 83.9% (CI 95%: 71.7–92.4) and the specificity was 84.2% (CI 95%: 72.1–92.5). The sensitivity varies from one specialty to the other, from 69.2% (CI 95%: 38.6–90.9) for intensive care to 93.3% (CI 95%: 68.1–99.8) for orthopedic surgery. The manual review of classification errors showed that the most frequent cause was an inaccurate temporal labeling of medical events, which is an important factor for HAI detection.

Conclusion: This study confirmed the feasibility of using NLP for the HAI detection in hospital facilities. Automatic HAI detection algorithms could offer better surveillance standardization for hospital comparisons.

Natural Language Processing

INFECTION CONTROL & HOSPITAL EPIDEMIOLOGY SEPTEMBER 2015, VOL. 36, NO. 9

ORIGINAL ARTICLE

Natural Language Processing for Real-Time Catheter-Associated Urinary Tract Infection Surveillance: Results of a Pilot Implementation Trial

Westyn Branch-Elliman, MD, MMSc;[1,2] Judith Strymish, MD;[3,4] Valmeek Kudesia, MD;[3,5] Amy K. Rosen, PhD;[6,7,8] Kalpana Gupta, MD, MPH[3,6,7]

BACKGROUND. Incidence of catheter-associated urinary tract infection (CAUTI) is a quality benchmark. To streamline conventional detection methods, an electronic surveillance system augmented with natural language processing (NLP), which gathers data recorded in clinical notes without manual review, was implemented for real-time surveillance.

OBJECTIVE. To assess the utility of this algorithm for identifying indwelling urinary catheter days and CAUTI.

SETTING. Large, urban tertiary care Veterans Affairs hospital.

METHODS. All patients admitted to the acute care units and the intensive care unit from March 1, 2013, through November 30, 2013, were included. Standard surveillance, which includes electronic and manual data extraction, was compared with the NLP-augmented algorithm.

RESULTS. The NLP-augmented algorithm identified 27% more indwelling urinary catheter days in the acute care units and 28% fewer indwelling urinary catheter days in the intensive care unit. The algorithm flagged 24 CAUTI versus 20 CAUTI by standard surveillance methods; the CAUTI identified were overlapping but not the same. The overall positive predictive value was 54.2%, and overall sensitivity was 65% (90.9% in the acute care units but 33% in the intensive care unit). Dissimilarities in the operating characteristics of the algorithm between types of unit were due to differences in documentation practice. Development and implementation of the algorithm required substantial upfront effort of clinicians and programmers to determine current language patterns.

CONCLUSIONS. The NLP algorithm was most useful for identifying simple clinical variables. Algorithm operating characteristics were specific to local documentation practices. The algorithm did not perform as well as standard surveillance methods.

Infect. Control Hosp. Epidemiol. 2015;36(9):1004–1010

Anomalies, anomalies, anomalies

- Analysis of time series data in infection control is troublesome
- Use of Statistical Process Control limits true detection of what is going on
- Anomaly detection algorithms can help fix this.

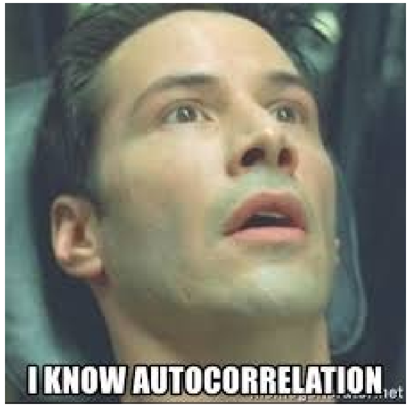
- Main issues:
    1. Autocorrelation
    2. Seasonality

Autocorrelation

- When something now is correlated with other things recently, but not so much a while ago

Example: Your MRSA rate this month is at least in part due to what it was last month (due to: patient carry over, organism longevity in the environment, staff processes, disinfectant use, etc.)

That same rate isn't as correlated with the MRSA rate 4 months ago (temporal autocorrelation).



The two seasons of St. Louis

- There are a lot of seasonal factors that are linked to infection
  - The July Effect (yikes)
  - Humidity (*Acinetobacter*)
  - Air conditioning (*Legionella*)
  - Dirty wounds (MVA)

A July Spike in Fatal Medication Errors: A Possible Effect of New Medical Residents

David P. Phillips, PhD[1] and Gwendolyn E. C. Barker, BA[2]

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J Gen Intern Med 25(8):774–9
DOI: 10.1007/s11606-010-1356-3

Influence of Relative Humidity and Suspending Menstrua on Survival of *Acinetobacter* spp. on Dry Surfaces

A. JAWAD,* J. HERITAGE, A. M. SNELLING, D. M. GASCOYNE-BINZI, AND P. M. HAWKEY
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JOURNAL OF CLINICAL MICROBIOLOGY, Dec. 1996, p. 2881–2887
0095-1137/96/$04.00+0

Automating the world (your world)

capo.ctrsu.org:3838/shiny/ipstat

American Journal of Infection Control 46 (2018) 124-32

Contents lists available at ScienceDirect

American Journal of Infection Control

journal homepage: www.ajicjournal.org

Major Article

Methods for computational disease surveillance in infection prevention and control: Statistical process control versus Twitter's anomaly and breakout detection algorithms

Timothy L. Wiemken PhD, MPH, FAPIC, CIC [a,*], Stephen P. Furmanek MPH, MS [b], William A. Mattingly PhD [b], Marc-Oliver Wright MT(ASCP), MS, CIC, FAPIC [c], Annuradha K. Persaud MPH [b], Brian E. Guinn PhD, MPH [b], Ruth M. Carrico PhD, RN, FNP-C, FSHEA, CIC [b], Forest W. Arnold DO, MSc [b], Julio A. Ramirez MD [b]

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American Journal of Infection Control 45 (2017) 216-21

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journal homepage: www.ajicjournal.org

Major Article

Process control charts in infection prevention: Make it simple to make it happen

Timothy L. Wiemken PhD, MPH, FAPIC, CIC [a,*], Stephen P. Furmanek MPH [a], Ruth M. Carrico PhD, RN, FNP-C, FSHEA, CIC [a], William A. Mattingly PhD [a], Annuradha K. Persaud MPH [a], Brian E. Guinn MPH [a], Robert R. Kelley PhD [b], Julio A. Ramirez MD [a]

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Major Article

Hand hygiene compliance surveillance with time series anomaly detection

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date	num	denom
1/1/09	2	456
2/1/09	3	452
3/1/09	8	345
4/1/09	9	345
5/1/09	6	234
6/1/09	7	345
7/1/09	8	352
8/1/09	5	245
9/1/09	10	345
10/1/09	5	234
11/1/09	7	234
12/1/09	2	234
1/1/10	4	234
2/1/10	7	234
3/1/10	5	234
4/1/10	3	342
5/1/10	6	243

QUESTIONS?

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