Statistics in Practice

Quantifying dependences in fingerprint evidence (and how you can get involved in the statistics community)

FOCUS Cluster Dinner Series

October 28, 2019

bit.ly/focus-oct2019

Maria Tackett
Duke University

A little about me...

🎓 B.S. in Mathematics

✗ Minor in Computer Science

✗ Minor in Economics

✗ Minor in German

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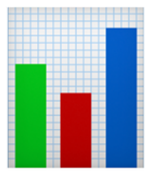

First statistics class junior year

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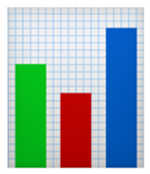


First statistics class junior year

M.S. in Statistics

Statistician @ Capital One

Design of Experiments

Regression Modeling

🎓 Ph.D. in Statistics

Assistant Professor of the Practice @ Duke UNIVERSITY

Research

Statistics Education

Statistics in Criminal Justice and Forensic Science

Teaching

Intro to Data Science

Regression Analysis

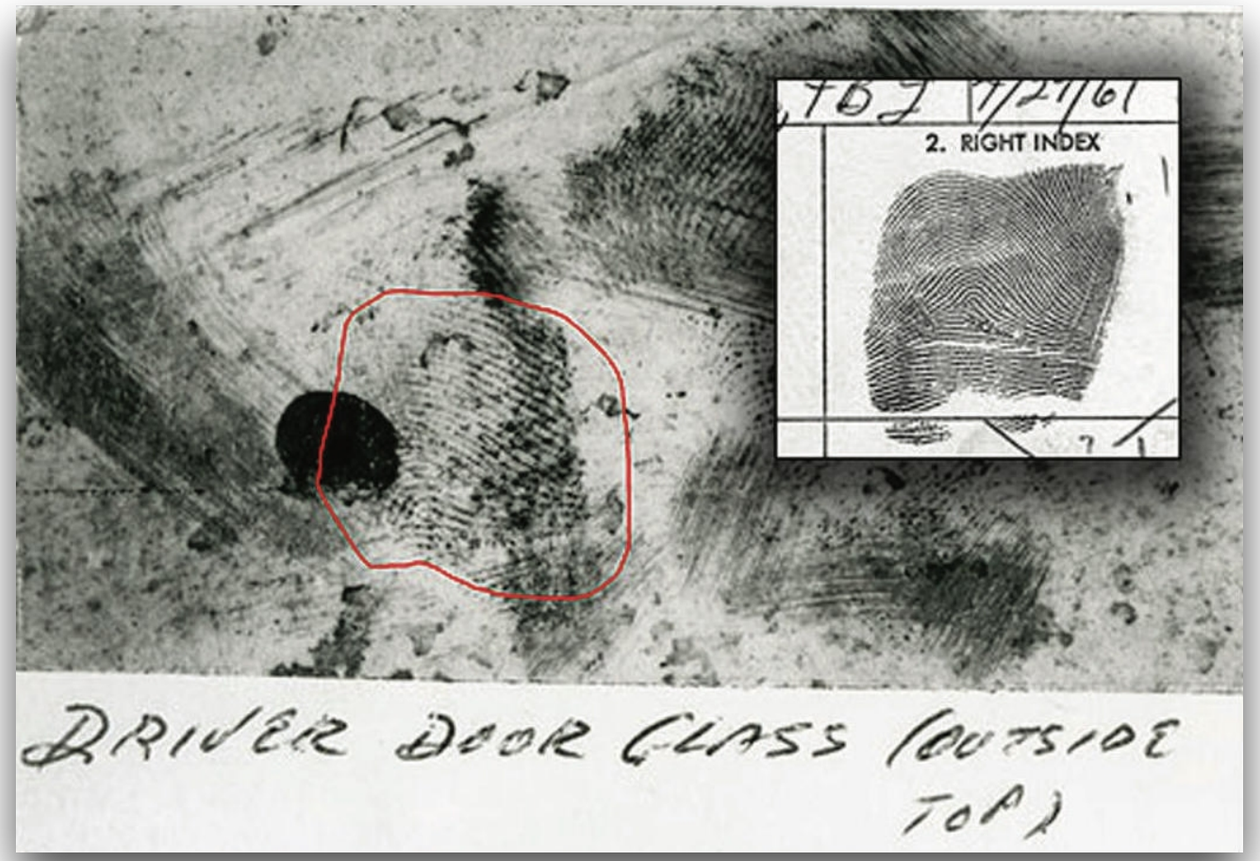
Quantifying dependences in fingerprint evidence

Dissertation Research

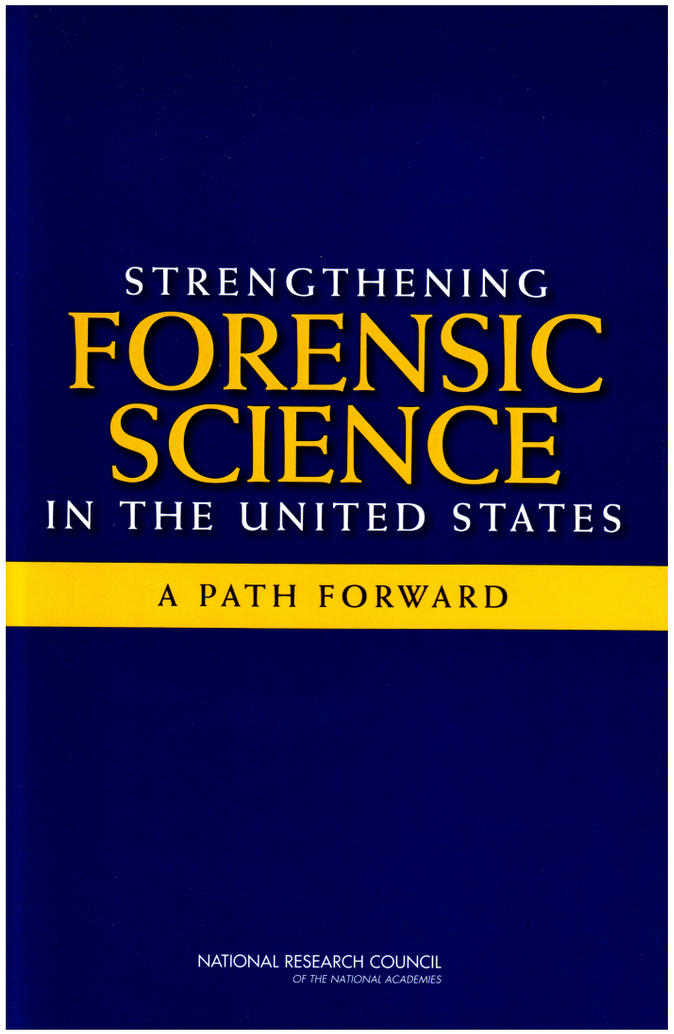
Used Bayesian methods to...

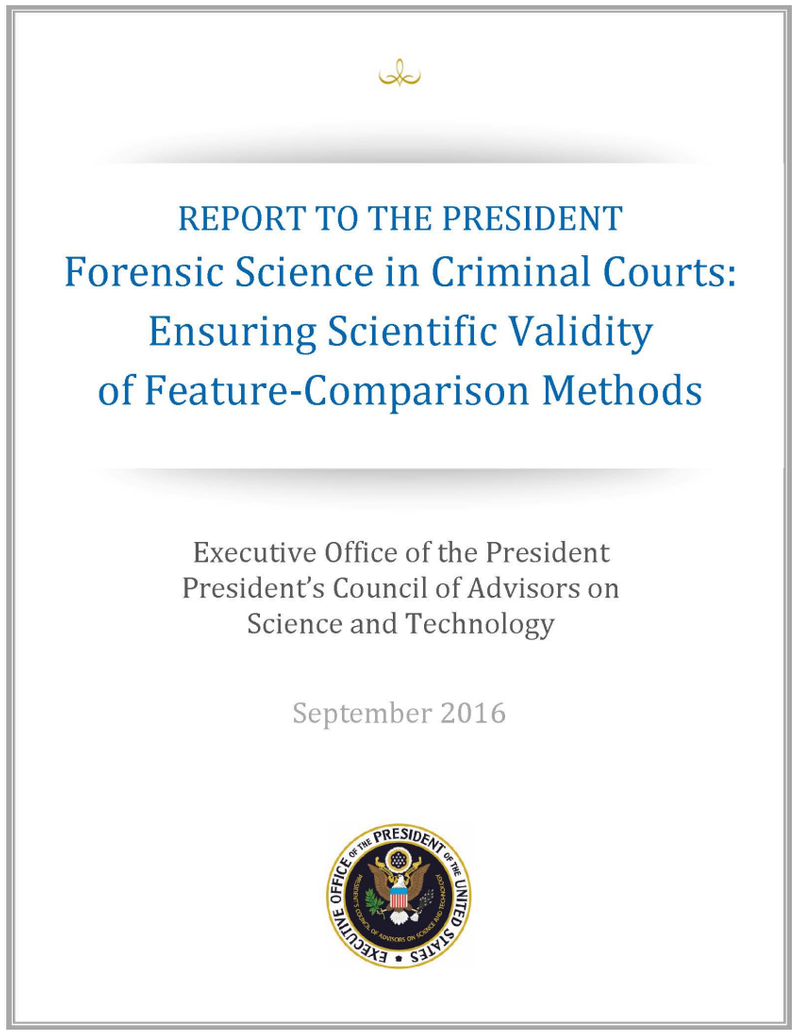
... decompose the sources of variability in two fingerprints

... develop a method to quantify certainty in fingerprint examiner's decision, adjusting for the number of fingerprints examined



Statistics in Forensic Science





csafe
Center for Statistics and
Applications in Forensic Evidence

General Framework: Lindley (1977)

Lindley (1977) introduced a Bayesian approach to interpreting forensic evidence. Suppose *Y* is a latent print recovered from a crime scene and *X* is a print from a person of interest. We want to test the hypotheses

H_0: *X* and *Y* were produced by the same source

H_1: *X* and *Y* were produced by different sources

$$\frac{P(H_0 \mid E)}{P(H_1 \mid E)} = \frac{P(H_0)}{P(H_1)} \times \frac{P(E \mid H_0)}{P(E \mid H_1)}$$

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Posterior odds of a match

$$\frac{\mathbf{P(H_0 \mid E)}}{\mathbf{P(H_1 \mid E)}} = \frac{P(H_0)}{P(H_1)} \times \frac{P(E \mid H_0)}{P(E \mid H_1)}$$

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Prior odds (non-fingerprint evidence)

$$\frac{P(H_0 \mid E)}{P(H_1 \mid E)} = \frac{\mathbf{P(H_0)}}{\mathbf{P(H_1)}} \times \frac{P(E \mid H_0)}{P(E \mid H_1)}$$

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Weight of fingerprint evidence

$$\frac{P(H_0 \mid E)}{P(H_1 \mid E)} = \frac{P(H_0)}{P(H_1)} \times \frac{\mathbf{P(E \mid H_0)}}{\mathbf{P(E \mid H_1)}}$$

Issue:

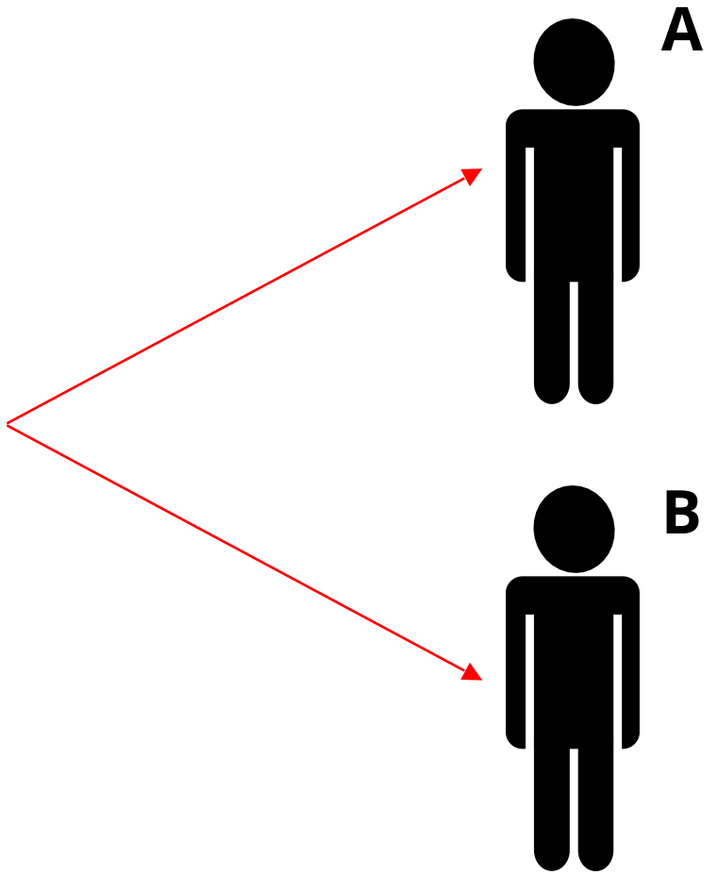
Examiners consider multiple candidates as a possible source of a latent fingerprint

Proposed Solution:

Quantify the weight of evidence in a way that accounts for the number of candidates examined

Scenario: Two primary suspects

Latent Print

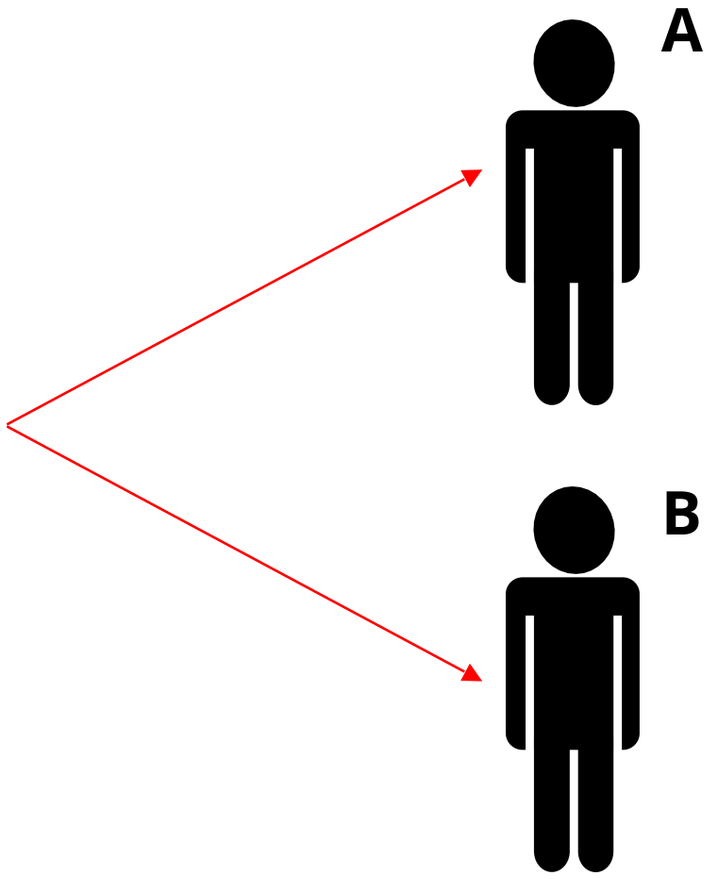


The latent print was created by

1. Candidate A
2. Candidate B
3. Neither candidate
4. Both candidates

Scenario: Two Primary Suspects

Latent Print



The latent print was created by

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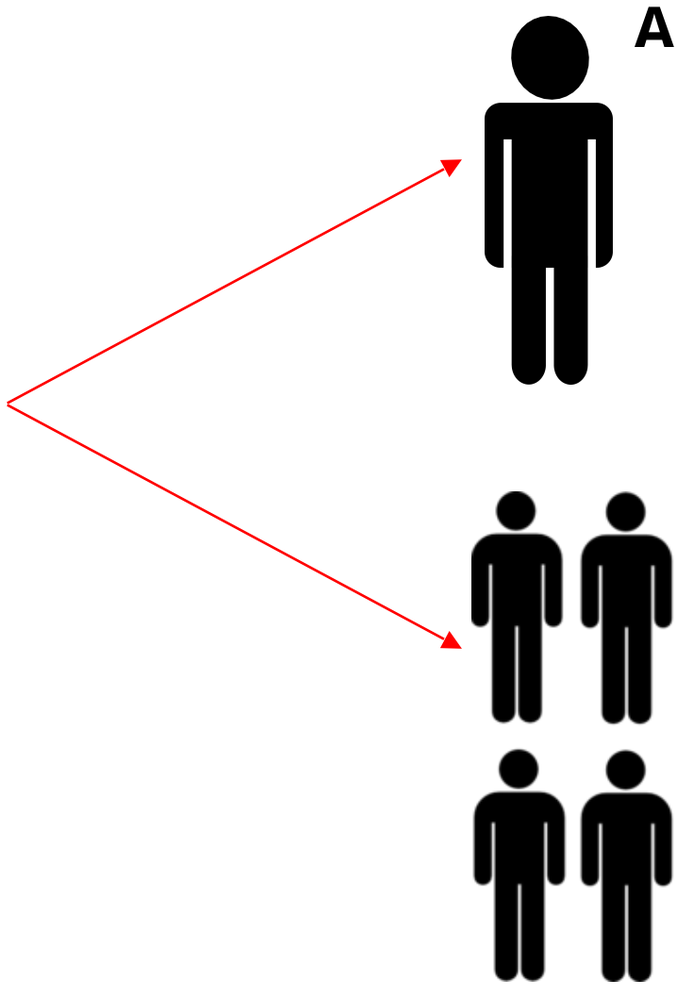
3. Neither candidate
4. ~~Both candidates~~

Scenario: Many suspects

Latent Print



The latent print was created by

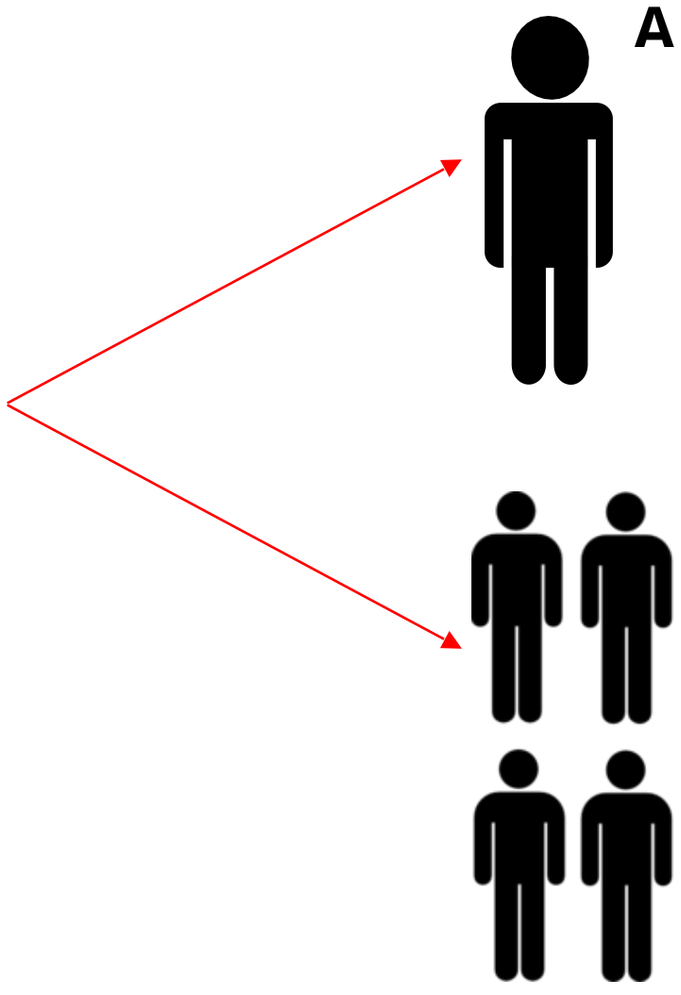
1. Candidate A
2. Candidate B
3. Candidate C

...

11. None of the candidates

Scenario: Many suspects

Latent Print



The latent print was created by

1. Candidate A
2. Candidate B
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...

11. None of the candidates

Constraint: At most one candidate could have created the latent print

Set of possible models

Constraint: At most one candidate could have created the latent print

For $i = 1, \ldots, K$,

$$M_i : \begin{cases} \theta_{X_i} = \theta_Y \\ \theta_{X_j} \neq \theta_Y \quad j = 1, \ldots, K \text{ such that } i \neq j \end{cases}$$

$$M_0 : \theta_{X_1} \neq \theta_Y \quad \theta_{X_2} \neq \theta_Y \quad \ldots \quad \theta_{X_K} \neq \theta_Y$$

θ_{X_i} : Measurements from candidate *i*

θ_Y : Measurements from the latent print

Weight of fingerprint evidence

By imposing this constraint on the model framework, we can measure the weight of evidence supporting the hypothesis that the latent print was created by Candidate *i* as

Weight of evidence that Candidate *i* created the latent print

=

How closely the print from Candidate *i* matches the latent print

X

Effect of evidence from other candidates

$$BF_i = BF_{i0} \times DF_i$$

Calculating $\mathbf{BF_i}$

Let $\mathbf{X} = X_1, \ldots, X_K$.

Suppose there are two models: $M_i : \theta_{X_i} = \theta_Y$ and $M_0 : \theta_{X_i} \neq \theta_Y$

Two Models: Weight of Evidence for M_i

$$BF_{i0} = \frac{P(M_i|\mathbf{X})/P(M_0|\mathbf{X})}{P(M_i)/P(M_0)}$$

If we extend this to $K + 1$ models, $M_0, \ldots, M_K$

$K + 1$ Models: Weight of Evidence for M_i

$$BF_i = \frac{P(M_i|\mathbf{X})/(1 - P(M_i|\mathbf{X}))}{P(M_i)/(1 - P(M_i))}$$

Calculating $\mathbf{BF_i}$

$$BF_i = \frac{P(M_i|\mathbf{X})/(1-P(M_i|\mathbf{X}))}{P(M_i)/(1-P(M_i))}$$

$$= \cdots$$

$$= BF_{i0}\left[1+\sum_{\substack{k=1\\k\neq i}}^{K}\frac{P(M_k)}{P(M_0)}\right]\Big/\left[1+\sum_{\substack{k=1\\k\neq i}}^{K}\frac{P(M_k)}{P(M_0)}BF_{k0}\right]$$

$$= BF_{i0} \times DF_i$$

$$= \text{ Bayes Factor } \times \text{ Dependency Factor}$$

Interpreting $\mathbf{BF_i}$

$$\mathbf{BF_i = BF_{i0} \times DF_i}$$

Bayes Factor, $\mathbf{BF_{i0}}$

- Indicates how closely the fingerprint from Candidate *i* matches the latent print
- Interpreted independent from the other candidates examined

Dependency Factor, $\mathbf{DF_i}$

- Indicates the effect of evidence from other candidates
- Interpretation:
    - $\mathbf{DF_i} > 1$: Additional candidates show weak evidence
    - $\mathbf{DF_i} < 1$: Additional candidates show strong evidence

Implications for fingerprint examiners

$$2\log(\mathbf{BF_i}) = 2\log(\mathbf{BF_{i0}}) + 2\log(\mathbf{DF_i})$$

✓ Provides a probative value to express level of uncertainty (Dror and Mnookin, 2010)

✓ Interpreted using a common scale for assessing the weight of evidence (Kass and Raftery, 1995)

✓ Eliminates the need for examiners to adjust their decision criteria based on the number of candidates examined

Example: Three Candidates Examined

Current Approach			Proposed Approach		
Candidate A	Candidate B	Candidate C	Candidate A	Candidate B	Candidate C
6.000	-5.889	-5.889	5.800	-5.889	-5.889
6.000	-2.197	-5.889	5.347	-2.197	-5.889
6.000	-2.197	-2.197	4.978	-2.197	-2.197
6.000	0.000	-5.889	4.562	0.000	-5.889
6.000	0.000	-2.197	4.305	0.000	-2.197
6.000	0.000	0.000	3.803	0.000	0.000
6.000	0.000	2.773	2.416	0.000	2.773
6.000	2.773	-5.889	2.760	2.773	-5.889
6.000	2.773	-2.197	2.652	2.773	-2.197
6.000	2.773	2.773	1.605	2.773	2.773
6.000	5.889	-5.889	0.003	5.889	-5.889
6.000	5.889	-2.197	-0.025	5.889	-2.197
6.000	5.889	0.000	-0.089	5.889	0.000
6.000	5.889	2.773	-0.356	5.889	2.773
6.000	5.889	5.889	-1.327	5.889	5.889

Evidence supporting Candidate *i* as source of latent print

- 6: Strong
- 2 to 6: Positive
- 0 to 2: Neutral

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How can you get involved?

Statistical Science

✓ STA 210: Regression Analysis

✓ STA 240L: Probability for Statistics

✓ STA 250: Statistics

✓ STA 360: Bayesian Inference and Modern Statistical Methods

✓ STA 440: Case Studies in the Practice of Statistics

\+ Electives!

On campus


DUKE
DATATHON
2019
DEADLINE
EXTENDED TO
MONDAY AT
11:59 P.M.!
Sign-up now at:
dukeml.org/register

On campus


Save the Date!
ASA
DATA
FEST
@ DUKE
April 3 - 5, 2020
PENN PAVILION
DUKE UNIVERSITY

On campus

Join us for the ...

Electronic Undergraduate Research Conference

Friday, November 1 Sociology Psychology 238

11:30 am - 12:20 pm	Virtual Video Presentation Session
12:20 pm - 12:30 pm	Opening Remarks
12:30 pm - 2:00 pm	Plenary Talks by USPROC Award Winners
2:00 pm - 3:00 pm	Keynote Address *Finding Your Balance: Foundations vs. Evolution in Data Science*
3:00 pm - 3:45 pm	Graduate School Information Session
3:45 pm - 4:30 pm	Panel Discussion About Careers in Industry and Government
4:30 pm - 4:40 pm	Closing Remarks

Snacks provided!

Join when you can!

More details available at
https://www.causeweb.org/usproc/eusrc/2019/program

Outside of Duke

Undergraduate Statistics Class Project Competition

December 20

https://www.causeweb.org/usproc/usclap

Undergraduate Statistics Research Project Competition

December 20

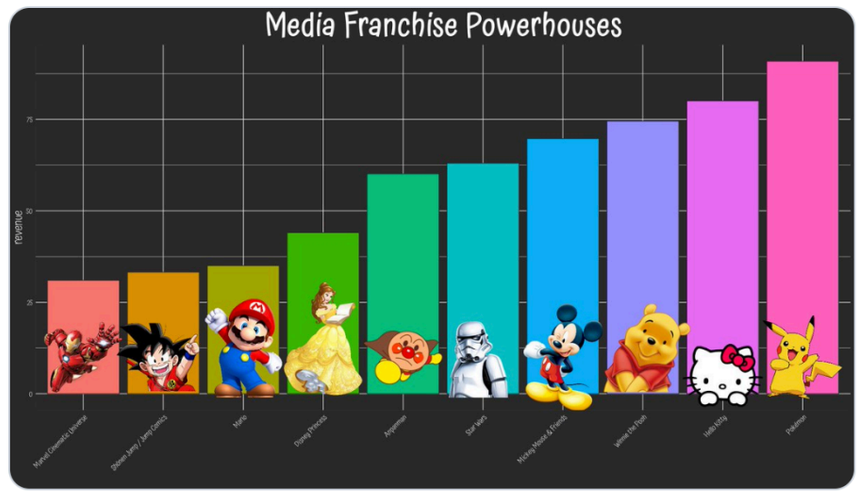
https://www.causeweb.org/usproc/usresp

Online

https://github.com/rfordatascience/tidytuesday

Romina Elena Mendez
@r0mymendez

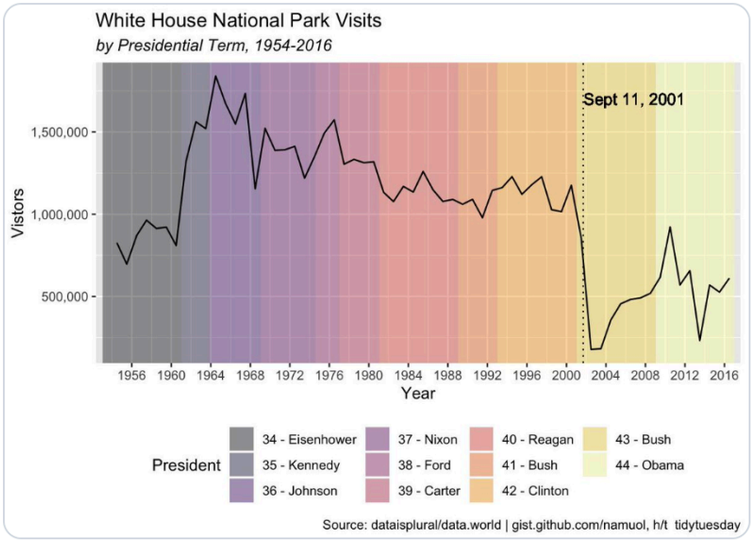
My #TidyTuesday about Media Franchise Powerhouses
the code is 👉bit.ly/2Xep8oL
#r4ds #datascience #Franchise #data #r #ggplot #rstats #dataviz #rstudio #Disney #MarioBros #winniePooh #princess #pokemon #starWars #Marvel



1:21 AM · Jul 6, 2019 · Twitter Web Client

K.G. Jewell
@KG_Jewell

A #TidyTuesday look a visits to the White House National Park by presidential term. A chance to experiment with ggplot geom_rects delineating eras in an xy plot, and add a dropline for the discontinuity after 9/11 security changes.
github.com/kjewell/nat_pa...



3:35 PM · Sep 17, 2019 · Twitter Web App

Rika Gorn 🎃
@RikaGorn

🗣️ Friends looking to get into analytics and #DataScience, participating in #TidyTuesday will give you such a huge payoff including: a portfolio, take home assignment prep, #rstats & #dataviz learning, comfort with cleaning messy datasets, a community!

9:22 AM · May 9, 2019 · Twitter for Android

Thank You!

bit.ly/focus-oct2019

Maria Tackett
Duke University

References

Dror, I. and Mnookin, J. 2010. The Use of Technology in Human Expert Domains: Challenges and Risks Arising from the Use of Automated Fingerprint Identification Systems in Forensic Science, *Law, Probability & Risk,* 9: 47 - 67.

Kass, R. and Raftery, A. 1995. Bayes Factors, *Journal of the American Statistical Association,* 90: 773 - 795.