A Statistical (Process Monitoring) Perspective on Human Performance Modeling in the Age of Cyber-Physical Systems

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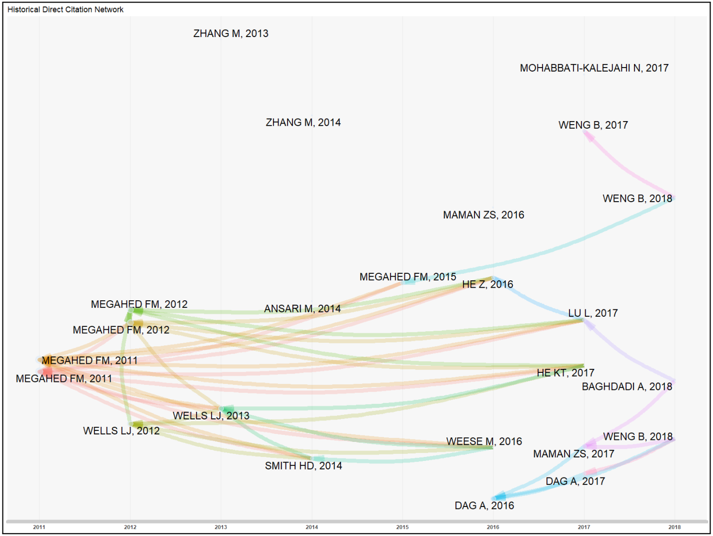
August 14th, 2019

Outline

My Research Portfolio's Evolution



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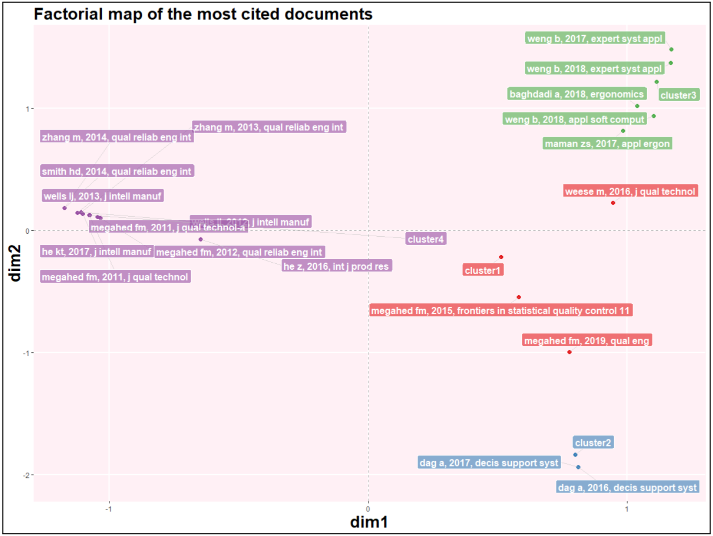

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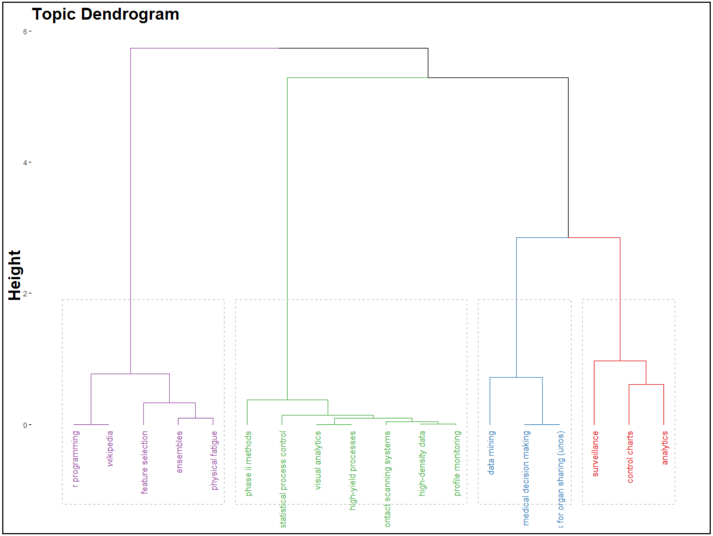
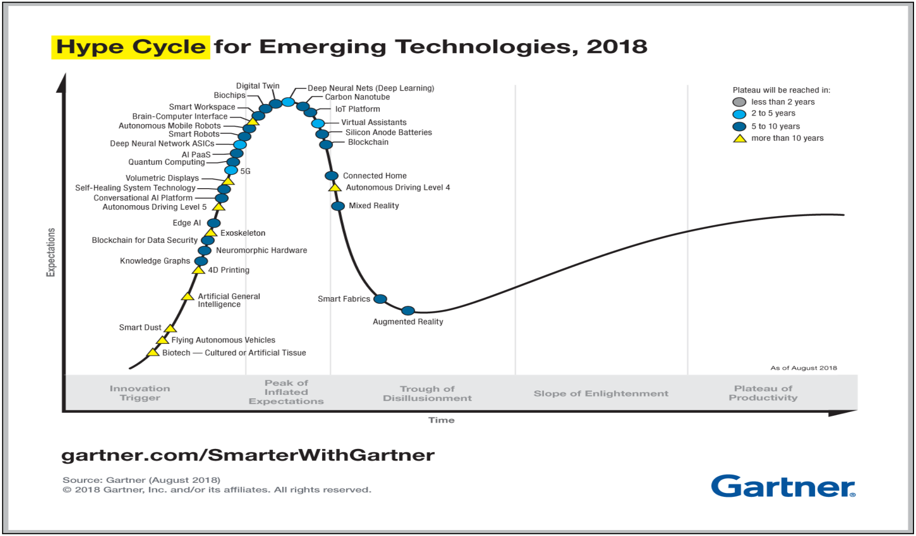


Outline

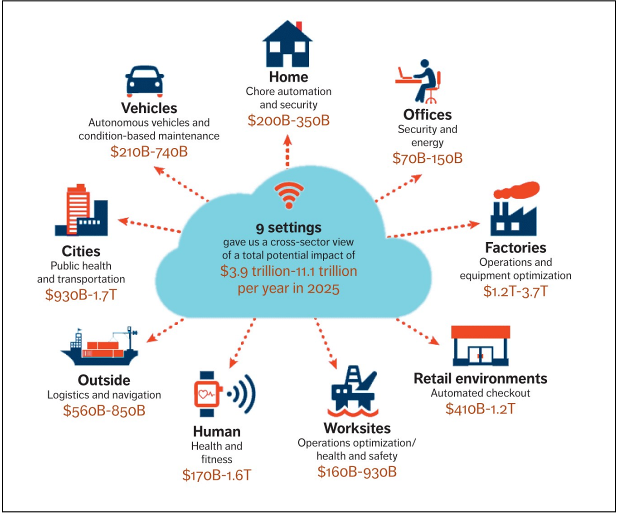
Gartner's Hype Cycle for Emerging Technologies



NSF's Alignment with the Gartner's Perspective

"Cyber-physical systems (CPS) are engineered systems that are built from, and depend upon, the seamless integration of computation and physical components. Advances in CPS will enable capability, adaptability, scalability, resiliency, safety, security, and usability that will expand the horizons of these critical systems. CPS technologies are transforming the way people interact with engineered systems, just as the Internet has transformed the way people interact with information. New, smart CPS drive innovation and competition in a range of application domains including agriculture, aeronautics, building design, civil infrastructure, energy, environmental quality, healthcare and personalized medicine, manufacturing, and transportation. Moreover, the integration of artificial intelligence with CPS creates new research opportunities with major societal implications." [1]

Expected Value for CPS Applications



Source: McKinsey&Company. The McKinsey Global Institute [2].

Humans: A Cornerstone of CPS/IoT Applications

- **From the McKinsey report [2], one can argue that data pertaining to human/workers is important to the following five applications:**
  - **Factories [Market size: $1.2T-3.7T]**
  - **Human health and fitness [Market size: $170B-1.6T]**
  - **Worksites [Market size: $160B-930B]**
  - **Logistics and Navigation [Market size: $560B-850B]**
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- **At a minimum, the market size for these five applications is estimated to be $2.16T in 2025.**

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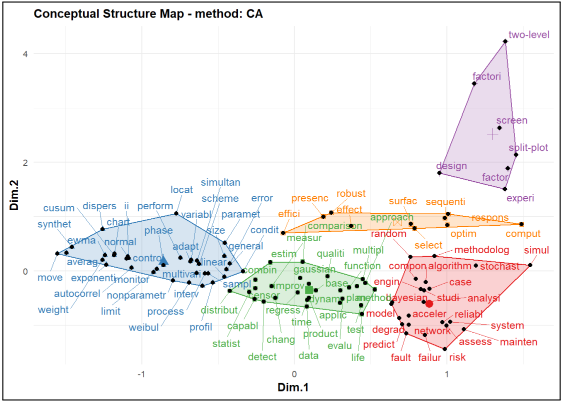
Is human performance monitoring an area of emphasis in our SQC research methodologies and/or applications?

SQC and Human Performance Monitoring

The answer is NO!!! Here is how we reached this conclusion:

(1) We "read" all 1576 articles published in: *JQT*, *Technometrics*, *QE*, and *QREI* in 2014 - August 1, 2019. Here is what we have learned:



SQC and Human Performance Monitoring

The answer is NO!!! Here is how we reached this conclusion:

(2) In the Frontiers of Statistical Quality Control 12, we had 20 outstanding contributions. The papers considered important application domains such as: web data, multi-stage processes, and single server queues.

None of the papers explicitly considered monitoring human performance data. However, the discussion in Lazariv and Schmid [3] can be easily thought of in the context of human performance monitoring applications.

SQC and Human Performance Monitoring

The answer is NO!!! Here is how we reached this conclusion:

(3) If we examine JQT as an example, it had three excellent special issues in 2018:

- **"statistical process control on big data streams"**
- **"quality engineering in advanced manufacturing"**
- **"reliability and maintenance modeling with big data"**

None of the 19 special issue papers considered human performance modeling.

SQC and Human Performance Monitoring

The answer is NO!!! Here is how we reached this conclusion:

(4) Note: In ISQC 2019, we have had two excellent talks that discuss the combination of CPS technologies with individualized health monitoring.

- **"Monitoring Two-state Processes Using Indirectly Observed Data" by: O. Hryniewicz, K. Kaczmarek-Majer, K. Opara**
- **"Personalized Health Management for Elderly Care" by: KL Tsui**

So hopefully, these talks lead to increased interests in an important area that affects public interests and health.

SQC and Human Performance Monitoring

The answer is NO!!! Here is how we reached this conclusion:

Why should SQC care about human performance monitoring applications? If you think of advanced manufacturing, which is our most common application area in SQC and industrial statistics:

In addition to the potential of CPS technologies, there is a direct link of human performance to quality outcomes. In a recent review of 73 published empirical studies by [4], the authors clearly stated that:

> *Quality deficits were associated with undesirable human effects of workload like fatigue and injury-related risk factors. Forty-six percent of the studies reported on efforts to improve HF in the [operations systems] with effect sizes for quality improvements reaching up to 86%.*

Outline

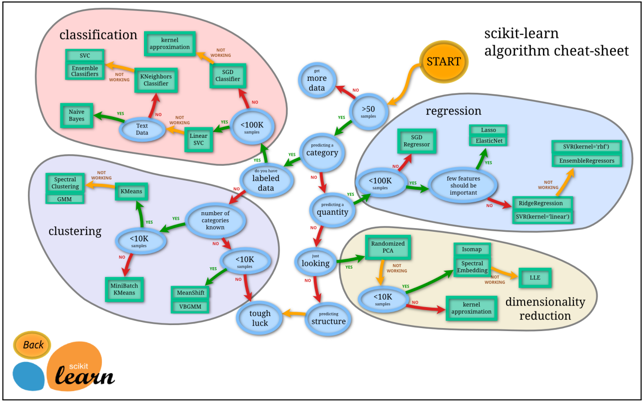
Common Frameworks for AI/ Machine Learning

The KDD Process	SEMMA	CRISP-DM
Pre KDD	————-	Business understanding
Selection	Sample	Data understanding
Pre processing	Explore	
Transformation	Modify	Data preparation
Data mining	Model	Modeling
Interpretation/Evaluation	Assessment	Evaluation
Post KDD	————-	Deployment

Table: A comparison of the three most commonly used AI/Machine Learning Frameworks. Table adapted from [5].

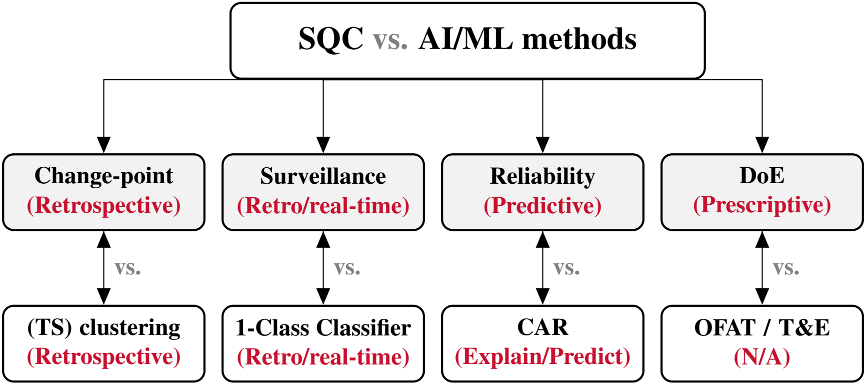
Common Frameworks for AI/ Machine Learning

These three frameworks encourage iterating, but do not provide sufficient guidance to practitioners/ researchers. Guidance: Typically focuses on the data mining / modeling step.



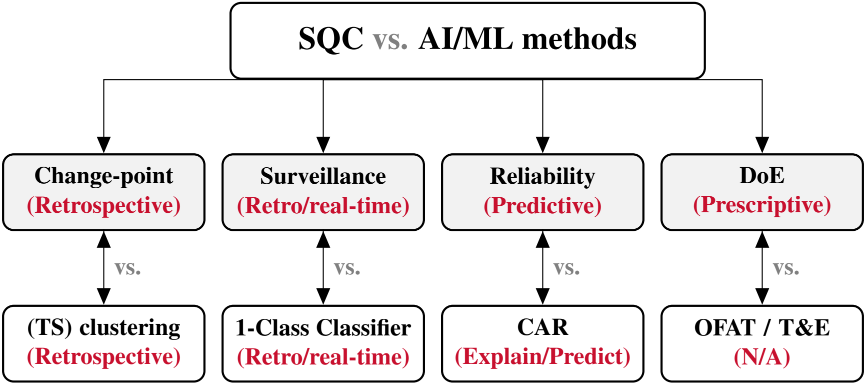
Source: SciKit-Learn [6]

Role of SQC in AI/ ML (CPS) Applications



Let us examine three examples (wearables, trucking & cyber security).

Role of SQC in AI/ ML (CPS) Applications



Let us examine three examples (wearables, trucking & cyber security).

Outline

Wearables: How I got involved?

Data sources

- **Real-time pings**: real-time data on vehicle number, date and time, latitude, longitude, driver identification number (ID), and speed. Collected every 1 to 10 minutes.
- **safety critical events, SCEs**: 1) hard brake (HB), 2) headway (HW), 3) collision mitigation (CM), and 4) rolling stability (RS).
- **Driver demographics**: driver *age*.
- **Road geometry**: *speed limits* and *the number of lanes* from the OpenStreetMap API.
- **Weather**: *precipitation intensity*, *precipitation probability*, *wind speed*, and *visibility*, from the Dark Sky API.

Data transformation

- **Trips**: real-time ping stopped for ≥ 20 minutes, the ping data will be separated into two different trips. A trip is *short continuous driving intervals* with a mean length of 1.8 hours.
- **Half-hour intervals**: trip length is heterogeneous (5 minutes to ≥ 8 hours), so trips were further divided into half-an-hour fixed intervals.
- **Shifts**: the trips will be further divided into different shifts if the driver was not moving for at least eight hours. A shift is therefore a long driving time with *intermittent short rests* (20 minutes to < 8 hours).
- **A proxy of driver fatigue**: cumulative summation of interval time within a shift for each driver as the *cumulative driving time*.

Data merging

Table 1: ping data

ping_time	speed	latitude	longitude	driver
2015-10-23 08:00:00	0	33.94360	-118.1681	canj1
2015-10-23 08:08:10	0	33.94358	-118.1681	canj1
2015-10-23 08:09:26	5	33.94288	-118.1681	canj1
2015-10-23 08:22:58	4	33.97146	-118.1677	canj1
2015-10-23 08:23:12	8	33.97178	-118.1677	canj1

Table 2: Transformed trips data

driver	trip_id	start_time	end_time	trip_time	distance
canj1	100160724	2015-10-23 08:09:26	2015-10-23 08:37:26	28	4.473
canj1	100160725	2015-10-23 09:04:24	2015-10-23 11:21:24	137	46.721
canj1	100160726	2015-10-23 12:00:36	2015-10-23 15:37:36	217	164.576
canj1	100160727	2015-10-23 16:38:10	2015-10-23 18:37:10	119	52.907
canj1	100160728	2015-10-26 07:49:04	2015-10-26 10:52:04	183	104.085

Table 3: Transformed 30-minute intervals

driver	interval_id	start_time	end_time	interval_time	distance
canj1	197089	2015-10-23 08:09:26	2015-10-23 08:38:00	28	4.538
canj1	197090	2015-10-23 09:04:24	2015-10-23 09:34:24	30	2.645
canj1	197091	2015-10-23 09:34:24	2015-10-23 10:04:24	30	0.984
canj1	197092	2015-10-23 10:04:24	2015-10-23 10:34:24	30	5.928
canj1	197093	2015-10-23 10:34:24	2015-10-23 11:04:24	30	17.348

Table 4: Transformed shifts data

driver	shift_ID	shift_start	shift_end	shift_length
canj1	1	2015-10-23 08:09:26	2015-10-23 18:37:56	628
canj1	2	2015-10-26 07:49:04	2015-10-26 15:06:58	437
canj1	3	2015-10-27 01:59:48	2015-10-27 07:58:56	359
canj1	4	2015-10-28 08:05:08	2015-10-28 20:20:32	735
canj1	6	2015-10-30 09:27:12	2015-10-30 21:18:22	711

Table 5: safety critical events

driver	event_time	event_type
canj1	2015-10-23 14:46:08	HB
canj1	2015-10-26 15:06:03	HB
canj1	2015-10-28 11:58:24	HB
canj1	2015-10-28 17:42:36	HB
canj1	2015-11-02 07:13:56	HB

Table 6: drivers

driver	age
canj1	46
farj7	54
gres0	55
hunt	48
kell0	51
lewr10	27
rice30	34
smiv	49
sunc	37
woow59	24

Table 7: Road geometry from the OpenStreetMap API

driver	latitude	longitude	speed_limit	num_lanes
farj7	30.32650	-89.86389	65	2
farj7	30.34032	-91.73116	65	2
farj7	30.34174	-91.72572	60	2
farj7	30.35075	-91.69085	60	2
farj7	30.35165	-91.68755	60	2

Table 8: weather from the DarkSky API

ping_time	latitude	longitude	precip_intensity	precip_probability	wind_speed	visibility
2015-10-23 08:09:26	33.94288	-118.1681	0	0	0.21	9.82
2015-10-23 08:22:58	33.97146	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:12	33.97178	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:30	33.97233	-118.1678	0	0	0.22	9.81
2015-10-23 08:38:00	34.00708	-118.1798	0	0	0.24	9.81

Bayesian random-effects logistic regression

$$
\begin{aligned}
Y_i &\sim \text{Bernoulli}(p_i) \\
\log \frac{p_i}{1-p_i} &= \beta_{0,d(i)} + \beta_{1,d(i)} \cdot \text{CT}_i + \sum_{j=1}^{J} x_{ij}\beta_j \\
\beta_{0,d} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2), \quad d = 1, 2, \cdots, D \\
\beta_{1,d} &\sim \text{i.i.d. } N(\mu_1, \sigma_1^2), \quad d = 1, 2, \cdots, D
\end{aligned}
\tag{1}
$$

- Y_i: whether SCEs occurred during the interval, 0 or 1,
- CT_i: cumulative driving time,
- $\beta_{0,d}$: random intercepts for each driver,
- $\beta_{1,d}$: random slopes for CT_i for each driver,
- x_{ij}: covariates, including age, road geometry, and weather.

Bayesian random-effects Poisson regression

$$
\begin{aligned}
Y_i &\sim \text{Poisson}(T_i \cdot \lambda_i) \\
\log \lambda_i &= \beta_{0,d(i)} + \beta_{1,d(i)} \cdot \text{CT}_i + \sum_{j=1}^{J} x_{ij}\beta_j \\
\beta_{0,d} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2), \quad d = 1, 2, \cdots, D \\
\beta_{1,d} &\sim \text{i.i.d. } N(\mu_1, \sigma_1^2), \quad d = 1, 2, \cdots, D
\end{aligned} \tag{2}
$$

- Y_i: the number of SCEs during the interval, a non-negative integer,
- T_i: length of the interval as an offset term,
- CT_i: cumulative driving time,
- $\beta_{0,d}$: random intercepts for each driver,
- $\beta_{1,d}$: random slopes for CT_i for each driver,
- x_{ij}: covariates, including age, road geometry, and weather.

Weakly informative priors and hyper-priors as recommended by Gelman [7].

$$
\begin{aligned}
\mu_0 &\sim N(0, 5^2) \\
\mu_1 &\sim N(0, 5^2) \\
\sigma_0 &\sim \text{Gamma}(1, 1) \\
\sigma_1 &\sim \text{Gamma}(1, 1) \\
\beta_2, \beta_3, \cdots, \beta_J &\sim N(0, 10^2)
\end{aligned} \tag{3}
$$

- μ_0, σ_0: hyper-parameters for $\beta_{0,d}$,
- μ_1, σ_1: hyper-parameters for $\beta_{1,d}$,
- $\beta_2, \beta_3, \cdots, \beta_J$: fixed parameters for covariates x_{ij}.

Non-homogeneous Poisson process: introduction

- The **intensity function** of a point process is

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(N(t, t+\Delta t] \geq 1)}{\Delta t}$$

- **Nonhomogeneous Poisson Process (NHPP)**: a Poisson process whose intensity function is non-constant.
- **Power law process (PLP)**: the intensity function of a NHPP is

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1}, \quad \beta > 0, \theta > 0.$$

- β is the shape parameter. θ is the scale parameter.
- $\beta > 1 \rightarrow$ reliability deterioration; $\beta > 1 \rightarrow$ reliability improvement.

Non-homogeneous Poisson process: data

- $T_{d,s,i}$: the time to the d-th driver's s-th shift's i-th critical event,
- d: driver index, $d = 1, 2, \cdots, D$
- s: shift index, $s = 1, 2, \cdots, S_d$,
- i: SCE index, $i = 1, 2, \cdots, n_{d,S_d}$
- $n_{d,s}$: the total number critical events of d-th driver's s-th shift.

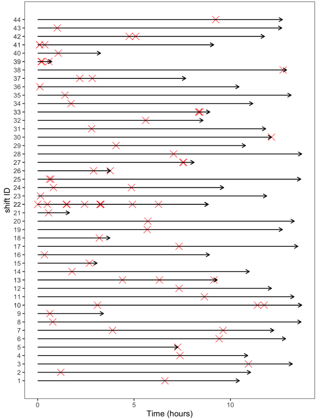


Figure: Arrow plot of time to SCEs in each shift

Bayesian random-intercepts NHPP

$$
\begin{aligned}
T_{d,s,1}, T_{d,s,2}, \cdots, T_{d,s,n_{d,s}} &\sim \text{PLP}(\beta, \theta_{d,s}) \\
\beta &\sim \text{Gamma}(1,1) \\
\log \theta_{d,s} &= \gamma_{0d} + \gamma_1 x_{d,s,1} + \gamma_2 x_{d,s,2} + \cdots + \gamma_k x_{d,s,k} \\
\gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2) \\
\gamma_1, \gamma_2, \cdots, \gamma_k &\sim \text{i.i.d. } N(0, 10^2) \\
\mu_0 &\sim N(0, 5^2) \\
\sigma_0 &\sim \text{Gamma}(1,1)
\end{aligned}
\tag{4}
$$

- a fixed β across drivers,
- random parameters $\theta_{d,s}$ across drivers
- $\theta_{d,s}$: random intercepts γ_{0d} for scale parameter θ,
- $x_{d,s,k}$: covariates.

Bayesian estimation with rstan

- Hamiltonian Monte Carlo with No-U-Turn sampler [8, 9],
- 4 chains, 1,000 warm-ups, 2000 iterations,
- Convergence diagnostics:
  - Gelman-Rubin statistics $\hat{R} < 1.1$ [10],
  - Effective sample size (ESS) > 500,
  - No divergent transitions after warmup,
  - Traceplots.
- All data and code available at https://github.com/caimiao0714/ISQC2019$_{t}ruck$.

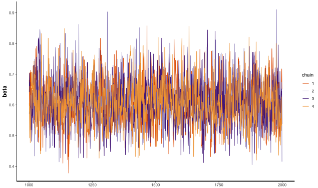


Figure: Example trace plot for the shape parameter in NHPP

Results for hierarchical Bayesian logit and Poisson regressions

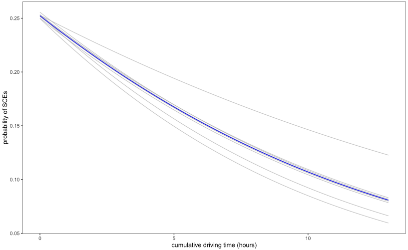


Figure: Cumulative driving time and estimated probability of SCEs from the hierarchical logistic model

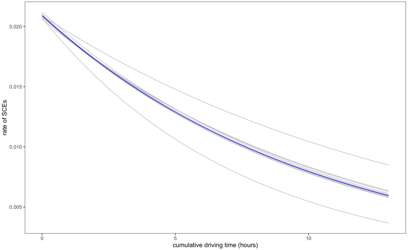


Figure: Cumulative driving time and estimated rate of SCEs from the hierarchical Poisson model

Results for hierarchical Bayesian NHPP

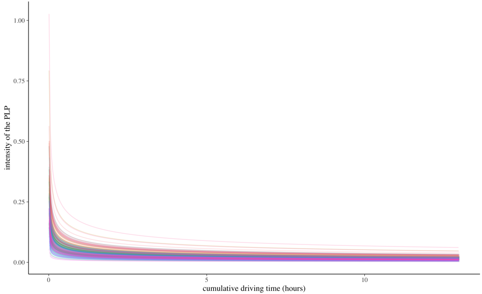


Figure: Cumulative driving time and estimated intensity of SCEs from the hierarchical NHPP.

- 196 shifts for the 10 sample drivers,
- y-axis is the intensity of SCEs,
- Each line represents a shift, each color represents a driver.

Human-Human Authentication

- User authentication
  - Differentiate one human user from another
- Prominent authentication approaches
  - Passwords
  - Traditional biometrics

Limitations of Existing User Authentication Solutions

- Passwords
  - Either insecure or unusable
- Traditional biometrics (e.g., fingerprints)
  - Invasive
  - High rejection rates
  - Require additional hardware
  - Susceptible to impersonation or spoofing

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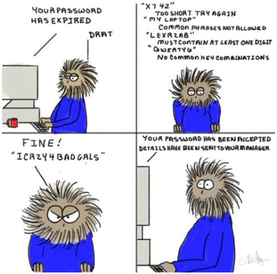

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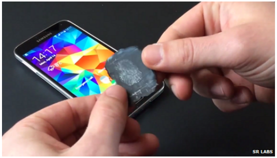


Behavioral biometrics

- Keystroke dynamics [Monrose et al. ; CCS'97]
- Mouse movement patterns [Zheng et al.; CCS'11]
- Touch gesture biometrics
  - Sliding horizontally and vertically [Frank et al. ; TIFS'13]
  - Sliding up, down, left, and right and tap [Li et al.; NDSS'13]
  - Horizontal slide and the pattern unlock [Luca et al.; CHI'12]

Gametrics

- Interactive game-based behavioral biometrics
- Why games?
  - Fully supported by web browsers and touch screen devices
  - Randomized, interactive and cognitive nature
  - Sufficient cues can be extracted in a short period of time

Game Cognitive Task

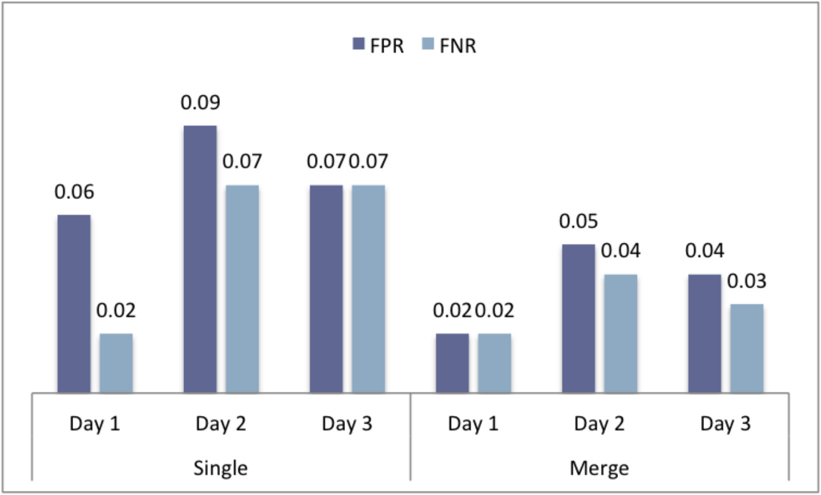
Features & Classification Metrics

- Features
  - Mouse dynamics / touch gesture
  - Cognitive ability
  - Others (i.e., distance-based features)
- Classifier
  - Random forest
- Classification metrics
  - **False Positive Rate:** Measures the security
  - **False Negative Rate:** Measures the usability

Inter- & Intra- Session Analysis

- Web-based study (MTurk)
- Data collection methodology:
  - Day 1: 98 participants – 60 challenges
  - Day 2: 62 participants – 36 challenges
  - Day 3: 29 participants – 36 challenges
- Number of successfully completed challenges = 9076
- Average solving time = 7.5s

Inter- & Intra-Session Results



Interactive Biometrics Discussion

- Efficiency
  - Short enrollment time
  - Short time to identify the user
  - Building and updating the classifier and testing a new instance take short time
- Application Scenarios
  - Point-of-entry
  - Integrated with graphical passwords
  - Fall-back authentication

Interactive Biometrics Limitations and Future Work

- Study the effect of user's behavior variation on the accuracy
- Test the accuracy when switching devices or hardware
- Add more complexity to the game challenges to increase the level of interaction, and improve the overall usability and security

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A Statistical (Process Monitoring) Perspective on Human Performance Modeling in the Age of Cyber-Physical Systems

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