Data Science for Speech Therapy

Clinical Research Methodology

Clinical Sharing for Continuous Education

ST Benjamin C

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Content

Data Science

- What is data science?
- What is ML?
- ML vs stats

Clinical Application

- ML in Speech Pathology
- Workflow of ML (prediction extubation success)
- Use case of ML in Speech Pathology (dysarthria severity)
- Barriers to ML

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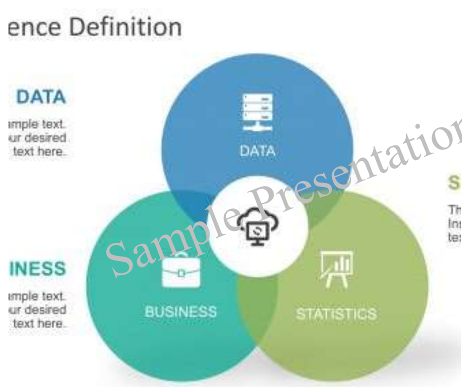
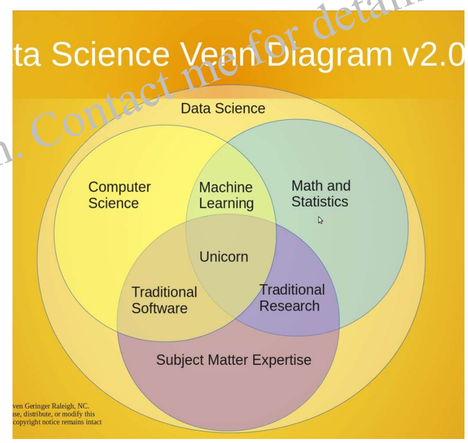
Many definitions





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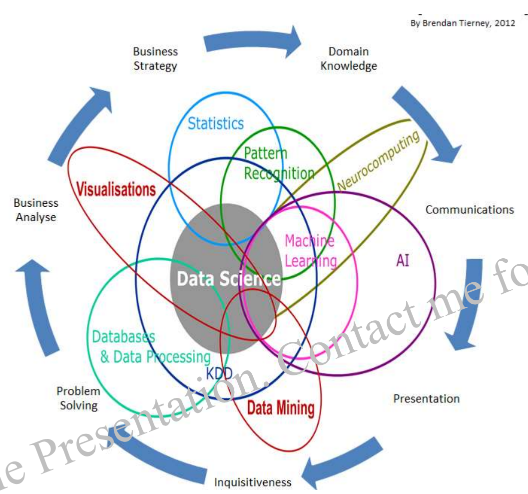
Synergy of disciplines



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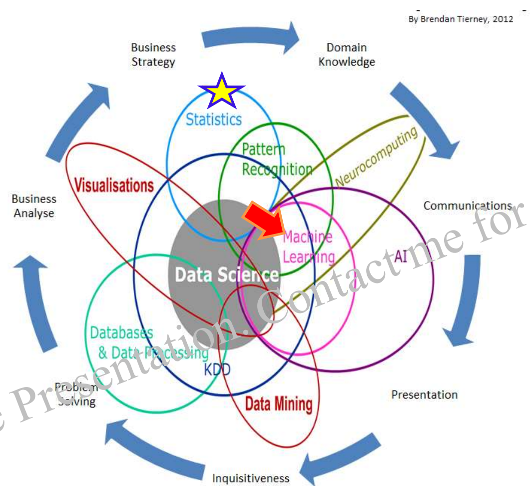
Clinical Research Methodology



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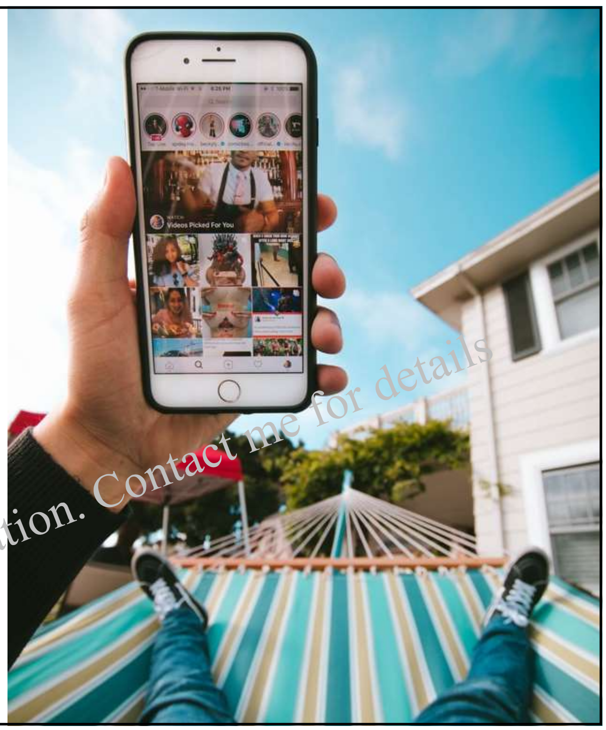
What is ML?



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ML vs stats

	Statistics	Machine learning
Approach	Inference	Prediction
Measurement	P-value, effect size	More than just p-value
Assumption of the dataset	Sample relates to population	Past dataset can used to predict future, unseen data
Dataset	Use all observations Unable to comment on individual observations	Train/test split Make statements for each observation

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	Statistics	Machine Learning
Technique	Simple Model	Simple model/ complex model
# of techniques	1 specific simple model	As many models as you desire
Pre-processing	Typically left out	Typically done
Capturing complex relationship	Not as effective	Better
Transparency	Interpretable	More opaque
Observations: Predictors	Observations>> predictors	Observations > predictors Predictors> observations

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Popularity of ML in clinical research

- No known literature review in speech pathology
- Reviews in other medical fields

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In cardiology

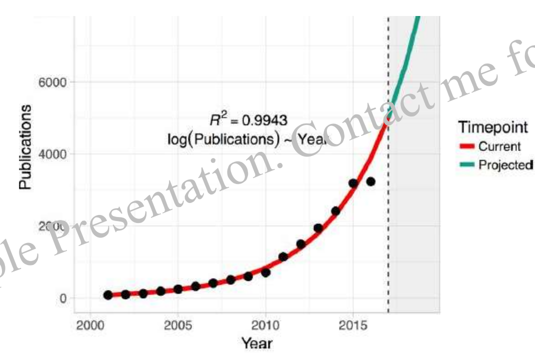

Figure 1 Projecting the growth of publications in PubMed with 'cardiology' and 'machine learning'. Data compiled using Medline (PubMed) trend (http://dan.corlan.net/medline-trend.html). Exponentiated regression of log number of publications on year is used to predict the future trend.

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ML in speech pathology

- An evaluation of measures to dissociate language and communication disorders from healthy controls using machine learning techniques
- Automatic classification of unequal lexical stress patterns using machine learning algorithms
- Pathological Voice Signal Analysis Using Machine Learning Based
- Calculation of upper esophageal sphincter restitution time from high resolution manometry data using machine learning

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Medical topics related to ST's work

- Data Science for Extubation Prediction and Value of Information in SICU

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[Data Science for Extubation Prediction and Value of Information in SICU (2019)]

- Crash course clinical aspect of extubation
- ML workflow
- Clinical and ML findings

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clinical aspects of extubation

- Parameters of respiratory physiology guide weaning BUT they may not support predicting extubation well
- No systematic approach on decision to extubate

1. Use routine clinical measurements
2. More ICU specific measurements
3. Readiness test
4. Clinical experience

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More specific ICU measurements (APACHE)

- Acute Physiology And Chronic Health Evaluation II
- Scored within 24hour of ICU admission
- 0-71
- higher scores correspond to more severe disease and a higher risk of death

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More specific ICU measurements (RSBI)

- Rapid Shallow Breathing Index
- handheld spirometer attached to the ETT while a patient breathes on RA for 1 min without any ventilator assistance.
- Pt who cannot tolerate independent breathing tend to breathe rapidly and shallowly and will therefore have a high RSBI.
- A lower RSBI (<65) → readiness to extubate

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Issue w current practice

- 6-47% pt have extubation failure and required reintubation
  - probability of mortality from 25 to 50%
  - increased duration of mechanical ventilation and prolonged ICU stay

→ Use ML to predict candidacy for extubation

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ML Pipeline

J. Clin. Med. 2019, 8, 1709

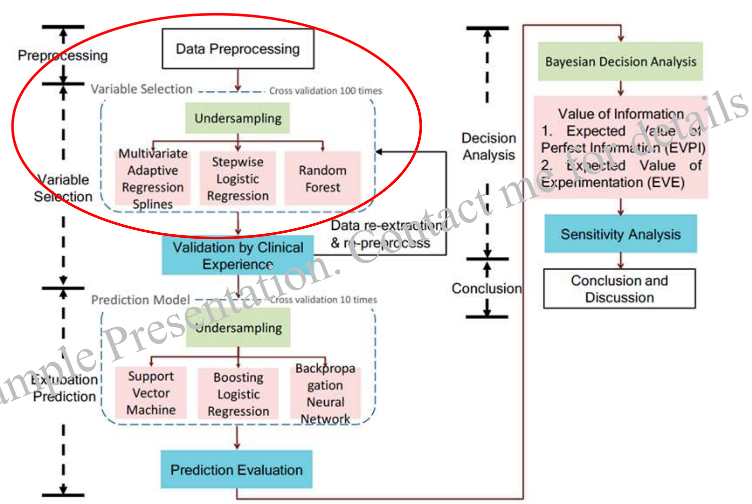

Figure 1. The data science framework of endotracheal extubation.

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Table 2. The results of variable selection methods.

Multivariate Adaptive Regression Splines		Stepwise Logistic Regression		Random Forest		Total Frequency	
Variables	Freq.	Variables	Freq.	Variables	Freq.	Variables	Freq.
ApacheII	98	ApacheII	94	ApacheII	100	ApacheII	292
Eye_Opening	42	Eye_Opening	64	WBC	74	WBC	155
WBC	41	WBC	40	Glu	59	Eye_Opening	114
Heart_Rate	36	RSBI	32	Na	58	Heart_Rate	111
Glu	30	Hct (ABG)	25	Heart_Rate	54	Glu	108
Na	30	Heart_Rate	21	Hct (ABG)	53	Na	103
RSBI	25	Glu	19	pO_2_FiO_2	38	Hct (ABG)	100
Platelets	24	Na	15	Weight	36	RSBI	90
Gender_men	24	PT_INR	11	ARTmean_BP	35	Platelets	64
Hct (ABG)	22	Verbal_Response	9	PT_INR	35	Weight	62
Verbal_Response	19	Gender_men	9	Platelets	33	Verbal_Response	61
Weight	17	Weight	9	RSBI	33	PT_INR	59
ARTmean_BP	13	Platelets	7	Verbal_Response	33	ARTmean_BP	54
PT_INR	13	ICU_Emergency	7	PIMAX	32	pO_2_FiO_2	53
pO_2_FiO_2	12	ARTmean_BP	6	Eye_Opening	8	PIMAX	44
ICU_Emergency	12	PIMAX	5	Gender_men	3	Gender_men	36
PIMAX	7	pO_2_FiO_2	3			ICU_Emergency	19

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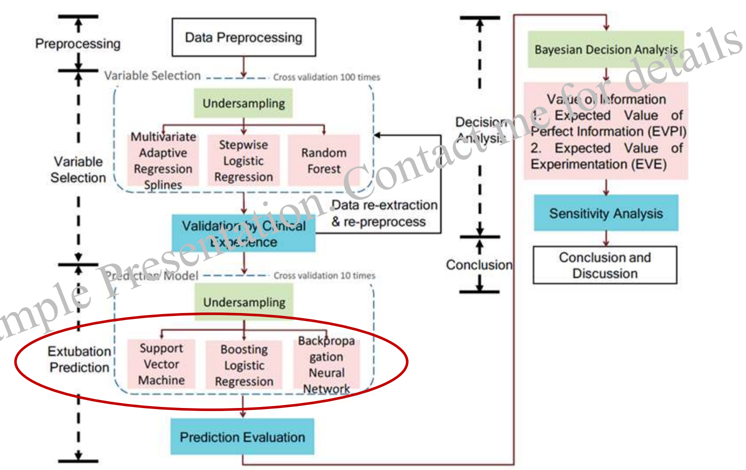

Figure 1. The data science framework of endotracheal extubation.

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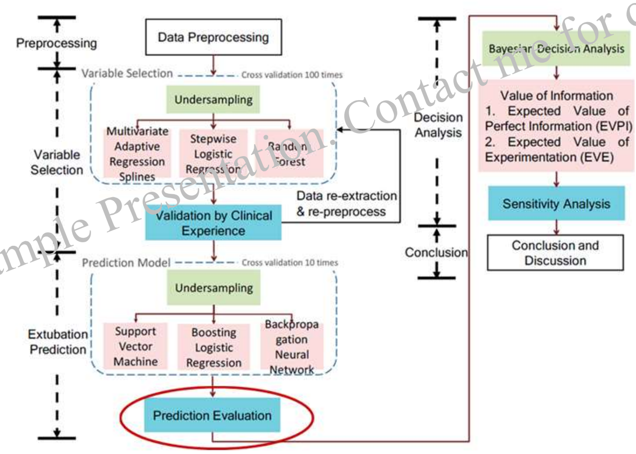

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Repeat ML pipeline with different dataset

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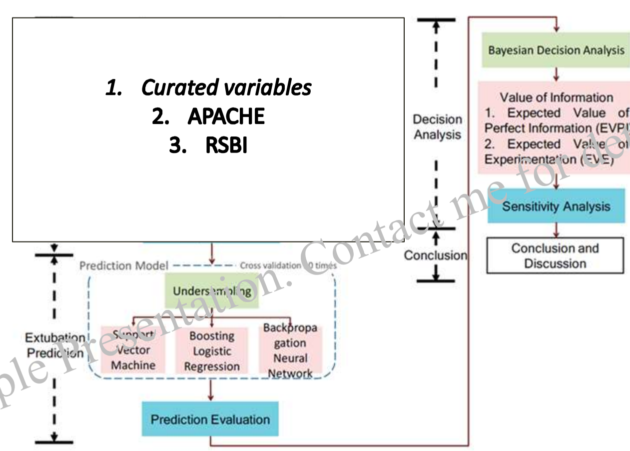

Figure 1. The data science framework of endotracheal extubation.

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ML findings

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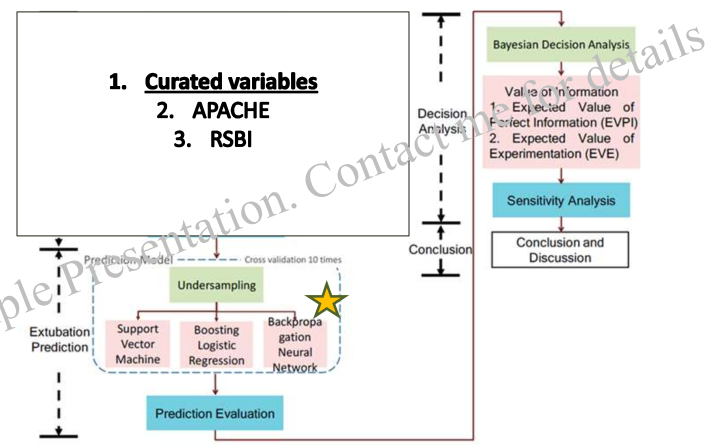

Figure 1. The data science framework of endotracheal extubation.

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ML findings

- Time and effort processing the variables pays off
- Using multiple models allow us to chose one with the highest prediction power

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Clinical findings

- Using curated predictors and the best model, the algorithm saves 0.625 days in ICU compared to clinical judgement alone
- Curated predictors reveal influential predictors for successful extubation

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Towards an automatic evaluation of the dysarthria level of patients w PD (2018)

Clinical component

Create an ax to measure dysarthria speech in PD

ML component

Use ML to predict ax scores

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Create an ax to measure dysarthria speech in PD

- Most PD assessment battery not specific to dysarthria
- An assessment which does not need physical consultation

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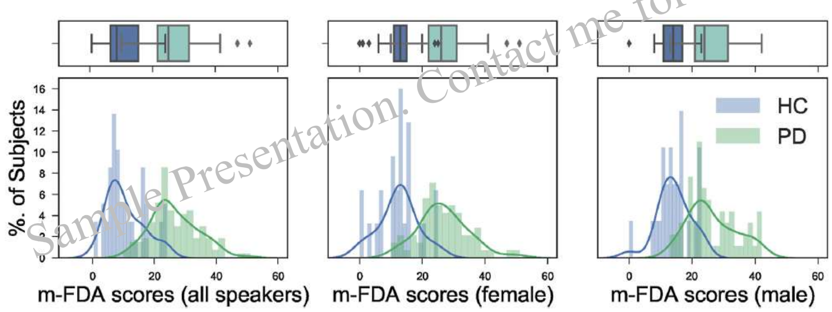

Fig. 1. Distribution of the m-FDA scores for all HC speakers and PD patients (left). m-FDA scores for female speakers (middle). m-FDA scores for male speakers (right). Significant differences between the scores of HC and PD speakers are found in all cases ($p < 0.001$).

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Use ML to predict ax scores

Acoustic signals from mFDA -->
4 speech dimensions + 1 engineered feature

1. Phonation
2. Articulation
3. Prosody
4. Intelligibility

i. I-vector

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- i-vectors were the most accurate to quantify the dysarthria level
- correlations of up to 0.69 between the real m-FDA scores (assigned by the clinician) and the predicted ones

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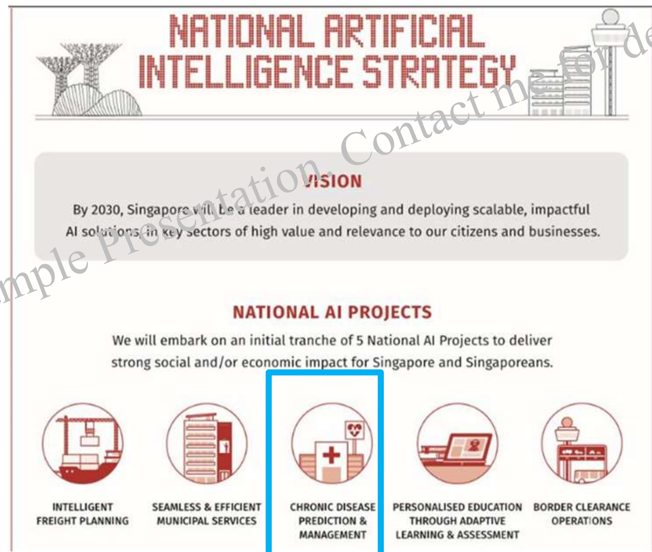
Why do we need to address barriers?



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Harvard Business Review (2019)

- **AI Can Outperform Doctors. So Why Don't Patients Trust It?**
- Adopting AI in Health Care Will Be Slow and Difficult

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Harvard Business Review (2019)

- ~~*AI Can Outperform Doctors. So Why Don't Patients Trust It?*~~
- Adopting AI in Health Care Will Be Slow and Difficult

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Adopting AI in Health Care Will Be Slow and Difficult (HBR 2019)

1. Regulatory Framework

Singapore releases AI model governance framework at World Economic Forum

WED, JAN 23, 2019 - 12:51 PM

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2. Approval of developed AI/ML

An A.I. for the eye: New tech cuts time for spotting signs of diabetic eye disease

By Timothy Goh

6 July 2019 | Tomorrow's Medicine, The Straits Times

Enrolled nurse Abel Kwan (far left) using a specialised camera, known as a Fundus, at a mock screening session with the Selena+ AI. The system will address the need for increased manpower to tackle diabetes and related eye diseases.ST PHOTO: GIN TAY

Self-learning retinal screening tech cuts time needed to spot signs of diabetic eye disease

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Adopting AI in Health Care Will Be Slow and Difficult (HBR 2019)

3. Black box medicine

- Identify variables that influence prediction at global level AND at individual level
- ? Individualized treatment

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