



# Prediction and Risk Scores

Tom Ron • ML4HC • April 2019



# Agenda

- Biases in electronic health record data due to processes within the healthcare system:  
retrospective observational study
- Meaningless comparisons lead to false optimism in medical machine learning



# **Biases in electronic health record data due to processes within the healthcare system: retrospective observational study**

Denis Agniel, Isaac S Kohane, Griffin M Weber

“The hour of the day the test was ordered, the day of the week, and the amount of time between consecutive tests is more predictive of three year survival than the actual value of the test result, for most tests”



# Experiment

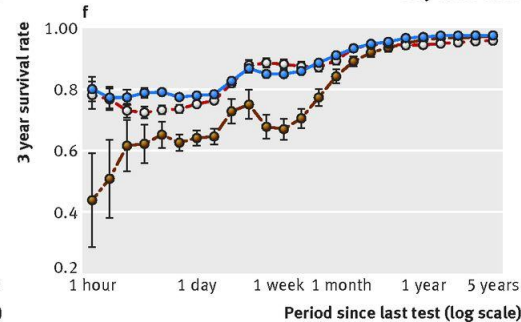
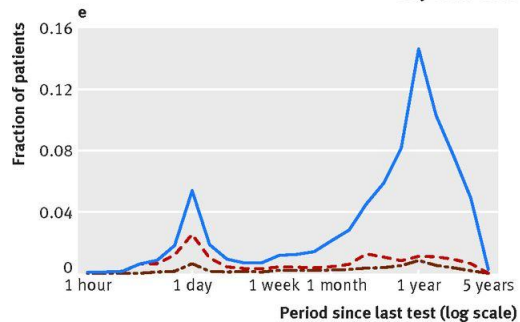
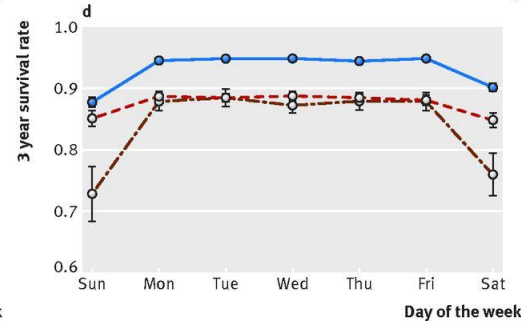
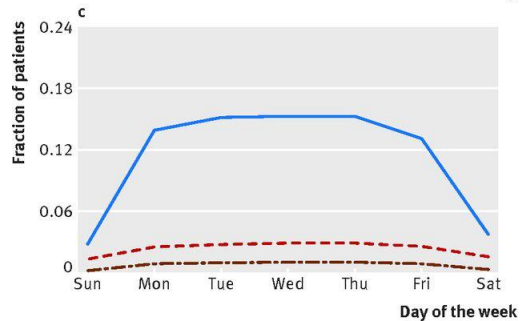
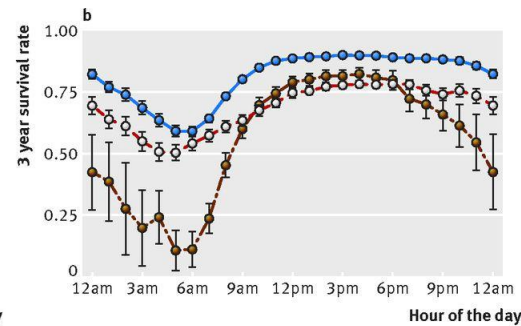
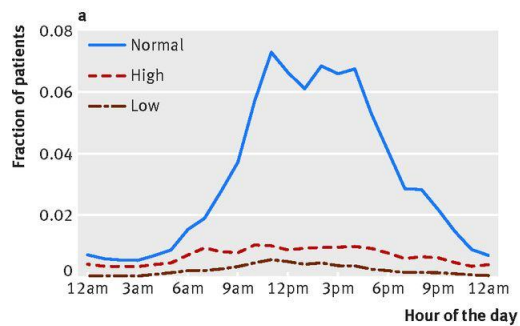
- **Goal:** predict 3 years survival
- **Data:** 8.8M observations (670k patients) of 272 laboratory tests from 2 hospitals were used in the experiments.
- **Features:** patients' pathophysiology (value + high \ low flag) and healthcare process dimensions (hour of day, day of week, previous test) of a single laboratory test observation



# Experiment

- First experiment - logistic regression + Age, Sex, Race (ASR) + test presence
- Second experiment - using GAM with logistic link, features ASR + ...

# Results





# Results

- The presence of a laboratory test in a patient's record, regardless of any other information about the test result, has a significant association with the odds ratio of death in 233 of 272 (86%)
- For 60% tests including both patient pathophysiology and healthcare process variables in the models is better than using patient pathophysiology or healthcare process alone.
- The time interval between consecutive tests is the single most predictive variable for 76 of 210 (36%) tests, followed by the value of the test result in 56 (27%) tests, and the hour of the day in 47 (22%) tests
- 30 day readmission as the outcome measure, rather than three year survival, and found similar results.



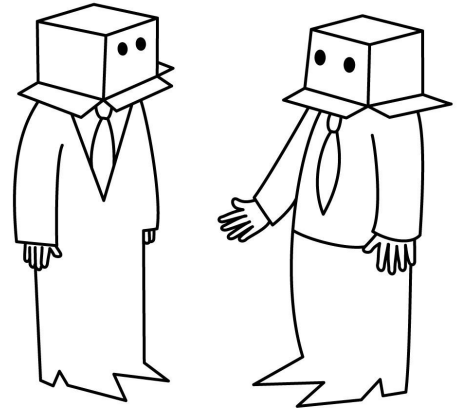
# Critic

- PoC - not clear how to go on from here
  - Severity score
  - Models with multiple tests
  - Anomalies and Fairness
  - Model changes in guidelines \ dynamics
- 3 years survival - not the doctor objective function



# Takeaways

- Think of features out of the box -
  - Who prescribed the test
  - Room in unit
- Synergy between clinician and ML researchers \ practitioners



*“What a coincidence!  
I’m finding it hard to think out of the box, too!”*



# Meaningless comparisons lead to false optimism in medical machine learning

DeMasi O, Kording K and Recht

“mental health conditions need long-term monitoring and clinical monitoring is expensive, but automatically tracking a user with ubiquitous sensors is cheap.”

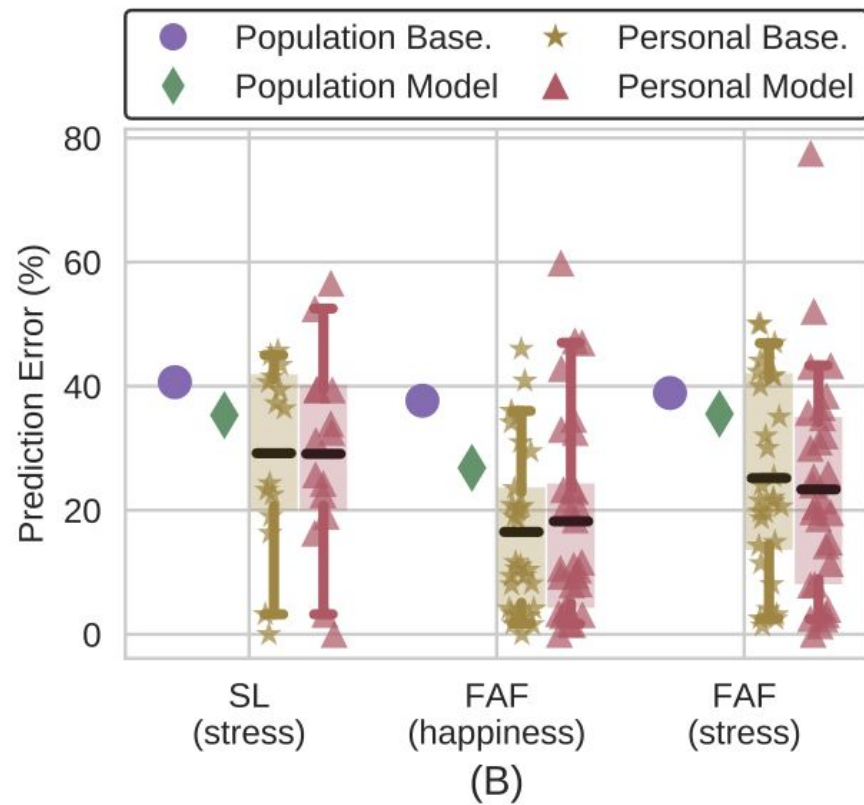
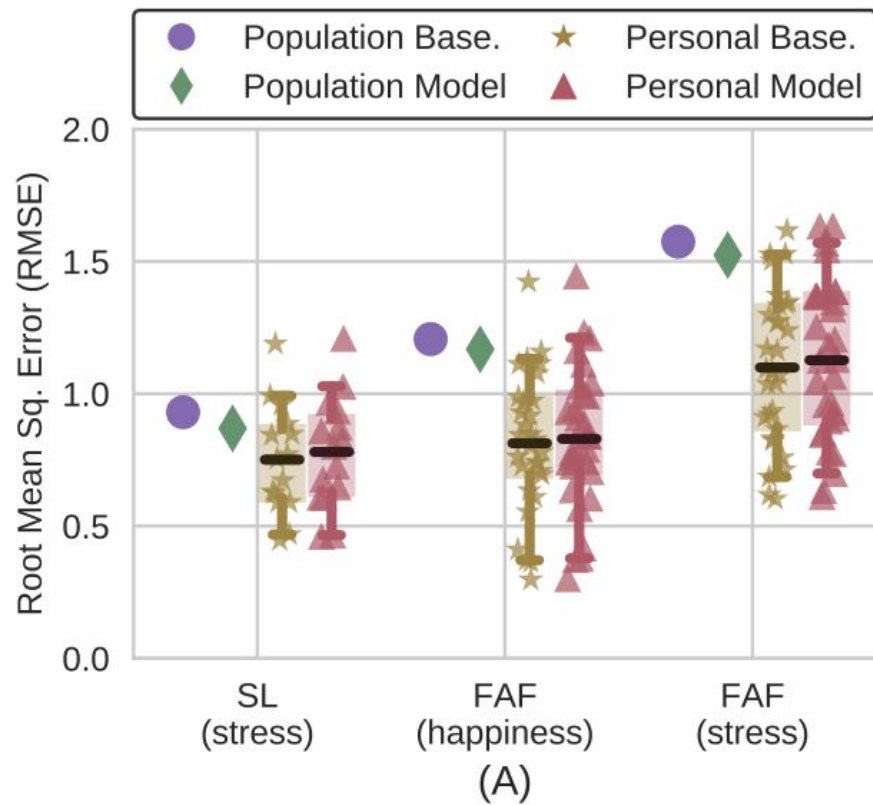
מה אתם הייתם עושים?



# Terminology

**Personal baseline** - each individual is at a constant state, but that state can differ between individuals.

**Population baseline** - all individuals are always at the same state.





# Experiment

Goal -

- Predict happy or stressed or not on a given day
- Predict average level of happiness or stress that a participant reported on a given day

Data - StudentLife and Friends and Family



# Experiment

## Preprocessing

- Full clustering - fit GMM to all locations for each participant to identify locations frequented by participants. Max 20 clusters. Home and work definitions.
- Stationary clustering - K-means clustering on stationary points only.

## Features

- Fraction of a day participant is not stationary
- Log likelihood of a day from the GMM to estimate how routine the day was
- # GMM clusters visited in a day



# User lift

User lift - the difference of the personal model with the personal baseline

Dataset	Problem	Model	Avg. Personal Baseline Error	Avg. Personal Model Error	Avg. User Lift (Error)	p-value
SL - Stress	binary	Log.Reg.	29.19%	29.09%	<b>0.10</b>	.481
FaF - Happiness	binary	SVM(rbf)	16.51%	18.67%	<b>-2.17</b>	.967
FaF - Stress	binary	SVM(rbf)	25.17%	23.35%	<b>1.82</b>	.240
SL - Stress	regression	Elastic Net	0.75	0.78	<b>-0.03</b>	.988
FaF - Happiness	regression	Elastic Net	0.81	0.83	<b>-0.02</b>	.999
FaF - Stress	regression	Elastic Net	1.10	1.13	<b>-0.03</b>	1.000





# Limitations

- Study cohort is not clinical population
- Sample size is small
- Study duration is limited



# Literature review

**Find relevant literature**

Choose papers for literature review

**Establish a baseline**

Extracting baselines from the different papers

**Identify error of baseline and best ML**

Extract results from the different papers

## Find relevant literature

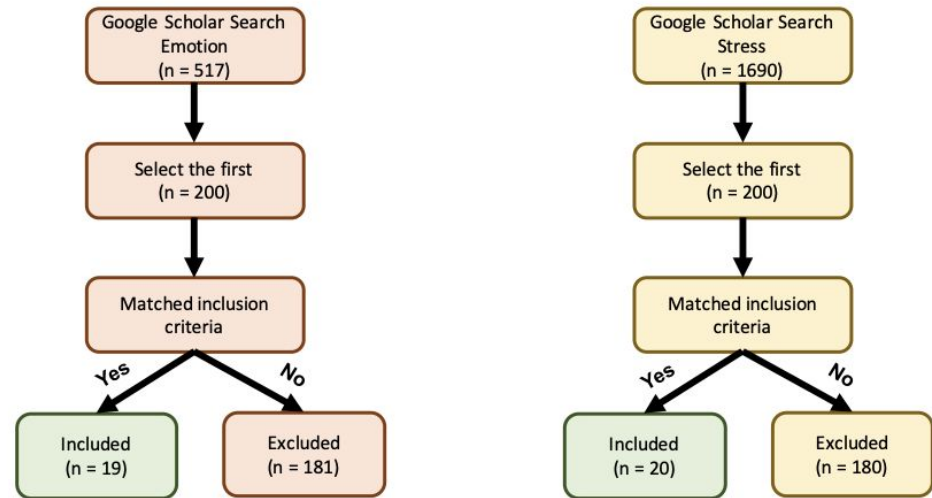
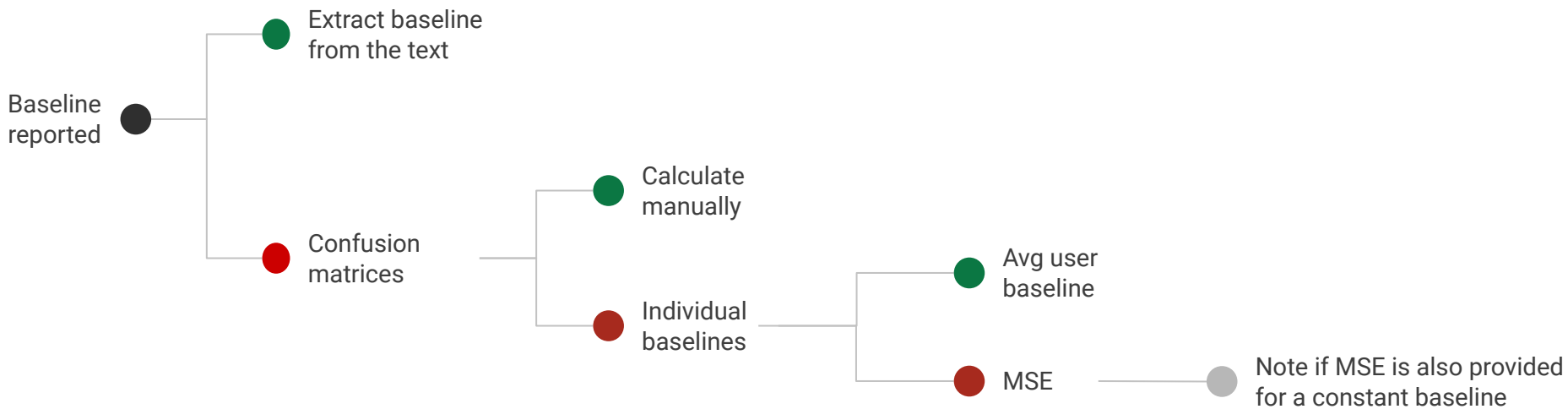


Fig 2. Diagram of literature review process.

## Establish a baseline





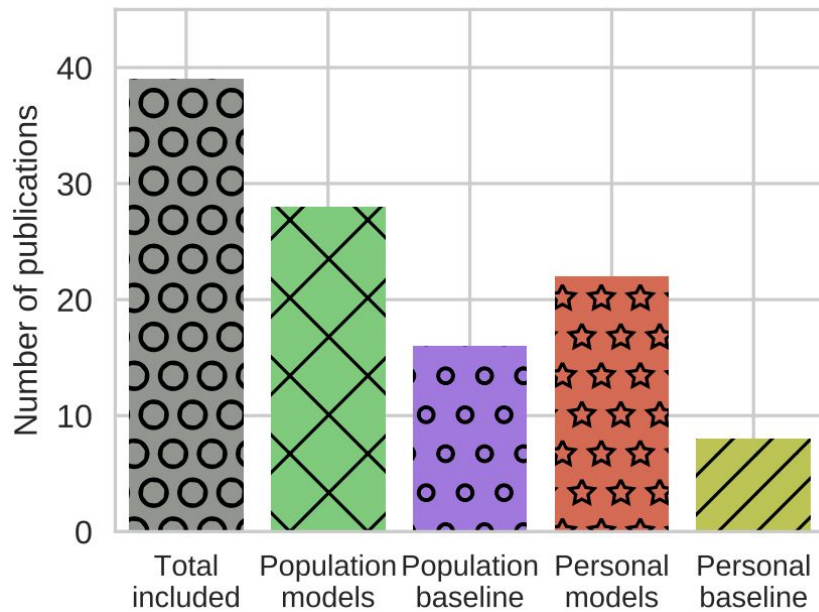
## Identify error of baseline and best ML

Model prediction error for multi-class classification

- Results are broken for personal models by individuals → average
- Accuracy for multiple objectives → best result for each objective
- Multiple feature sets and models → best performing model
- Folds in cross validation scheme - ignored.
- Uniform baseline based on classes probability

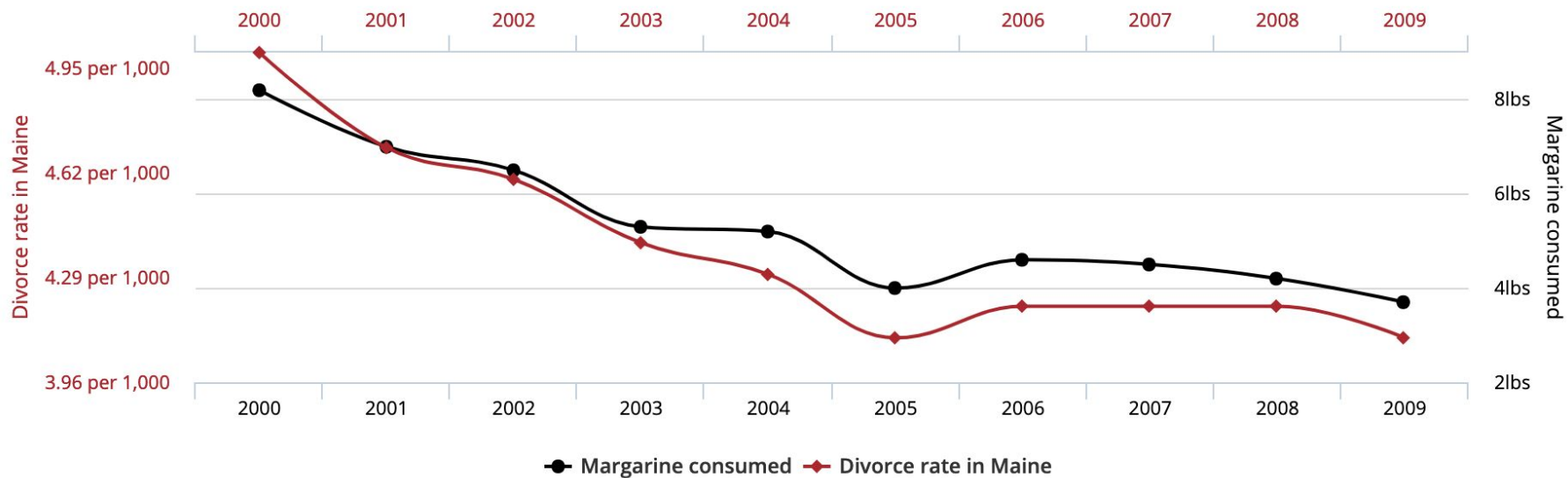
# Literature review

- 77% of the publications reviewed compared to population baselines.
- When personal baselines are reported algorithms often add little or nothing



# Divorce rate in Maine correlates with Per capita consumption of margarine

Correlation: 99.26% ( $r=0.992558$ )



tylervigen.com

Data sources: National Vital Statistics Reports and U.S. Department of Agriculture



# Takeaways

- Read with critical eyes - sample size, duration, clinical population, can the result be generalized, reproduced.
- Results should be meaningful
- Gap between theory and ready to deploy model



*That's all Folks!*



# References

Agniel D, Kohane IS, Weber GM. Biases in electronic health record data due to processes within the healthcare system: retrospective observational study. *BMJ* 2018;361 doi: 10.1136/bmj.k1479

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