Life and Health Risk Assessment Using Non-Traditional Data using Deep Learning

LYDIA.ai

Anthony Lee, Co-Founder & CEO of Lydia AI

2024-10-10

Anthony Lee

Co-founder & CEO

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R&D in machine learning since 2015 from University of Toronto

Co-inventor

- Method and system of using hierarchical vectorisation for representation of healthcare data (2021)
- Method and system for mapping text phrases to a taxonomy (2020)
- System and method for outputting groups of vectorized temporal records (2018)

2022 Credit Suisse Social Impact Award

Young Scholar Innovation Award (2022)

Tatler Gen T. 2022 Power & Purpose Leaders of tomorrow

At Lydia AI, we use machine learning to unlock new sources of data to make risk predictions

Our investors

Alibaba Entrepreneurs Fund | INFORMATION VENTURE PARTNERS | Government of Canada / Gouvernement du Canada | 500 | SparkLabs VENTURES

Our Partnerships

衛生福利部中央健康保險署 National Health Insurance Administration, Ministry of Health and Welfare | Toronto Machine Learning Summit | SOCIETY OF ACTUARIES | 財團法人人工智慧科技基金會 Artificial Intelligence Foundation

Our Industry recognition

Gartner	KPMG	DIA TOP 250	C100	50 Technologie Fast 50 CANADA
2022 July Market Guide for AI Startups	2022 Tech Innovator Taiwan Top 3	2022 Digital Insurance Agenda Top Award	2022 Canadian C100 Fellowship	2022 Deloitte Companies-to-watch

Our Mission

To protect the health & prosperity of the next billion people

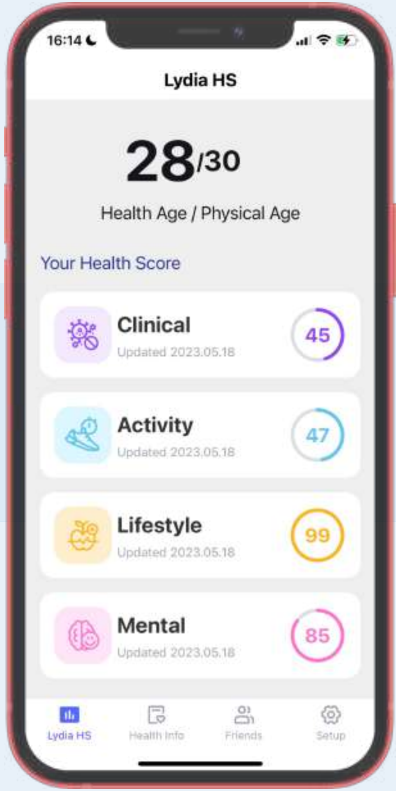
Lydia AI risk scoring spans multiple dimensions of health, from clinical to physical activity

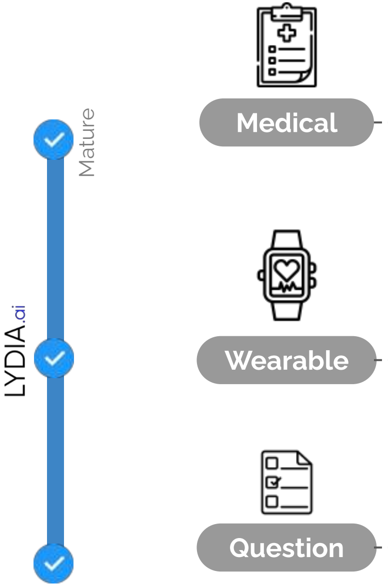
Clinical Score
Factors in medical history and health predictions

Activity Score
Factors in activity history based on wearable data

Lifestyle Score
Factors in lifestyle habits (i.e., alcohol, smoking)

Mental Health
Determines major depression based on wearable data





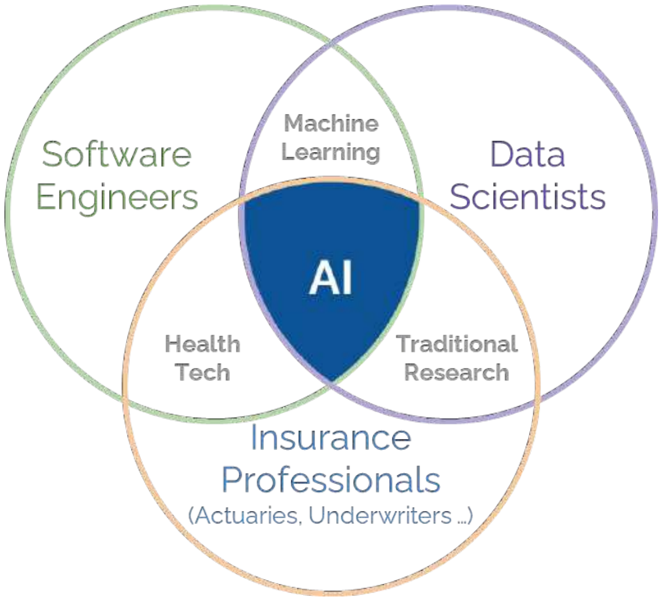
Medical: inpatient/outpatient, diagnosis codes, treatment codes, prescription codes, procedure codes, duration of disease, drug regimen, blood, urine lab test results

Activity: steps, heart rate, energy expenditure, workout duration & frequency

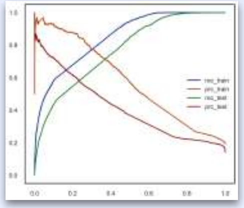
Lifestyle: questionnaire, dietary habits/calories, sleep onset/duration/stages

Mental: physical activity, questionnaire, heart rate, pulse, oxygen, sleep movement

Bridging the gap between AI/ML and traditional insurance

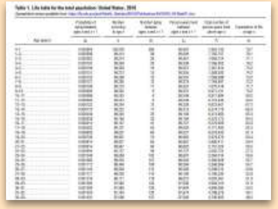


ML Health Risk Predictions



"health_age_score": 50,
"actual_age": 40,
"mortality_risk": 0.345,
"cancer_risk": 0.224,
"chronic_disease_risk": 0.1042

Traditional Actuarial Science and UW Methodology



WellAged App or API Integration

A history of ML in insurtech: risk scoring using external data

External Data → Kick-out models → Auto Approval

External data availability determines useable models

Medical Data & Health Checkup Data
- Predict mortality
- Predict first diagnosis of critical illness incidence
- Predict hospitalization incidence and duration

Open Data
- Predict Smoker & Non-Smoker

Bank Data
- Predict credit-based mortality
- Predict UW acceptance

A history of ML in insurtech: RGA & Transunion Credit based Mortality

TransUnion × RGA

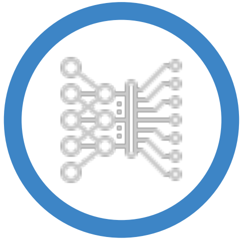
Developed the US TrueRisk Life Model

- Predicts credit-based mortality for life insurance
- Core model built on 40 million lives and over 3 million deaths
- Scores validated on 18 million lives
- Study shows 5 times segmentation (96-100 compared to 1-5)

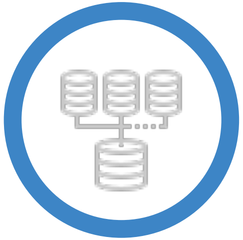
Source: 2018 SOA Predictive Analytics Seminar Presentation

All risk score model building behaves in a similar framework

Data source
Identify external data source from target country



Model training
Retrain models on localized data source



Validation dataset
Create validation dataset, representative of target population, to assess model

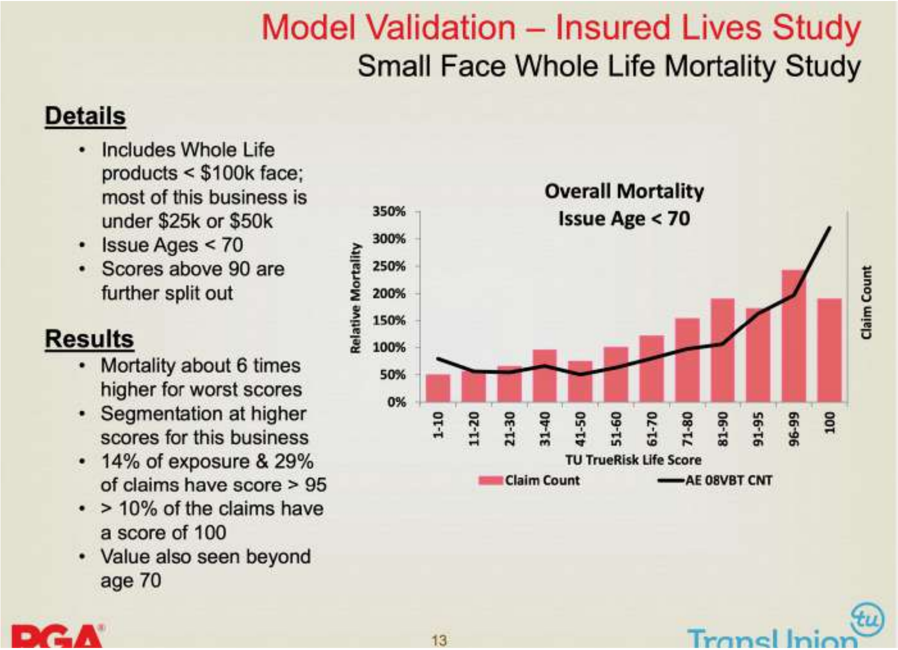
How does what we learn from the RGA credit-mortality score help us?

Risk scoring offers more granular risk segmentation

Risk scoring often indicates value even above age of insurability

Use cases from risk scoring include:

- Underwriting triage
- Cross-sell / upsell existing in-force
- Faster policy approvals
- Modifying UW rules

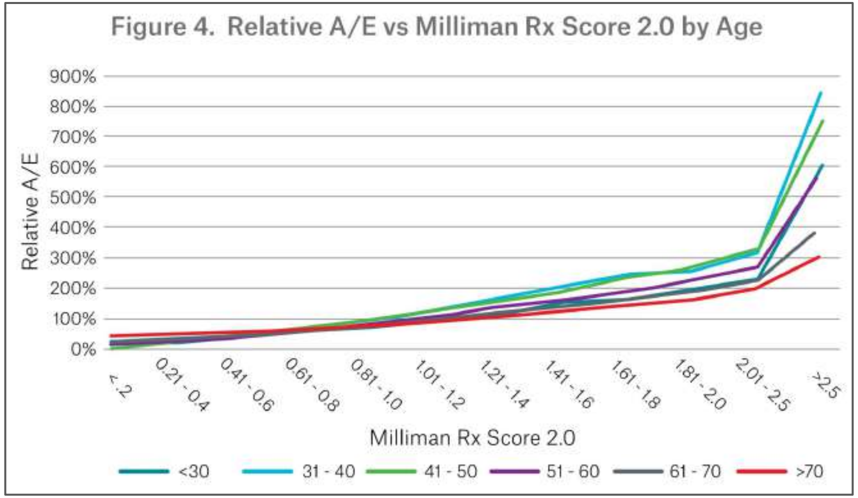


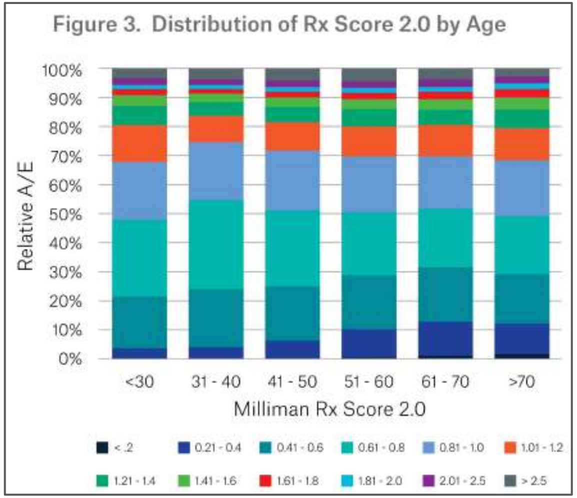
Multiple risk scores have been implemented by (re)insurers to focus specifically on pre-approvals, preferred kick-out, and UW relaxation in the US

	LexisNexis RISK SOLUTIONS	ExamOne A Quest Diagnostics Company	ExamOne A Quest Diagnostics Company	Milliman IntelliScript®
	Risk Classifier (LNRC)	**Clinical Lab Data**	**LabPiQture**	**Rx Score (Irix)**
Data Type	Credit score motor vehicle records public records	Historical lab test results	Three sub-scores: Prescription history, Lab test results, Diagnosis codes	Prescription data
Data Size	2.2M de-identified gen pop & insured 5 years, 51k deaths	83k insured lives, 7 years from FUW,	4.2M de-identified health data, 63k deaths	25m gen insured lives, 468k deaths, 104m exposure years
Validation	Munich RE, Gen Re, PartnerRe	Munich RE, Gen Re, RGA	Munich RE, Gen Re, hannover re	Munich RE

Milliman Rx Score (Irix) 2.0: Drug Data Only

Each life entered the study between the first quarter of 2005 and the last quarter of 2016. **Deaths were sourced from the Social Security Death Master File** and third party proprietary databases.
The study population is comprised of **468,491 deaths** out of **104 million exposed life-years.**
The expected mortality basis was taken from the **2015 VBT primary select** and ultimate ANB tables split by age and gender with a 1 percent mortality improvement





X-axis is Milliman Rx Score; lines are age buckets;
Y-axis is relative A/E

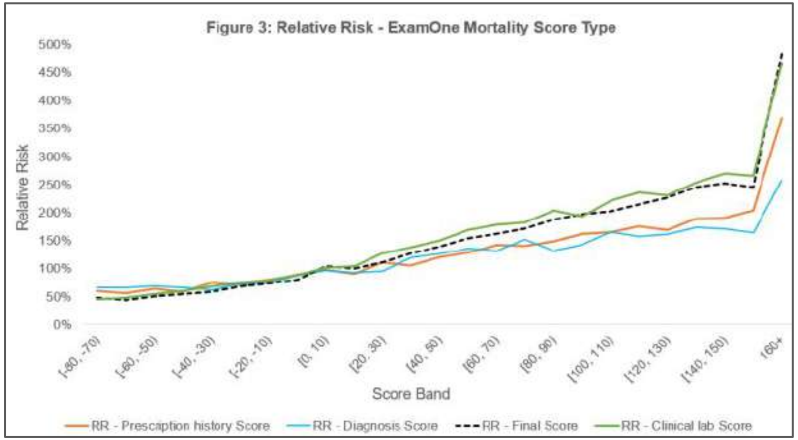
All age groups follow the same pattern, where mortality risk increases as Rx scores increase

X-axis is age group; y-axis is relative A/E. % of people with corresponding Milliman Rx Score 2.0

We see that the distribution of scores is about the same across age groups.

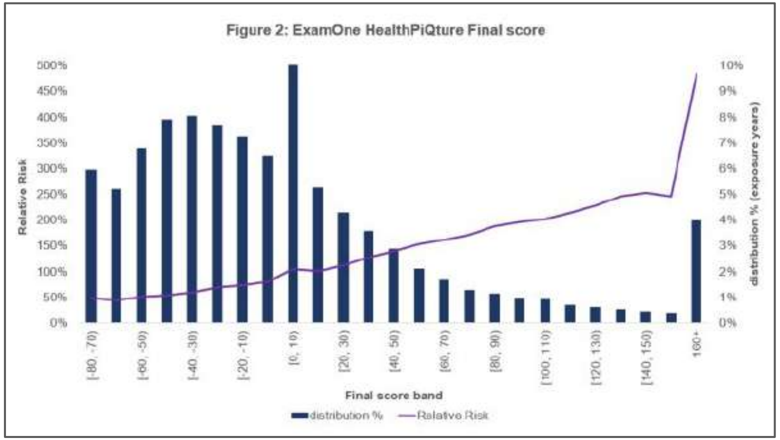
ExamOne LabPiQture: Clinical Lab Data with Medical Data

Munich Re performed a mortality study on a final, clean version of the ExamOne data set with 62,415 deaths. The expected basis was the Society of Actuaries (SOA) 2015 Select and Ultimate Valuation Basic Table (VBT) with mortality improvement from 2015 onwards and dis-improvement prior to 2015.



X-axis risk scoring bands, with lower bands = lower risk
Y-axis is risk of mortality relative to cohort; lines represent mortality trends between scores

Among the component scores, clinical lab scores are best at segmenting mortality followed by prescription history and diagnosis scores.

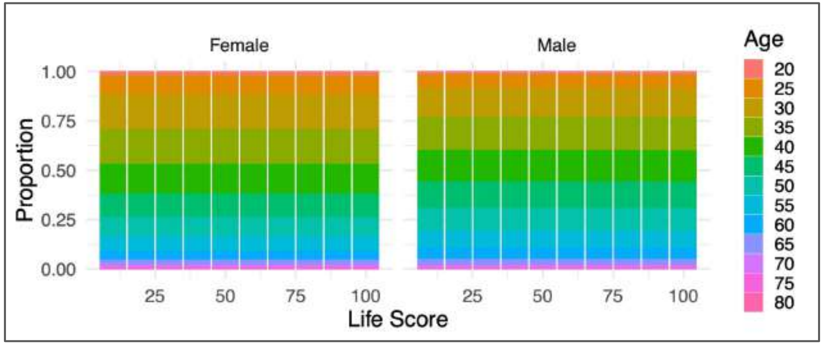


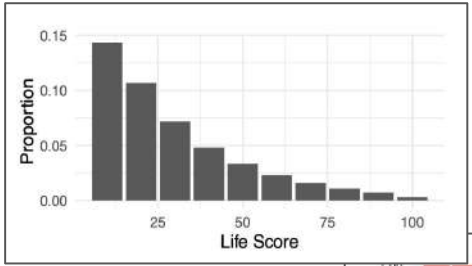
X-axis risk scoring bands, with lower bands = lower risks
Y-axis is risk of mortality relative to cohort.

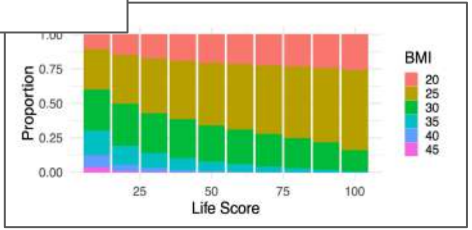
All age groups follow the same pattern, where mortality risk increases as final Score increases.

MassMutual LifeScore360: Commercial UW + Claims Input

MassMutual has a consolidated, digital record of nearly one million applications for which a lab test was ordered during 1999–2014. After removing applica tions with a high degree of missing values, typically incom- plete or withdrawn applications, this reduces to 908k records with 9.16M exposure years and 15.7k observed deaths.







X-axis risk scoring bands, with higher numbers = higher risk
Y-axis is proportion of population with corresponding age group

Among the component scores, clinical lab scores are best at segmenting mortality followed by prescription history and diagnosis scores.

X-axis risk scoring bands, with % of population with BMI from 20-to-45; Y-axis is proportion of people in each corresponding Life Score decile

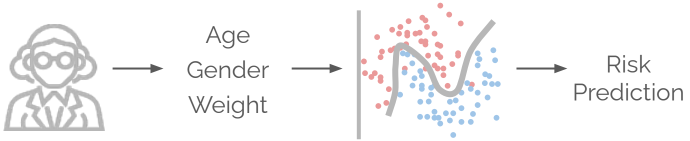
Top figure describes of heart condition as a function of life score. The gradually decreasing in between. Distribution of BMI as a function of life score. The highest scores have a greater proportion of healthy-range BMI. As the score decreases, the proportion of upper and lower BMI extremes gradually increases.

Methodological differences have moved from feature engineering to few shot or zero shot learning

New tools offer advantages when data is complex and labels are few.

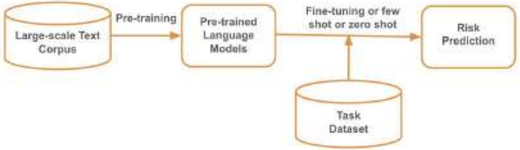
Traditional Machine Learning

Humans selected limited features to use for predictions



Pre-trained Language Models

Models automatically leverage extensive features for predictions



Challenges with existing tools

Dependency on
large labelled datasets

Data imbalance and
distribution issues

Complexity of feature engineering

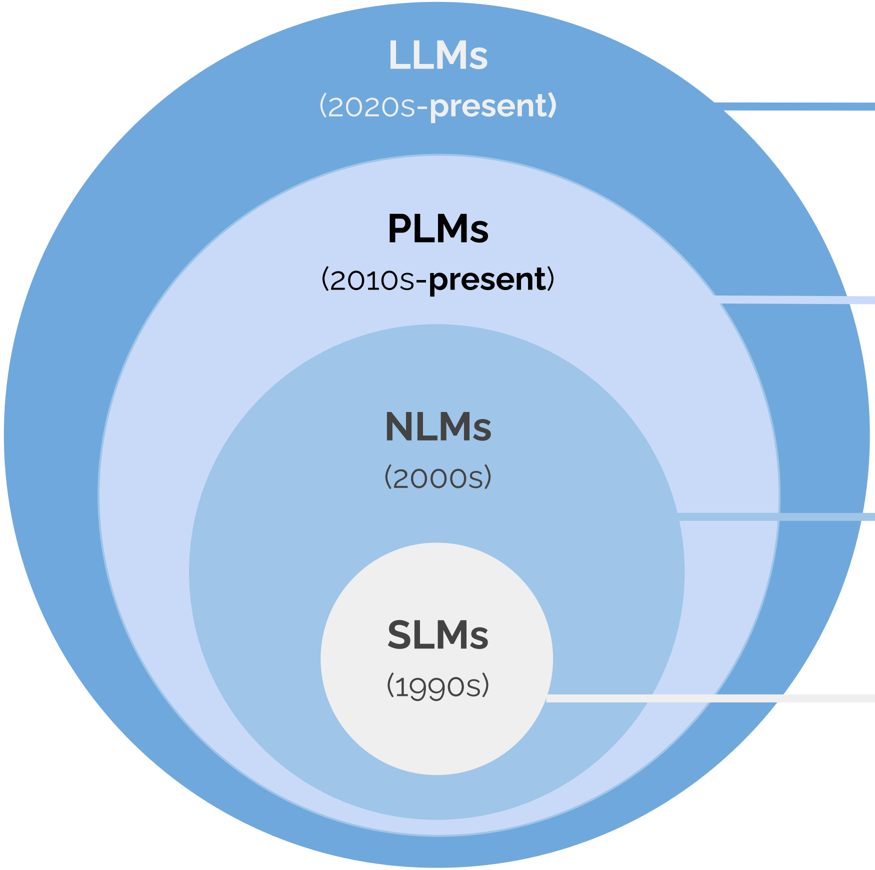
Solutions with new tools

Complex data
integration capabilities

Automated feature
extraction

Zero-shot and few-shot learning

AI/ML Methods have evolved significantly since the 90s



Large Language Models
GPT3, GPT4, PaLM

Pre-trained Language Models
ELMo, BERT, GPT2, BART, extending transformer architecture

Neural Language Models
word2vec, RNNs, contextualizing language and nuance

Statistical Language Models
n-gram models, information retrieval, natural language processing

Deep learning methods versus traditional methods to learn multiple levels of features

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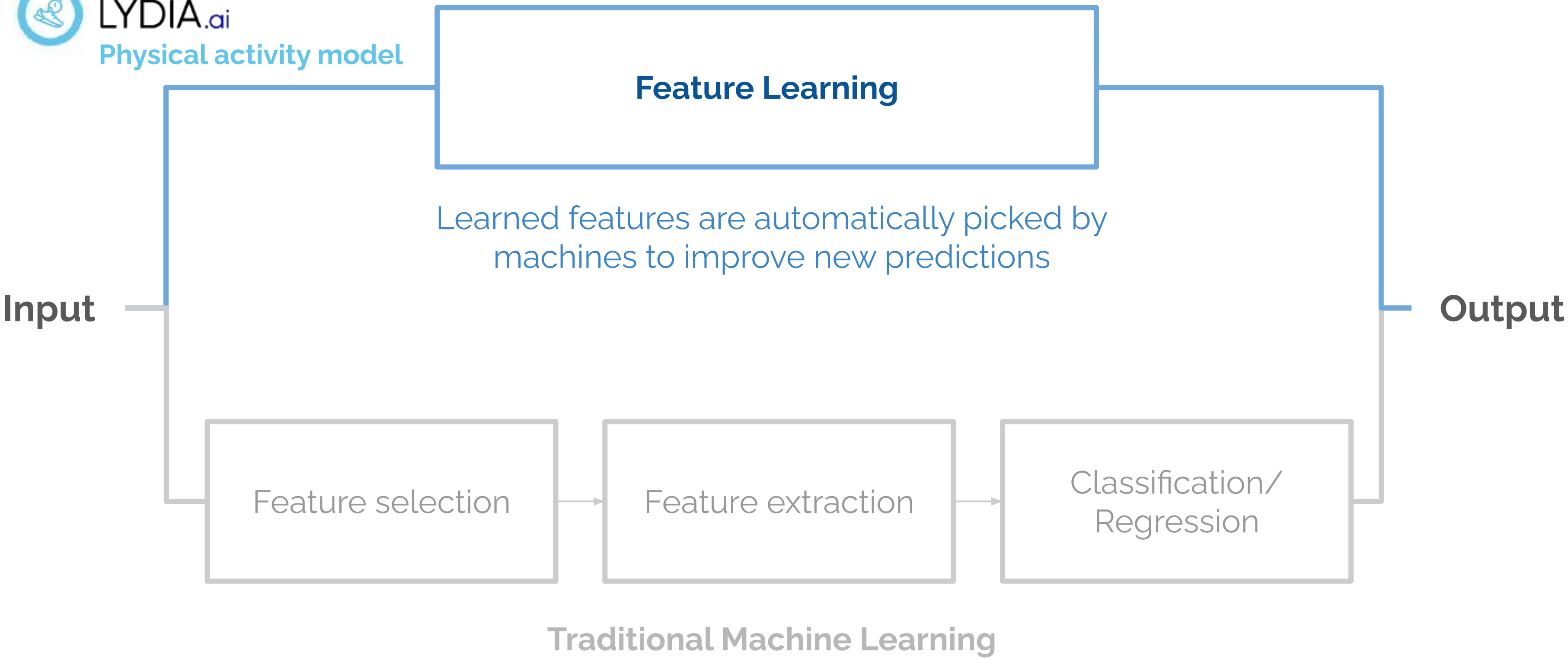
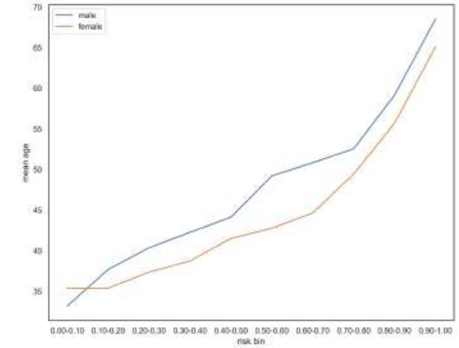
Physical activity model

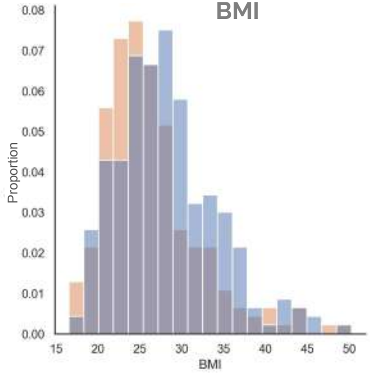


For example Lydia AI's activity score looks at activity data from Apple Health

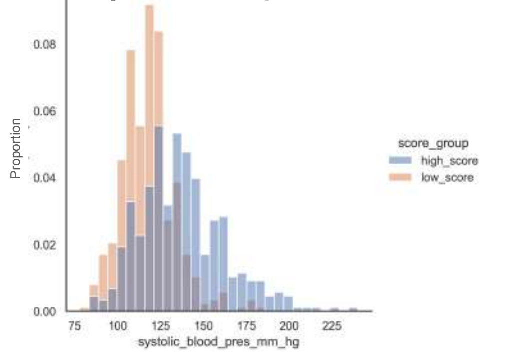
Correlation of health score to **age**



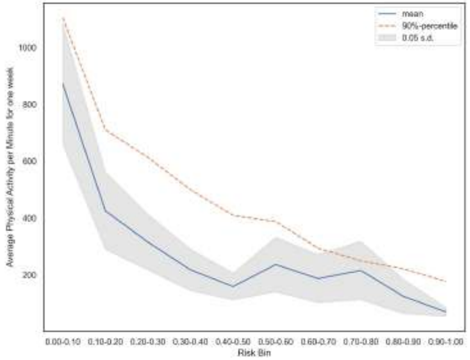
Correlation of health score to **BMI**



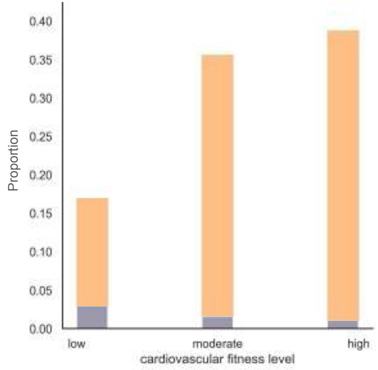
Correlation of health score to **systolic blood pressure**



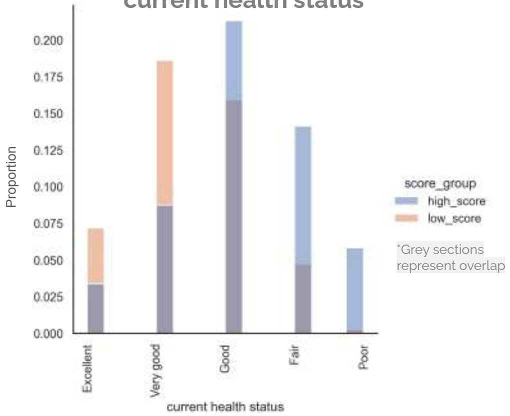
Correlation of health score to **avg physical activity**



Correlation of health score to **cardiovascular fitness**[1]



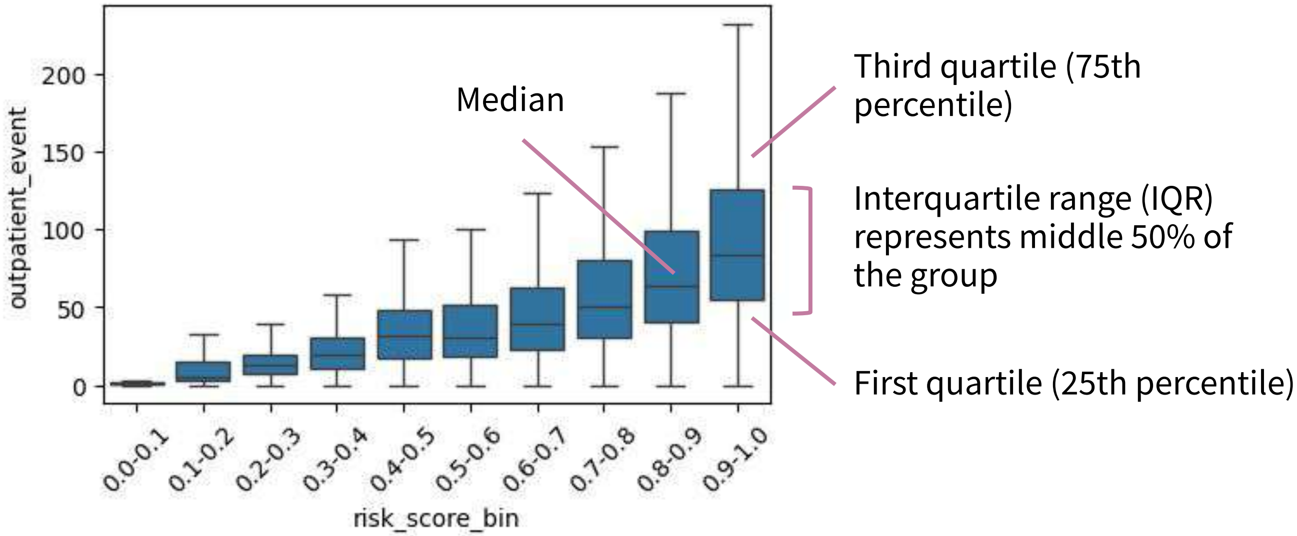
Correlation of health score to **current health status**



[1]Based on gender-age specific cut-points of maximal oxygen consumption (VO2 max) measurements

We maintain the tradition of grouping people by "deciles" and looking at correlations between "deciles" and clinical indices

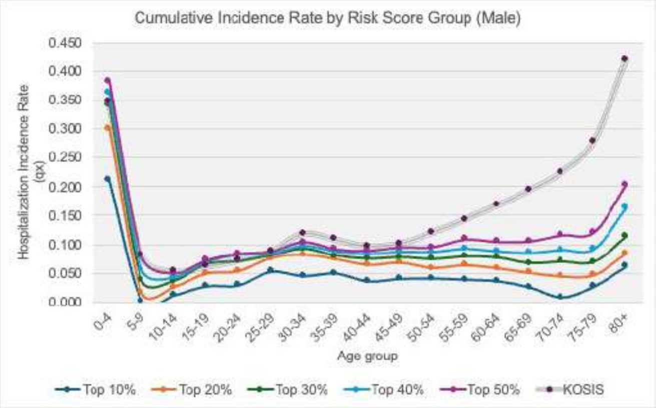
- **Box Plot and Interquartile Range (IQR)**



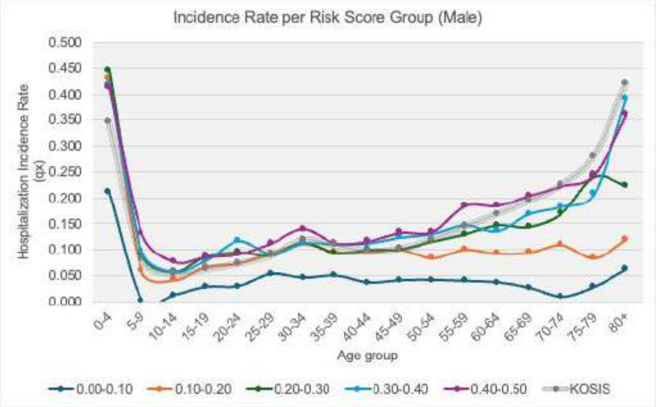
- **Sample Correlated Feature maybe "Diagnosis Code Count"**

  Total diagnosis counts (non-unique) across patient history, inclusive of primary diagnosis and secondary diagnosis codes

We can understand each decile by its respective incidence rates as benchmarked with industry or country incidences (i.e., mortality, hospitalization)



	Male Hospitalization rate (qx)									
Age	Top 10%	Top 20%	Top 30%	Top 40%	Top 50%	Top 60%	Top 70%	Top 80%	Top 90%	Top 100%
0-4	0.211	0.301	0.342	0.364	0.384	0.378	0.368	0.358	0.357	0.368
5-9	0.002	0.016	0.037	0.056	0.079	0.086	0.096	0.104	0.118	0.143
10-14	0.012	0.026	0.037	0.043	0.050	0.052	0.054	0.057	0.062	0.071
15-19	0.028	0.049	0.066	0.070	0.073	0.075	0.076	0.078	0.082	0.086
20-24	0.029	0.053	0.070	0.082	0.084	0.087	0.088	0.092	0.095	0.098
25-29	0.053	0.076	0.081	0.084	0.088	0.092	0.095	0.100	0.106	0.112
30-34	0.045	0.082	0.092	0.097	0.104	0.112	0.119	0.128	0.138	0.152
35-39	0.050	0.074	0.080	0.088	0.092	0.100	0.108	0.118	0.129	0.146
40-44	0.036	0.064	0.075	0.084	0.089	0.094	0.102	0.111	0.123	0.142
45-49	0.040	0.068	0.077	0.087	0.095	0.102	0.109	0.118	0.129	0.147
50-54	0.041	0.059	0.074	0.087	0.096	0.104	0.113	0.126	0.140	0.157
55-59	0.039	0.063	0.079	0.093	0.109	0.123	0.137	0.150	0.167	0.188
60-64	0.036	0.058	0.077	0.088	0.105	0.121	0.140	0.163	0.192	0.219
65-69	0.026	0.050	0.067	0.086	0.106	0.123	0.146	0.170	0.211	0.245
70-74	0.009	0.044	0.070	0.090	0.116	0.147	0.172	0.208	0.243	0.284
75-79	0.028	0.047	0.070	0.092	0.122	0.159	0.199	0.240	0.283	0.334
80+	0.062	0.084	0.114	0.163	0.204	0.238	0.281	0.331	0.384	0.443
Overall	0.039	0.065	0.078	0.088	0.098	0.107	0.118	0.132	0.150	0.173

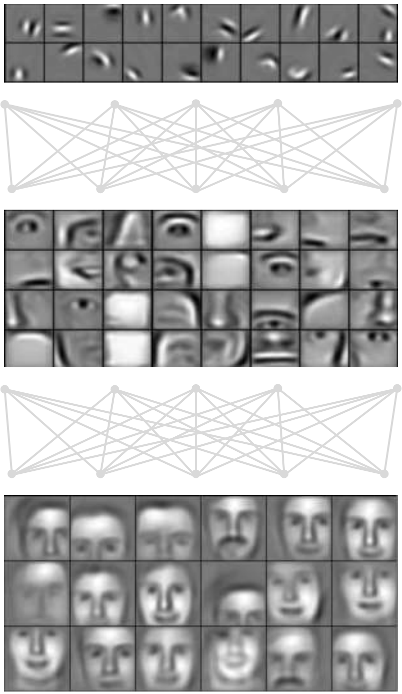


	Male Hospitalization rate (qx)									
Age	0.00-0.10	0.10-0.20	0.20-0.30	0.30-0.40	0.40-0.50	0.50-0.60	0.60-0.70	0.70-0.80	0.80-0.90	0.90-1.00
0-4	0.211	0.431	0.445	0.417	0.414	0.361	0.338	0.331	0.351	0.408
5-9	0.002	0.059	0.092	0.097	0.132	0.115	0.139	0.160	0.286	0.420
10-14	0.012	0.041	0.057	0.057	0.077	0.073	0.075	0.126	0.211	0.380
15-19	0.028	0.067	0.087	0.079	0.086	0.098	0.096	0.140	0.308	0.345
20-24	0.029	0.073	0.095	0.117	0.091	0.103	0.116	0.176	0.229	0.408
25-29	0.053	0.094	0.090	0.091	0.113	0.118	0.139	0.210	0.303	0.471
30-34	0.045	0.111	0.114	0.112	0.140	0.152	0.185	0.267	0.354	0.471
35-39	0.050	0.096	0.093	0.111	0.113	0.152	0.181	0.250	0.334	0.479
40-44	0.036	0.095	0.100	0.112	0.116	0.124	0.159	0.203	0.281	0.465
45-49	0.040	0.100	0.102	0.124	0.133	0.141	0.157	0.189	0.256	0.429
50-54	0.041	0.084	0.116	0.130	0.135	0.147	0.166	0.212	0.274	0.424
55-59	0.039	0.101	0.130	0.147	0.184	0.194	0.208	0.222	0.288	0.423
60-64	0.036	0.093	0.147	0.136	0.184	0.193	0.224	0.268	0.349	0.437
65-69	0.026	0.095	0.144	0.169	0.204	0.213	0.254	0.309	0.347	0.463
70-74	0.009	0.110	0.170	0.183	0.222	0.258	0.266	0.336	0.372	0.492
75-79	0.028	0.084	0.240	0.208	0.244	0.310	0.364	0.377	0.417	0.539
80+	0.062	0.120	0.223	0.393	0.359	0.393	0.415	0.476	0.541	0.624
Overall	0.039	0.095	0.109	0.120	0.143	0.160	0.193	0.249	0.323	0.456

We see further complexity in ML models that deal with edge cases and large evolving data patterns

Facial Recognition Example

Lee H, Grosse R, Ranganath R, Ng AY. Unsupervised learning of hierarchical representations with convolutional deep belief networks.

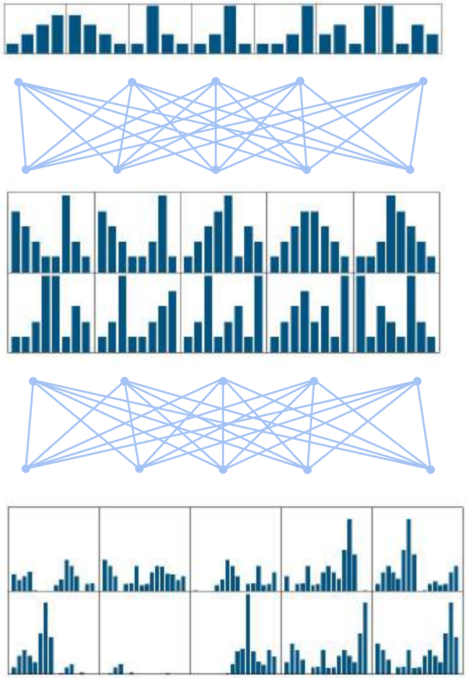


Raw image details – edges, blobs, contrasting lines, …

Face parts – noses, eyes, eyebrows, ears, cheeks, …

Face models – translation invariant face archetypes

Lydia AI Uses 1-D Convolutional Neural Network

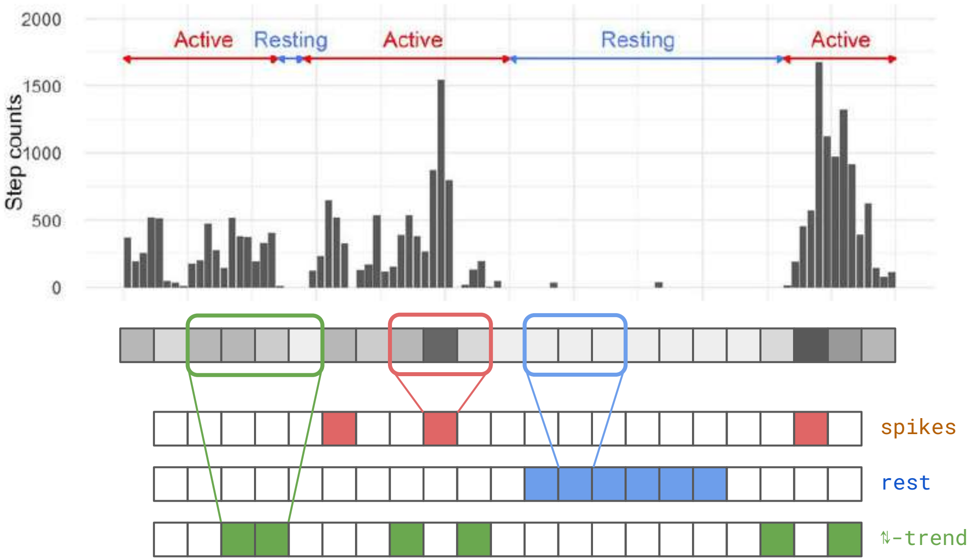


Local features – trends, spikes, waves, etc.

Mid-range patterns – combinations of local features that are useful for the predictive task at hand

Long range patterns – signal patterns that occur on longer time scales and whose presence or absence allows the model to come to a decision

Local features are found in activity signals when looking at steps, as opposed to being pre-engineered as rules by bioinformaticians



Actual step counts per 15 minutes in 24 hours sampling frequency

Visual representation sampled down to hourly frequency (more steps =darker color)

Visual representation of 3 local features in hourly signal: spikes, rests and ⇅-trends

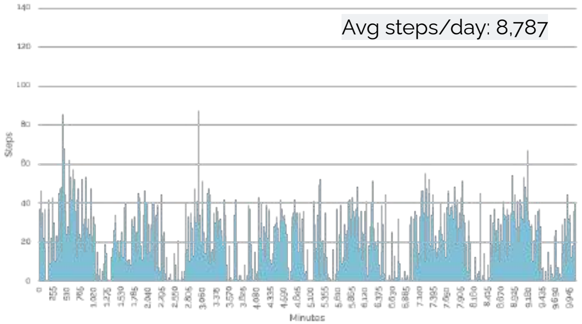
Over 30,000+

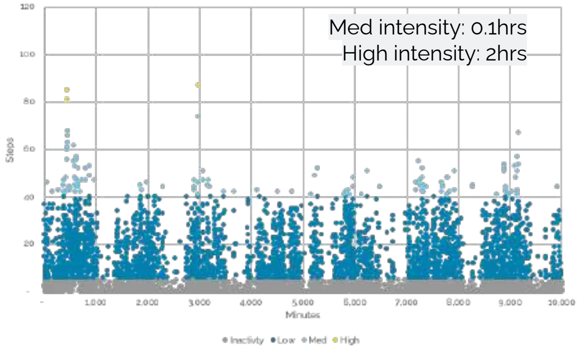
dimensions of features

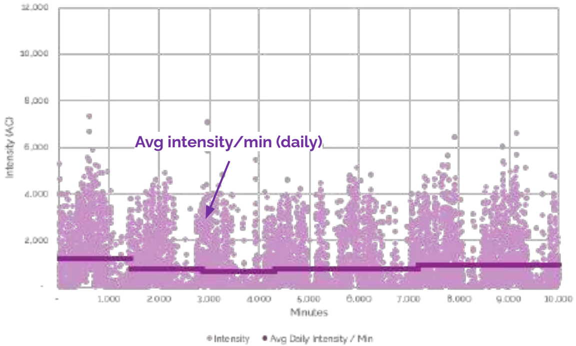
Sample #66123

Age: 29 | Gender: Female

Physical Activity and Movement Intensity
(Model inputs)







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Activity Score
0.90-1.00

Low score = Low risk; High score = High risk

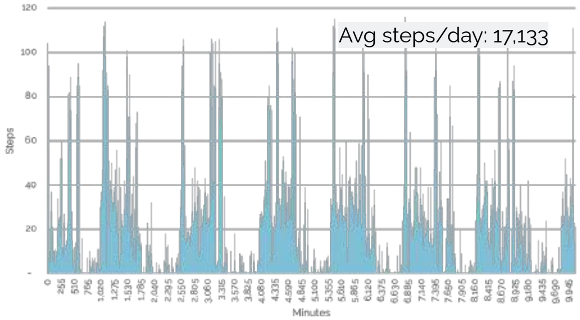
Health Profile Information
(Non-model inputs)

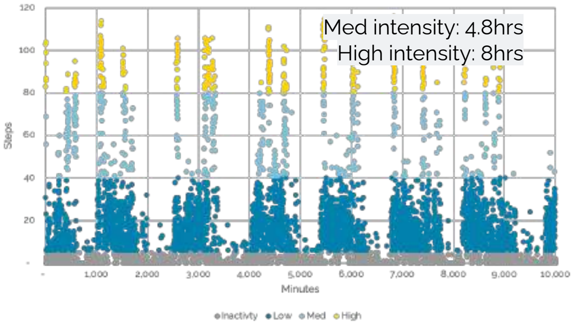
Medical conditions & prior treatments (Questionnaire)	Asthma, Overweight, Arthritis; Chronic Bronchitis
Prescription drugs	ALBUTEROL, ALBUTEROL; IPRATROPIUM, ALPRAZOLAM, FLUTICASONE; SALMETEROL, METHYLPHENIDATE, MONTELUKAST, OMEPRAZOLE, OXYCODONE, QUETIAPINE
Blood pressure measurements	Systolic blood pressure: 120 mm Hg Diastolic blood pressure: 6 mm Hg
BMI	45.9
Height / Weight	165.6cm / 126kg
Alcohol usage	NA
Smoking status	Smoker / ~16 cigarettes over past 30 days
Lab test measurements	See attached data

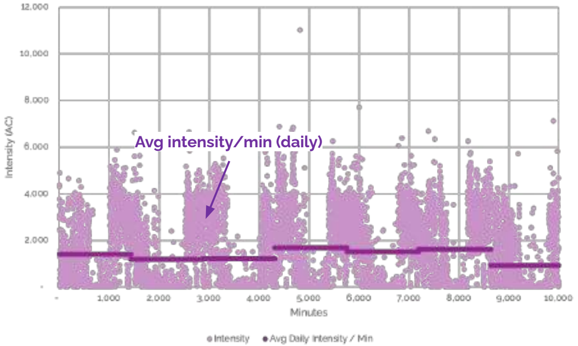
Sample #67032

Age: 32 | Gender: Female

Physical Activity and Movement Intensity
(Model inputs)







LYDIA.ai

Activity Score
0.00-0.10

Low score = Low risk; High score = High risk

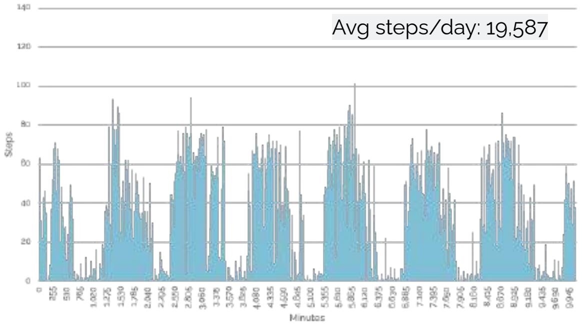
Health Profile Information
(Non-model inputs)

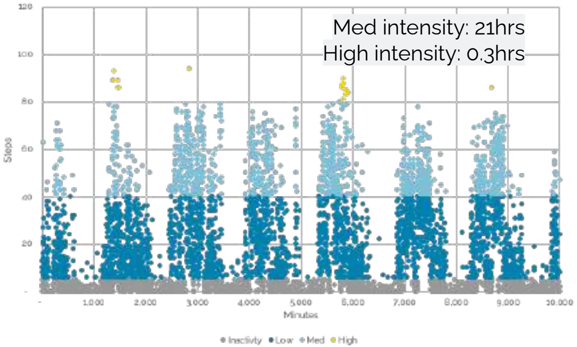
Medical conditions & prior treatments (Questionnaire)	No declared prior medical conditions (incl. no cardiovascular issues or chronic illnesses)
Prescription drugs	NA
Blood pressure measurements	Systolic blood pressure: 100 mm Hg Diastolic blood pressure: 54 mm Hg
BMI	21.1
Height / Weight	160.1cm / 54kg
Alcohol usage	None over past 12 months
Smoking status	Non-smoker
Lab test measurements	See attached data

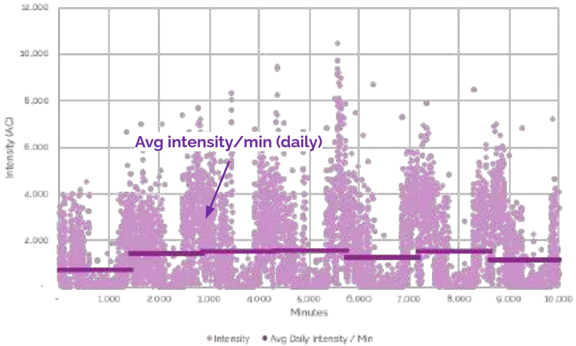
Sample #63753

Age: 33 | Gender: Male

Physical Activity and Movement Intensity
(Model inputs)







LYDIA.ai

Activity Score
0.20-0.30

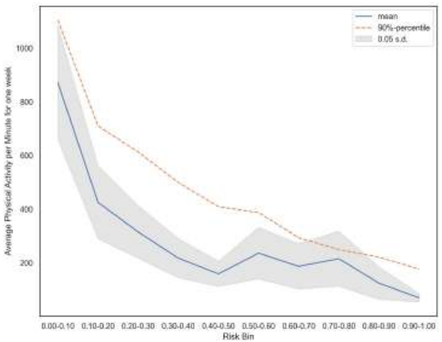
Low score = Low risk; High score = High risk

Health Profile Information
(Non-model inputs)

Medical conditions & prior treatments (Questionnaire)	No declared prior medical conditions (incl. no cardiovascular issues or chronic illnesses)
Prescription drugs	NA
Blood pressure measurements	Systolic blood pressure: 116 mm Hg Diastolic blood pressure: 62 mm Hg
BMI	26
Height / Weight	165.4cm / 71kg
Alcohol usage	~1 times over past 12 months
Smoking status	Non-smoker
Lab test measurements	See attached data

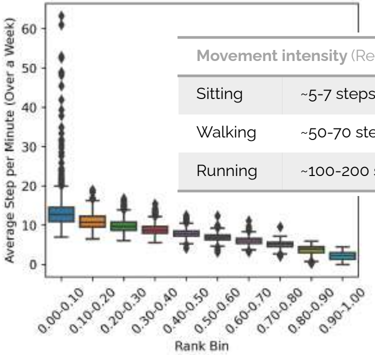
We now understand average number of steps, intensity of activity and consistency in activity pattern are all key factors in affecting the physical activity score

Average physical activity



On average, the higher average steps over a 7-day period will likely result in a better score

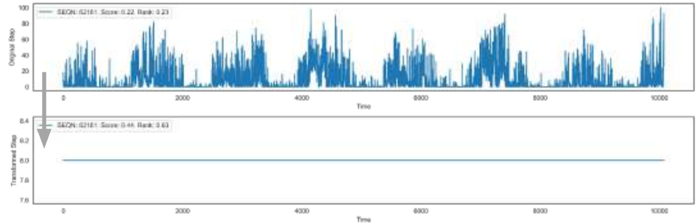
Intensity of activity

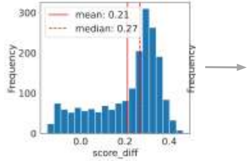


Movement intensity (Reference)	
Sitting	~5-7 steps per minute
Walking	~50-70 steps per minute
Running	~100-200 steps per minute

Higher average intensity of activity (steps per min), will likely result in a better score

Consistent movement in activity pattern



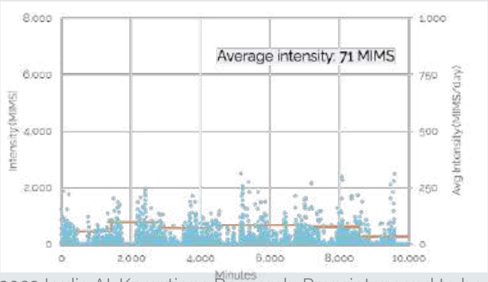


When replacing an individual's steps by their weekly average (i.e. removing all patterns), the score is poorer on average by 0.21

Consistent patterns that show trends of high vs. low activity will likely result in a better score

Case study

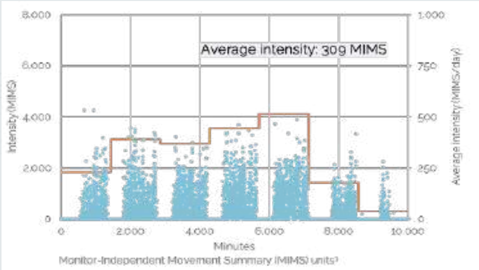
Score bin: **0.90 – 1.00**



- Lower number of steps per week
- Lower average intensity of activity
- Lower range of movement pattern

Case study

Score bin: **0.00 – 0.10**



- Lower number of steps per week
- Lower average intensity of activity
- Lower range of movement pattern

We can even zero in on specific user segments to focus on life-stage specific needs

Japanese women from teens to 20s: Correlation between activity and PMS

Journal: BMC Sports Sci Med Rehabil. 2022; 14: 175.

Result Highlights:

- A survey of 381 Japanese female university students (average age 20.44) found that those who engaged in **more than 3,000 MET minutes of physical activity per week had lower overall PMS symptom scores, including lower physical and psychological symptoms**, compared to those with less activity.

***3,000 MET minutes per week is equivalent to about 60 minutes of walking and 30 minutes of jogging per day, indicating moderate exercise levels.**

$$Walking\ MET - \frac{minutes}{week} = 3.3 * walking\ minutes * walking\ days$$

$$Moderate\ MET - \frac{minutes}{week} = 4.0 * moderate - intensity\ activity\ minutes * moderate - intensity\ days$$

$$Vigorous\ MET - \frac{min}{week} = 8.0 * vigorous - intensity\ activity\ minutes * vigorous - intensity\ days$$

$$Total\ physical\ activity\ MET - minutes/week = sum\ of\ walking + moderate + vigorous\ MET - minutes/weekscores$$

We can even zero in on specific user segments to focus on life-stage specific needs

Women in their 20s to 30s: Correlation between Activity and Sleep

Journal: Front. Public Health, 03 November 2022

Result Highlights:

Physical Activity

- **Moderate exercise** has a positive effect on reproductive health, while excessive exercise may negatively impact the menstrual cycle.
- **Lack of exercise** can lead to obesity, increasing the risk of polycystic ovary syndrome (PCOS).
- **Excessive exercise** can disrupt the hypothalamus-pituitary-gonadal axis (HPT axis), affecting hormone balance and sperm quality.
- **Sleep deprivation** can raise thyroid-stimulating hormone (TSH) levels, potentially causing irregular or absent menstruation.
- **Short sleep duration** in men is linked to reduced sperm quality and an increase in anti-sperm antibodies, which can damage healthy sperm.

Sleep

Sleep deprivation can increase thyroid-stimulating hormone (TSH) levels, potentially causing irregular menstruation or amenorrhea.

In men, **shorter sleep duration is associated with reduced semen quality.** Studies have found that men who sleep less tend to have poorer sperm quality, and an increase in anti-sperm antibodies. These antibodies can damage healthy sperm, potentially leading to a decline in sperm quality.

We can even zero in on specific user segments to focus on life-stage specific needs

Women in their 30s to 40s: Correlation between activity and peri-pregnancy or postpartum depression

Journal: [Journal of Affective Disorders 246 (2019)]

Result Highlights:

- Average participant age: 33.3 years (±2.9 years).
- **Effects of Exercise During Pregnancy**: Physical activity during pregnancy has been suggested to prevent postpartum depression and is also beneficial for managing depression symptoms during pregnancy.
- **Effects of Exercise Postpartum**: Physical activity after childbirth has been shown to help in both preventing and treating postpartum depression.
- **Recommended Exercise:** Moderate-intensity exercise for 30 minutes or more, 1 to 4 times a week, is recommended to reduce the risk of postpartum depression.

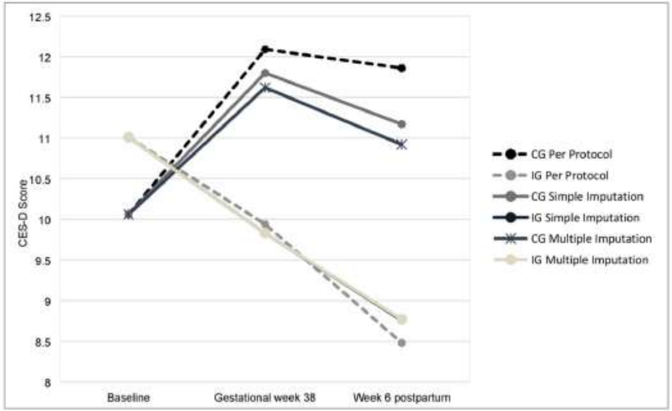


Figure 2 CES-D score at the three time points. CESD-D, Center for Epidemiological Studies-Depression Scale; CG, control group; IG, intervention group.

We can even zero in on specific user segments to focus on life-stage specific needs

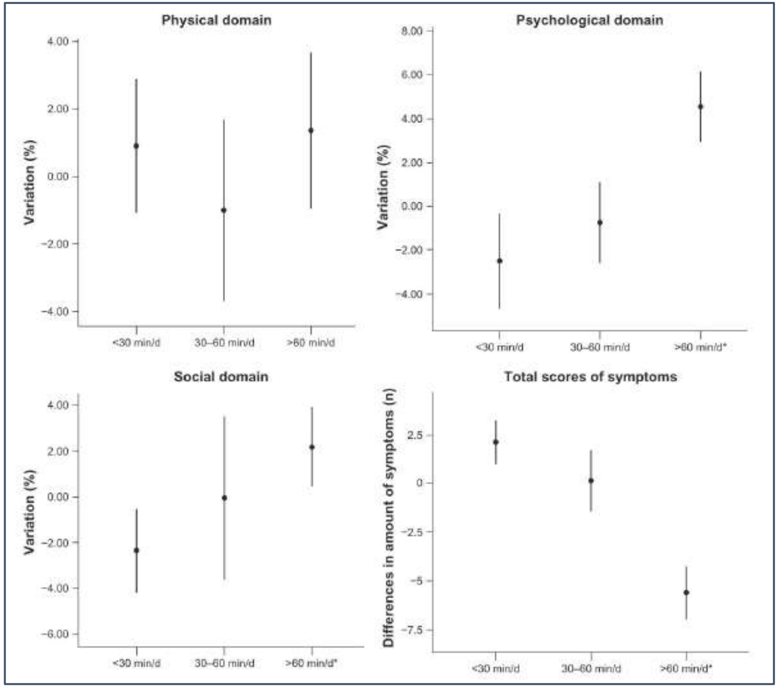
Women in their 40s and 50s: menopause and postmenopause

Journal: [International Journal of Women's Health]

Result Highlights:

Participants were divided into three groups for comparison:
Group A: Less than 30 minutes of physical activity per day.
Group B: 30 to 60 minutes of physical activity per day.
roup C: More than 60 minutes of physical activity per day.

Results showed that more than 60 minutes of moderate-intensity physical activity per day led to significant effects, including:
Reduction in menopausal symptoms.
Improved quality of life, particularly in psychological and social aspects.
Decreased menopausal symptoms correlated with potential weight loss benefits.

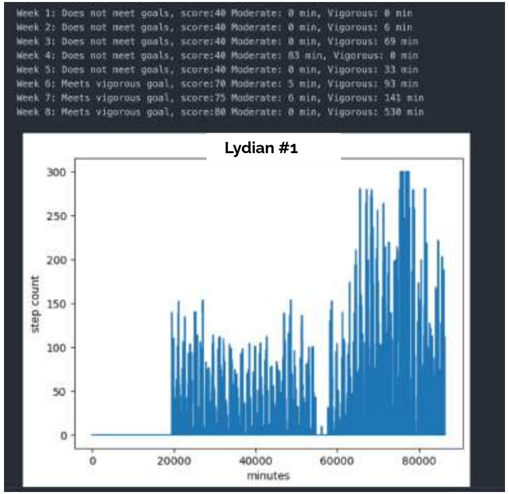


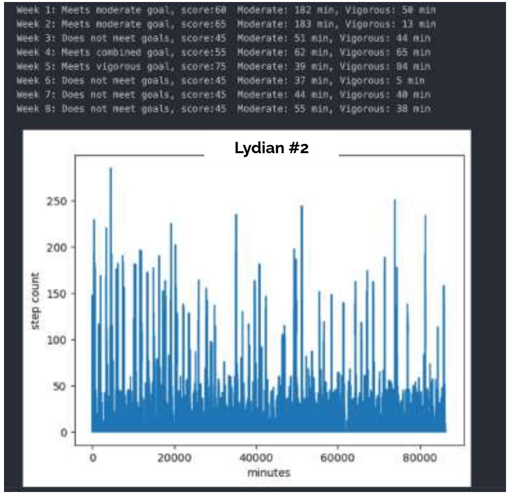
The fun part of operating a health AI is forcing everyone to exercise to see real-world results

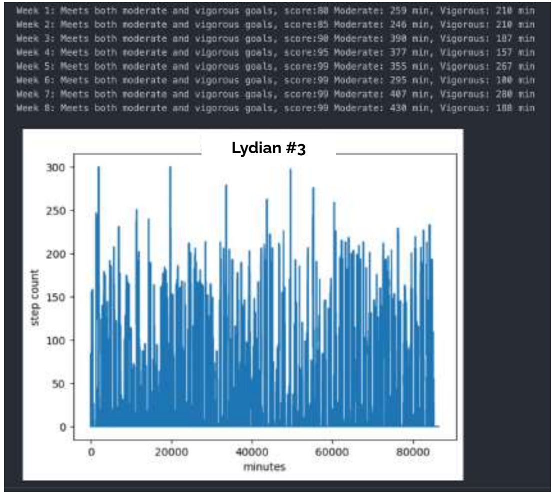
Scoring is based on activity consistency and changes:

- Maintaining the same activity level results in a 5-point increase.
- Moving up to a higher level of activity results in a 10-point increase per level.
- Decreasing the activity level results in a 10-point deduction.

The default score is set at 40, with a minimum of 0 and maximum of 99.







Risk scoring and activity goals and collected data show strong correlation over time *(p<0.001)*

Scoring is based on activity consistency and changes:

- Maintaining the same activity level results in a 5-point increase.
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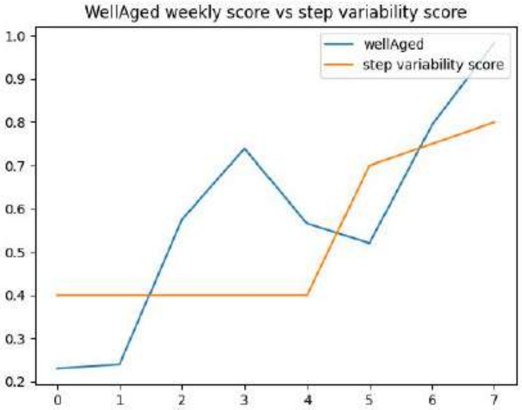
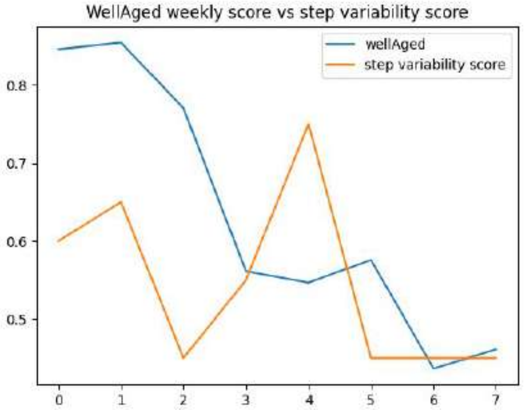
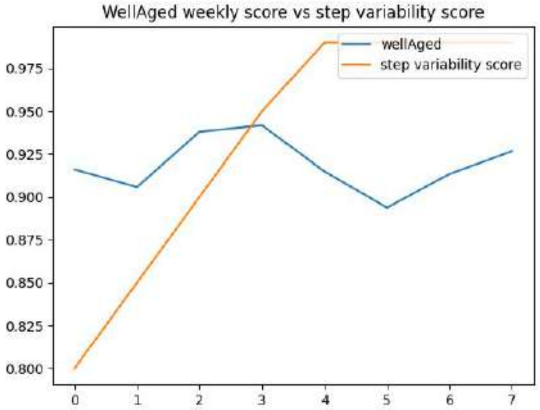
- Decreasing the activity level results in a 10-point deduction.

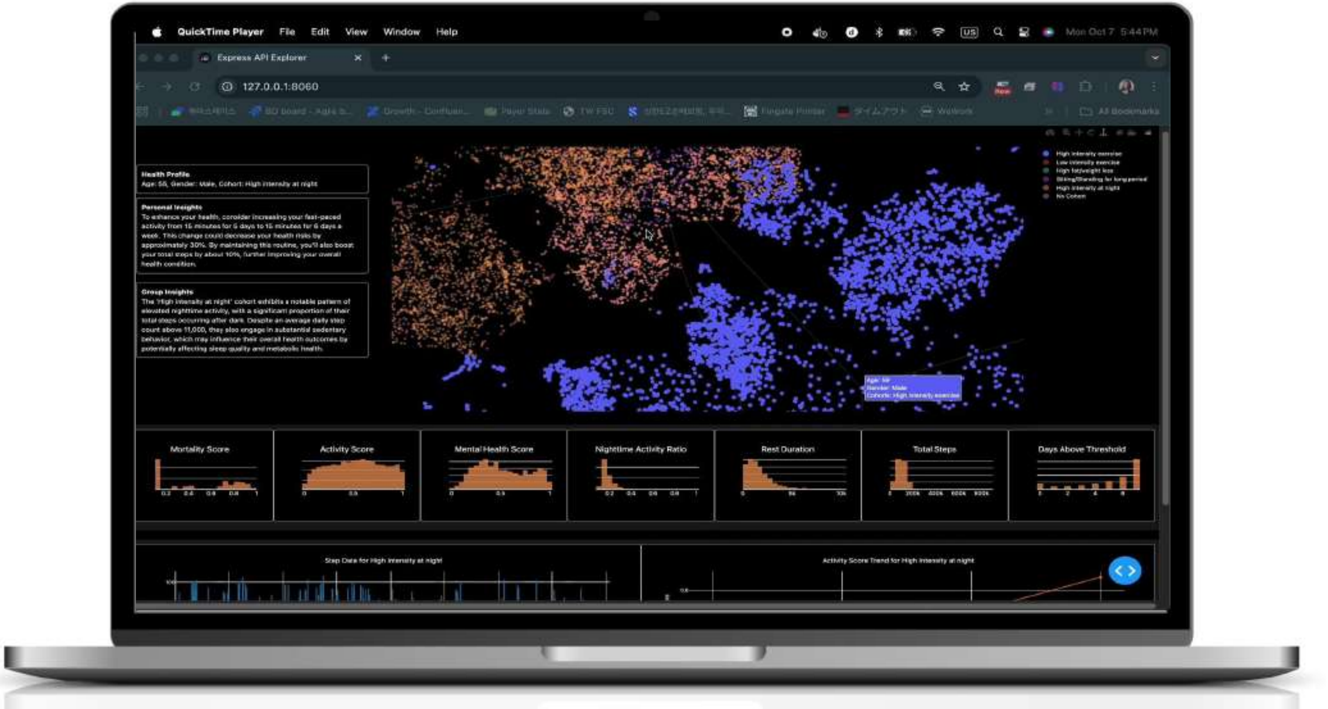
The default score is set at 40, with a minimum of 0 and maximum of 99.







Understanding how to make customers healthier through data will be one of the tasks for health actuaries in the next three years



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Summary

- **The Future of Risk Assessment:**
  - A shift towards personalization and real-time analytics driven by advanced ML/AI techniques.
  - Integration of non-traditional data opens new avenues for understanding and mitigating risks.
- **Ethical and Collaborative Approach:**
  - Emphasis on data privacy, security, and ethical use of AI.
  - Building partnerships within the industry to enhance collective capabilities.
- **Our Call to Action:**
  - Encourage stakeholders to embrace innovative technologies and collaborative efforts.
  - **Explore opportunities to integrate causal inference methodologies for deeper insights**.

Setting the stage for causal inference in risk assessment

- **The Importance of Understanding Causality:**
  - Recognizing not just correlations but causal relationships enhances risk assessment accuracy.
  - Facilitates the design of effective interventions and personalized strategies.
- **Complementing Our Approach:**
  - While Lydia AI focuses on predictive analytics using non-traditional data, understanding causality adds depth to our insights.
  - Collaboration with experts in causal inference can lead to more robust risk models.
- **Introduction to Upcoming Topics:**
  - The next presentation by **Kaz from Sumitomo Life Insurance** will delve into ***causal inference methods***.
  - Discussions will cover foundational concepts, removal of biases, and practical applications in life insurance.
- **Working Collaboratively:**
  - Shared goals in leveraging data and technology for better risk assessment
  - Developing a new generation of wellness programs and personalized insurance solutions **not just about giving discounts** but about rewarding current health discipline, incentivizing healthy and responsible behavior, and helping high-risk indviduals plan better