Artificial Intelligence and the Future of Universities

Dimitris Bertsimas

MIT

Special Thanks to My Doctoral Students Who have taught me at least as much as I taught them

Leonard Boussioux

Wes Gurnee

Yu Ma

Irra Na

Kimberly Villalobos Carballo

Cynthia Zheng

Agenda

- Motivation
- Holistic AI for Medicine (HAIM)
- HAIM in action
- Holistic AI for Hurricanes
- Implications to the future of Universities
- Implications to the future of OR
- A research and Education agenda for the future

Some observations from Medicine

- **Let us think how medical doctors make decisions**
- **They utilize:**

  scans (MRIs, CTs, Xrays, etc.)

  language (radiology reports, doctors and nurses notes)

  tabular data (electronic medical records)

  time series,   genomic information

- **Can machines use multi-modal data to make medical diagnoses and decisions?**

Some observations from Agriculture

- **Let us think what data is available**

    Images (Google earth)

    Meteorological data (temperature, rain, pressure, etc.)

    Earth related data (ground, crops, etc.)

    Yield data

- **Can machines use multi-modal data to make better decisions on what crops, at what time with what fertilizers and antibiotics?**

Some reflections on Climate Change

- **How do we predict the direction and magnitude and hurricanes?**
- PDE models of the physical dynamics developed over the last 100+ years
- What data is available?

  Images (pictures of hurricanes)

  Physical data (temperature, rain, pressure, etc.)

  Language (global warming articles, books, etc.

- **Can machines use multi-modal data to make better predictions on the magnitude and direction of hurricanes?**

A Human-centric Analogy

- The five basic human senses:

  touch, sight, hearing, smell and taste

- Multi-modality is a fundamental characteristic of human Life

- Why not for Machines?

HAIM
Holistic Artificial Intelligence for Medicine

Integrated multimodal artificial intelligence framework for healthcare applications

Luis R. Soenksen, Yu Ma, Cynthia Zeng, Leonard D.J. Boussioux,

Kimberly Villalobos Carballo, Liangyuan Na, Holly M. Wiberg,

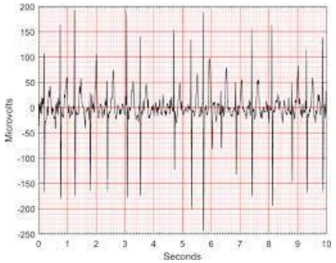
Michael L. Li, Ignacio Fuentes, Dimitris Bertsimas

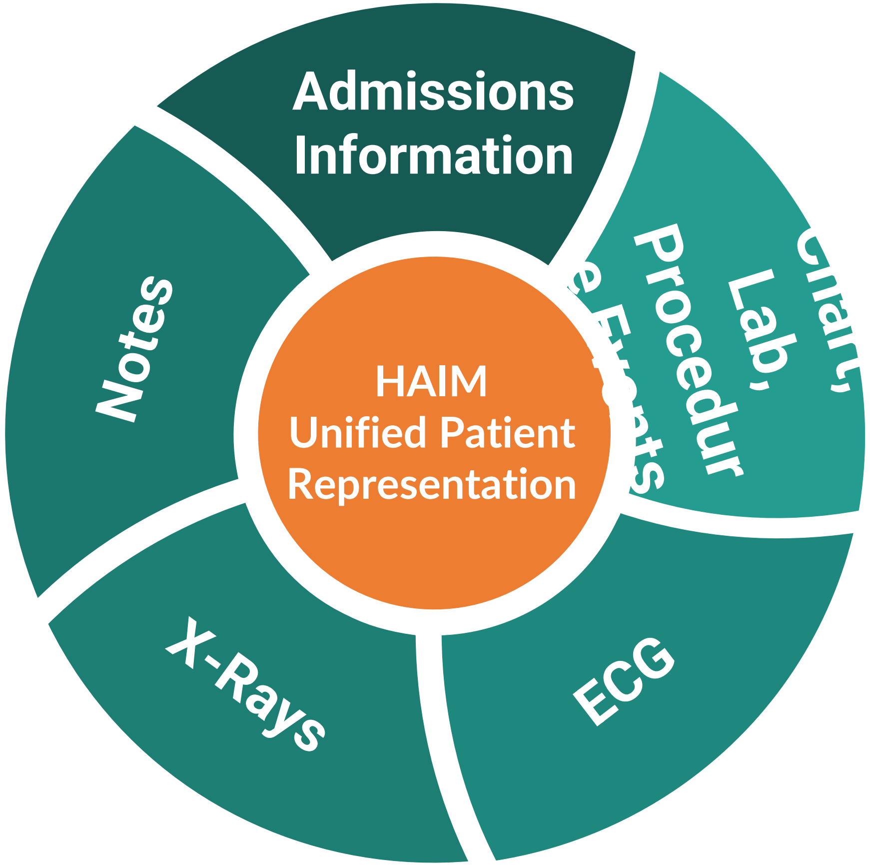
Nature Digital Medicine, September 2022.

The vision of HAIM

- The Story of IBM Watson
- Can we use a holistic perspective of AI (computer vision, NLP, ML) to improve the ability of models to make predictions and prescriptions in Medicine?

How to combine different modalities of data?

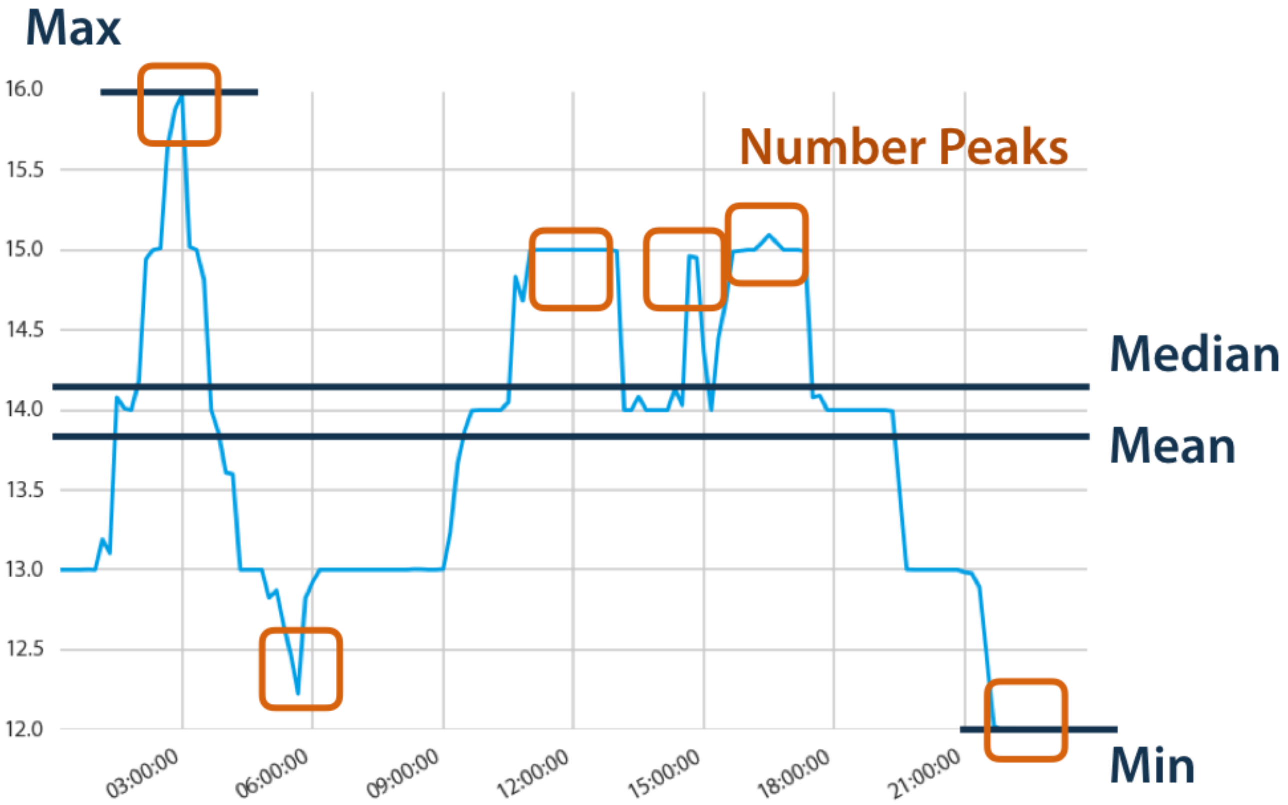




Structured (Tabular) EHR Data

charttime	storetime	itemid	value	valuenum	valueuom	warning	label	abbreviation	linksto	category	unitname	param_type
2167-11-07 20:00:00	2167-11-07 20:35:00	220045.0	57	57.0	bpm	0.0	Heart Rate	HR	chartevents	Routine Vital Signs	bpm	Numeric
2167-11-07 20:00:00	2167-11-07 20:29:00	220046.0	120	120.0	bpm	0.0	Heart rate Alarm - High	HR Alarm - High	chartevents	Alarms	bpm	Numeric
2167-11-07 20:00:00	2167-11-07 20:29:00	220047.0	50	50.0	bpm	0.0	Heart Rate Alarm - Low	HR Alarm - Low	chartevents	Alarms	bpm	Numeric
2167-11-07 20:00:00	2167-11-07 20:35:00	220210.0	19	19.0	insp/min	0.0	Respiratory Rate	RR	chartevents	Respiratory	insp/min	Numeric
2167-11-07 20:00:00	2167-11-07 20:35:00	220277.0	98	98.0	%	0.0	O2 saturation pulseoxymetry	SpO2	chartevents	Respiratory	%	Numeric
...	...	...	...	...	...	...	...	...	...	...	...	...

Time Series


Max
Number Peaks
Median
Mean
Min
16.0
15.5
15.0
14.5
14.0
13.5
13.0
12.5
12.0
03:00:00
06:00:00
09:00:00
12:00:00
15:00:00
18:00:00
21:00:00

Extract unstructured text using ClinicalBERT

Time	Sample Event Strings
Day 1	'Education Readiness/Motivation: High’
Day 1	'Troponin T: 0.13 ng/mL, Warning: outside normal'
Day 2	'Respiratory Rate: 23 insp/min'
Day 3	'Platelet Count: 217 K/luL’

Patient Summary:
Education Readiness/Motivation: High. Troponin T: 0.13 ng/mL, Warning: outside normal. Respiratory Rate: 23 insp/min. Platelet Count: 217 K/luL.

BioBERT embedding (768-element vector)

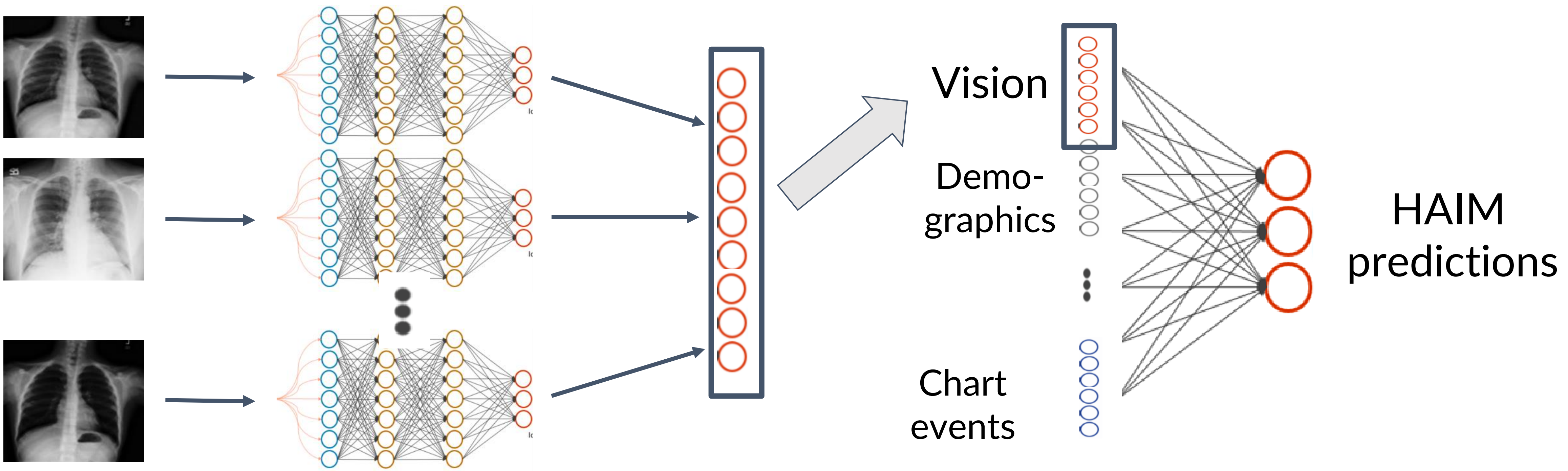
Extract unstructured text using ClinicalBERT from ECG

ECGs

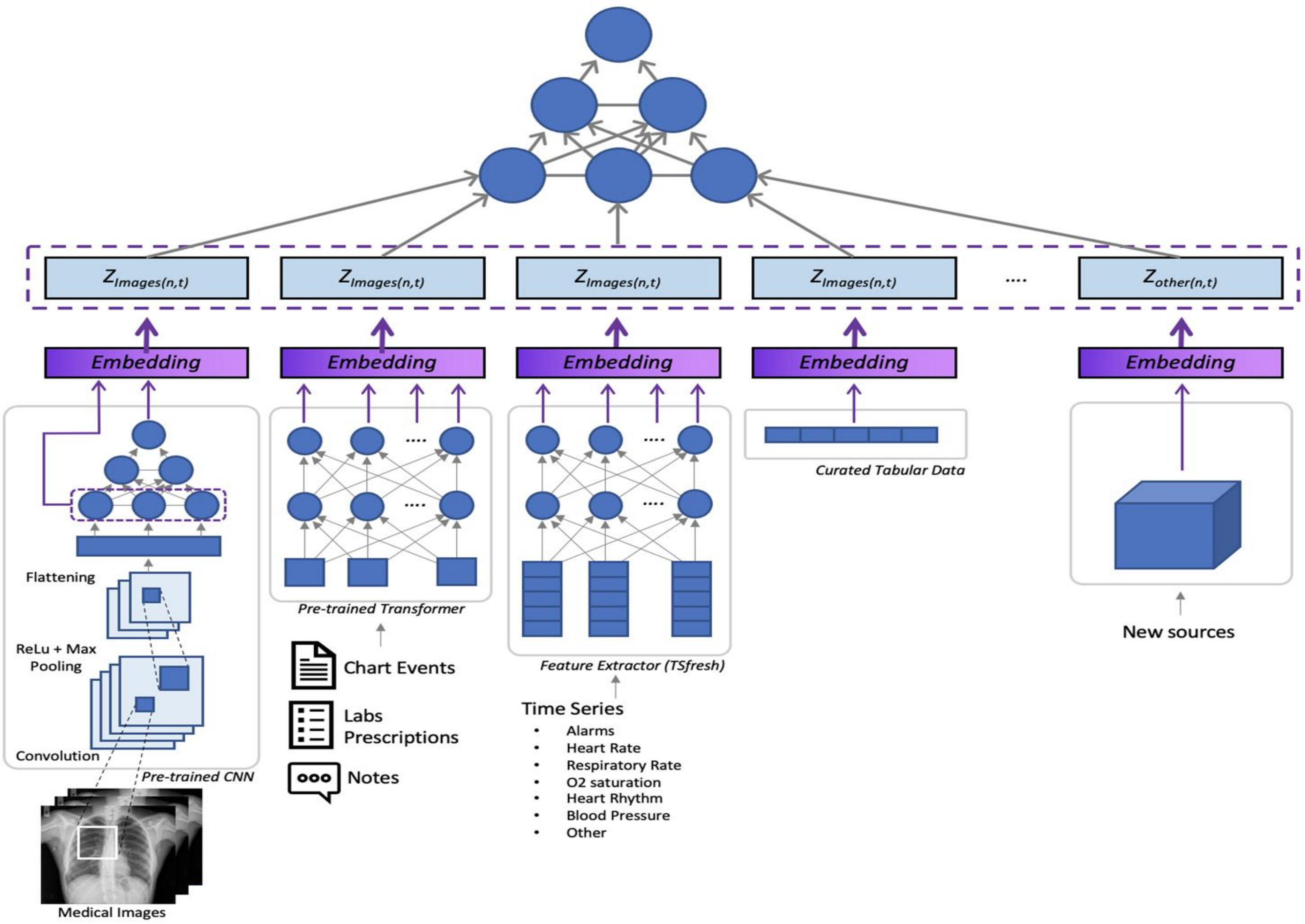
Clinical indication for ECG: I51.9 - Ill-defined symptoms of heart disease. Regular supraventricular tachycardia, most likely sinus tachycardia. Non-specific intraventricular conduction delay. Diffuse non-specific ST-T wave abnormalities. Compared to tracing #1 sinus tachycardia has replaced sinus rhythm with frequent premature atrial contractions and premature ventricular contractions.

→ **BioBERT embedding (768-element vector)**

Images

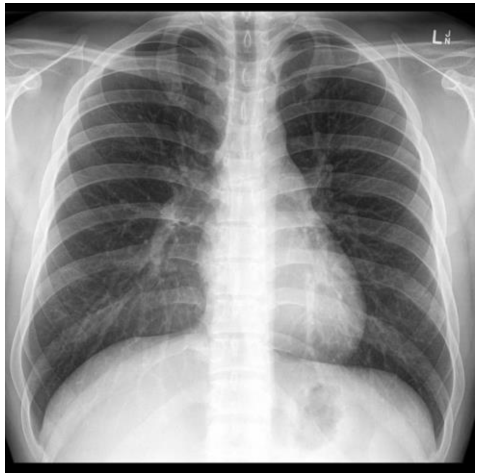


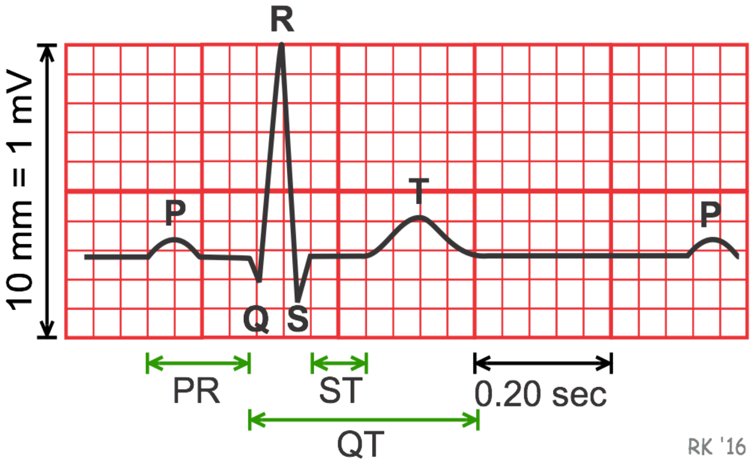
Unified HAIM framework

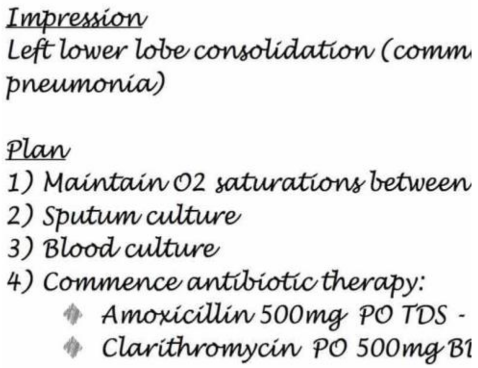


The MIMIC-IV Dataset

- Ample sample size: 34,537 patient records
- Patients of the emergency ICU rooms
- Records gathered from Beth Israel Deaconess Medical Center
- Data of multiple-modalities including:
  - Chest X-RAY
  - EHR
  - Radiology notes
  - ECG






<u>Impression</u>
Left lower lobe consolidation (comm
pneumonia)

<u>Plan</u>
1) Maintain O2 saturations between
2) Sputum culture
3) Blood culture
4) Commence antibiotic therapy:
- Amoxicillin 500mg PO TDS -
- Clarithromycin PO 500mg B

Beth Israel Lahey Health

Targets

- **Mortality Prediction**
  - Predict if patient is deceased/sent to hospice or alive at their hospital discharge

- **Diagnosis**
  - Predict if patient has a certain disease
  - Fracture, Lung Lesion, Enlarged CM, Consolidation, Pneumonia, Ateleclasis, Lung Opacity, Pneumothorax, Edema, Cardiomegaly

- **Length of Stay**
  - Predict if patient exits hospital in 48 hours

An Unexpected Result

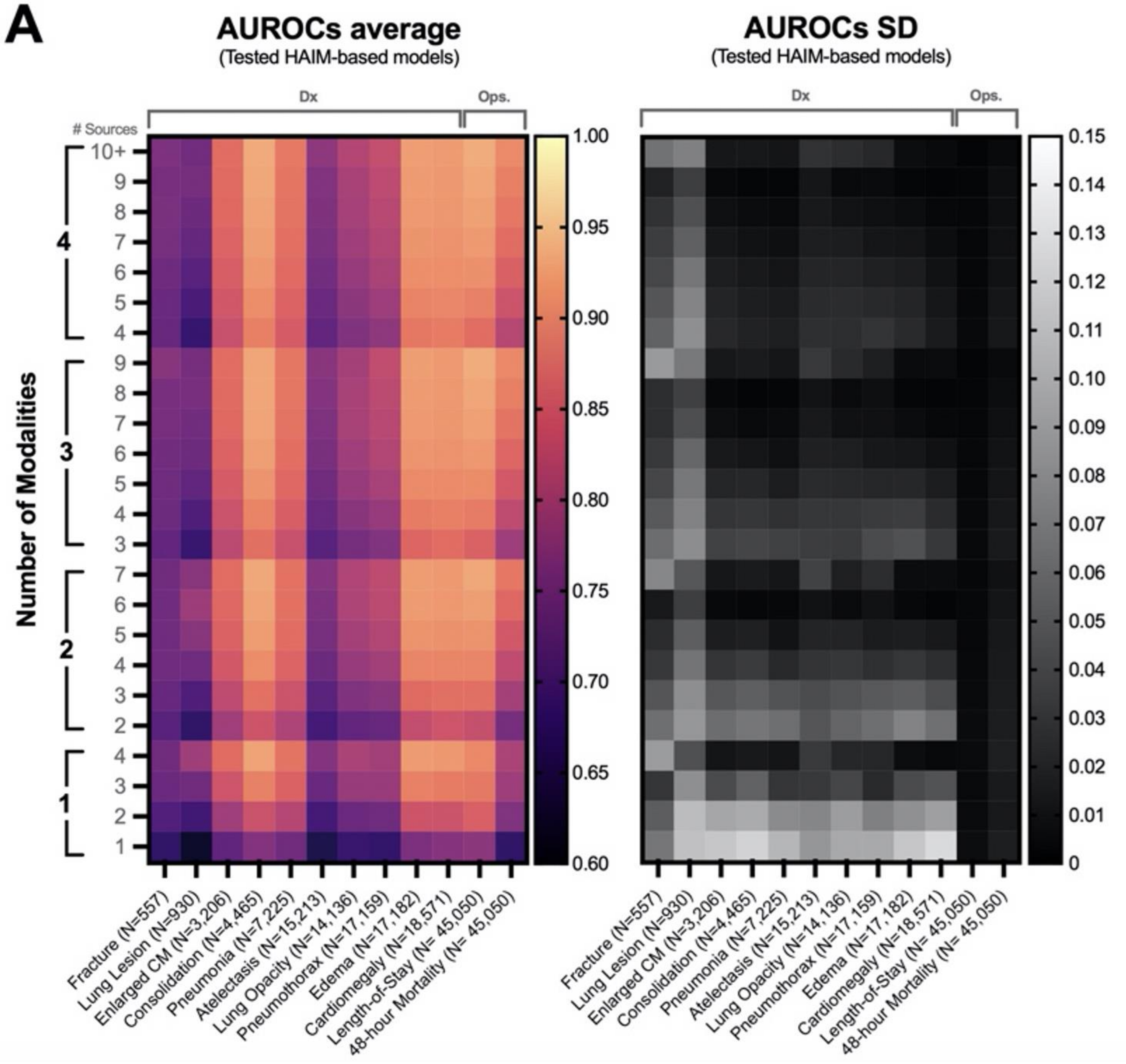
- Train: Jan-March 2021, Val: April 2021, Test: May 2021.
- $\approx$ 15k patients, $\approx$ 65k samples, 60 features from lab data.
- Sentence settings: Skip missing, replace numbers with words, use descriptive sentence, add metadata (selected using single column mortality predictions on validation set)

Target	Tabular	TabText	Tabular + Tabtext
Discharge 24hr	74.6	73.7	**75.6** (+1.34%)
Discharge 48hr	74.5	74.0	**76.2** (+2.28%)
Enter ICU 24hr	75.0	77.4	**81.3** (+8.40%)
Enter ICU 48hr	65.8	72.0	**72.2** (+9.73%)
Leave ICU 24hr	73.5	73.3	**76.2** (+3.67%)
Leave ICU 48hr	72.1	72.7	**75.2** (+4.30%)

HAIM Significantly Outperforms Single Modality

Goal	HAIM
Mortality Prediction	11-33% Improvement
Disease Classification	6-22% Improvement
Length of Stay	8-20% Improvement

The Power of Multi-Modality



Work With Irra Na and Kimberly Villalobos Carbalo

Close Collaboration with Hartford Hospital Network over a decade

We have been working very closely with hospital leadership, doctors, nurses, IT, bed managers, etc. via weekly meetings, emails and visit trips.

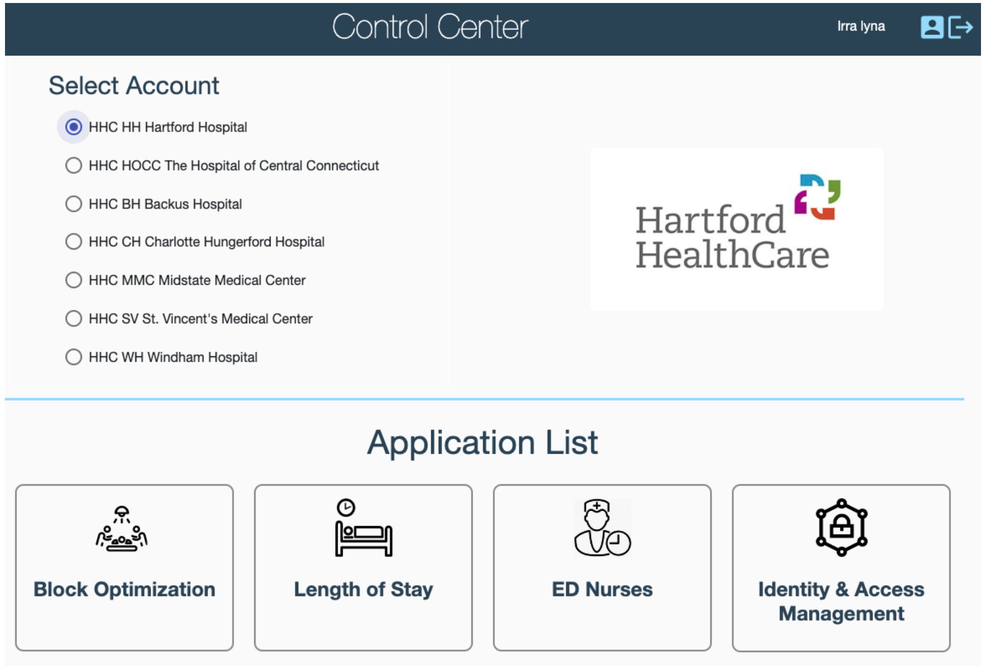
Hartford HealthCare

- Largest hospital system in Connecticut
- Operating revenue of $5 billion
- 7 diverse hospitals, ranging from academic to community, from large to small (~2500 beds)
- Representative of typical US hospital networks

Highlight on Practical Implementation

Deployment

Deployed an end-to-end software in production



Impact

- Hundreds of users (physicians, nurses, etc.)
- Assists with operational decisions daily at 7 hospitals
- Projected annual revenue uplift in millions of dollars
- Scaling to other hospital systems in the world

Problem & Motivation

Develop and implement machine learning models to predict patient operational characteristics

- Discharge next 24 hr & 48 hr
- Final destination
- Mortality risk
- ICU risk next 24 hr & 48 hr

for all patients hospitalized in Hartford HealthCare

Provide clinical and operational assistance

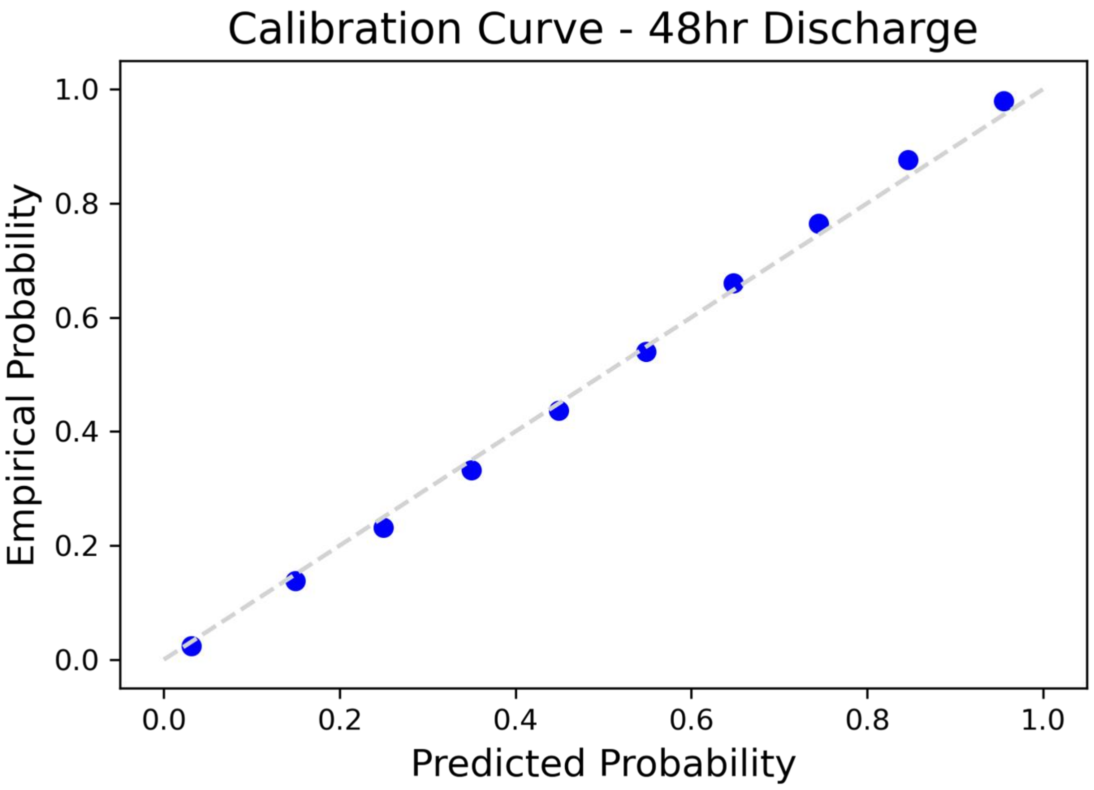
- Identify and prioritize patients
- Reduce length of stay and save costs
- Prepare for treatment and disposition plans
- Warn possible deteriorations
- Allocate hospital resources

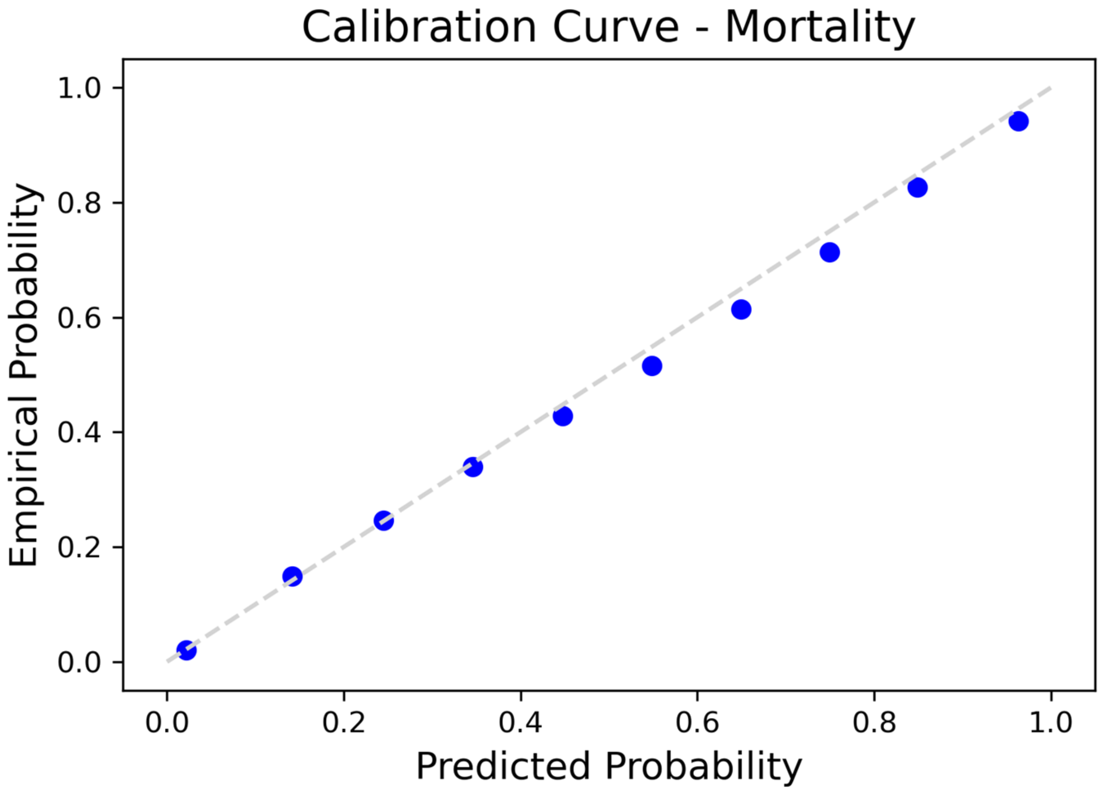
for physicians, nurses, case and bed managers

AUC Metrics for All 7 Hospitals

		HH	CH	BH	HOCC	MMC	SV	WH
Mortality		0.915	0.902	0.919	0.905	0.925	0.902	0.888
Destination		0.858	0.871	0.884	0.884	0.879	0.869	0.802
Discharge	In 1 day	0.832	0.812	0.857	0.844	0.837	0.848	0.768
	In 2 days	0.830	0.816	0.852	0.843	0.836	0.841	0.757
Enter ICU	In 1 day	0.867	0.853	0.868	0.868	0.872	0.850	No ICU unit
	In 2 days	0.834	0.813	0.818	0.811	0.847	0.812	
Leave ICU	In 1 day	0.896	0.830	0.871	0.883	0.887	0.820	
	In 2 days	0.896	0.848	0.865	0.880	0.876	0.833	

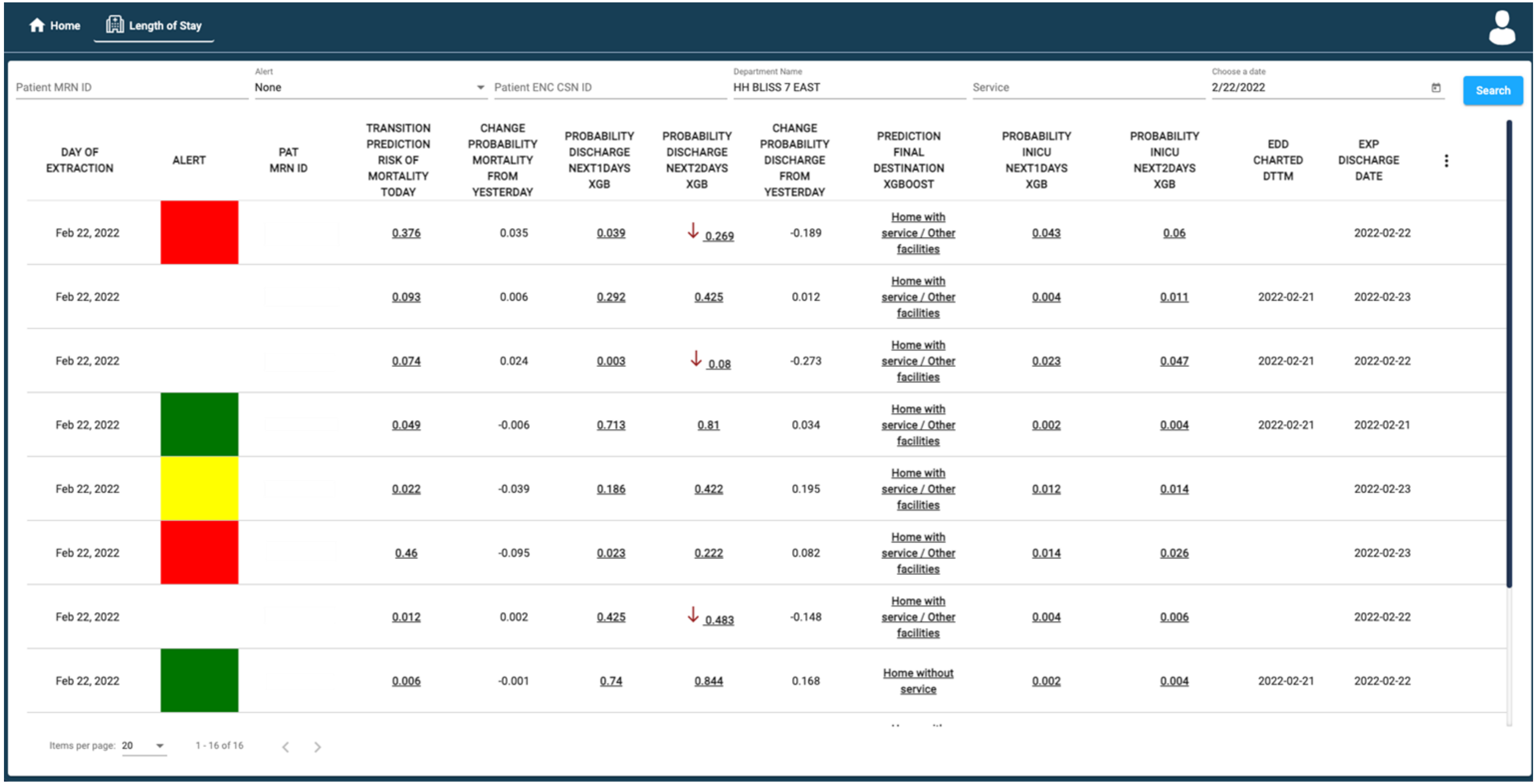
Probabilities Calibration





Predicted probabilities closely match empirical evidence.

Demo - Software in Production



DAY OF EXTRACTION	ALERT	PAT MRN ID	TRANSITION PREDICTION RISK OF MORTALITY TODAY	CHANGE PROBABILITY MORTALITY FROM YESTERDAY	PROBABILITY DISCHARGE NEXT1DAYS XGB	PROBABILITY DISCHARGE NEXT2DAYS XGB	CHANGE PROBABILITY DISCHARGE FROM YESTERDAY	PREDICTION FINAL DESTINATION XGBOOST	PROBABILITY INICU NEXT1DAYS XGB	PROBABILITY INICU NEXT2DAYS XGB	EDD CHARTED DTTM	EXP DISCHARGE DATE
Feb 22, 2022			0.376	0.035	0.039	↓ 0.269	-0.189	Home with service / Other facilities	0.043	0.06		2022-02-22
Feb 22, 2022			0.093	0.006	0.292	0.425	0.012	Home with service / Other facilities	0.004	0.011	2022-02-21	2022-02-23
Feb 22, 2022			0.074	0.024	0.003	↓ 0.08	-0.273	Home with service / Other facilities	0.023	0.047	2022-02-21	2022-02-22
Feb 22, 2022			0.049	-0.006	0.713	0.81	0.034	Home with service / Other facilities	0.002	0.004	2022-02-21	2022-02-21
Feb 22, 2022			0.022	-0.039	0.186	0.422	0.195	Home with service / Other facilities	0.012	0.014		2022-02-23
Feb 22, 2022			0.46	-0.095	0.023	0.222	0.082	Home with service / Other facilities	0.014	0.026		2022-02-23
Feb 22, 2022			0.012	0.002	0.425	↓ 0.483	-0.148	Home with service / Other facilities	0.004	0.006		2022-02-22
Feb 22, 2022			0.006	-0.001	0.74	0.844	0.168	Home without service	0.002	0.004	2022-02-21	2022-02-22

Example Patient - from Yellow to Green

Green alert if discharge probability in the next 24 hours or 48 hours is over 0.5.

Yellow alert if 48 hr discharge probability is between 0.35-0.5 and probability increases by over 0.1 from yesterday.

Comparison with Humans

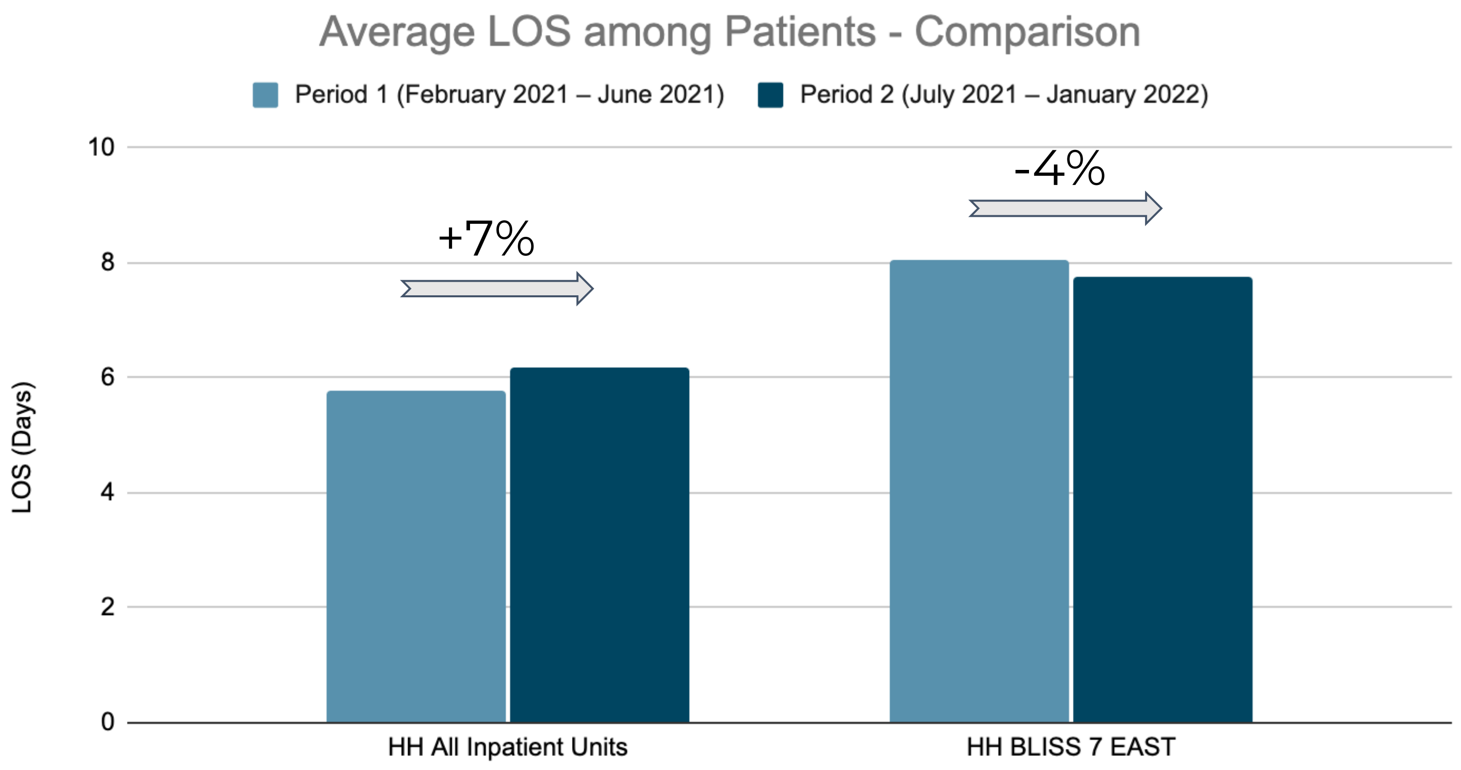
Metric	HH	CH	BH	HOCC
AUC	+0.186	+0.198	+0.180	+0.209
Proportion of discharges detected	+3%	+6%	+1%	+16%
Precision of predicted discharges	+10%	+11%	+12%	+12%

Compared with EDDs by doctors, the predictive models:

- **Have higher AUCs**
- **Identify more patients who can be discharged**
- **Make more accurate predictions**

* Results are validated on all inpatients from April to October in 2021

Illustration of Impact on LOS Reduction



* Unit HH BLISS 7 EAST started using our predictions for clinical assistance starting July 2021
* Most inpatient units at HH have not used our predictions

Since incorporation of discharge model predictions, Unit HH BLISS 7 EAST had an average reduction of LOS

Overall estimate of benefit $70 million per year.

Current Work: applications of HAIM

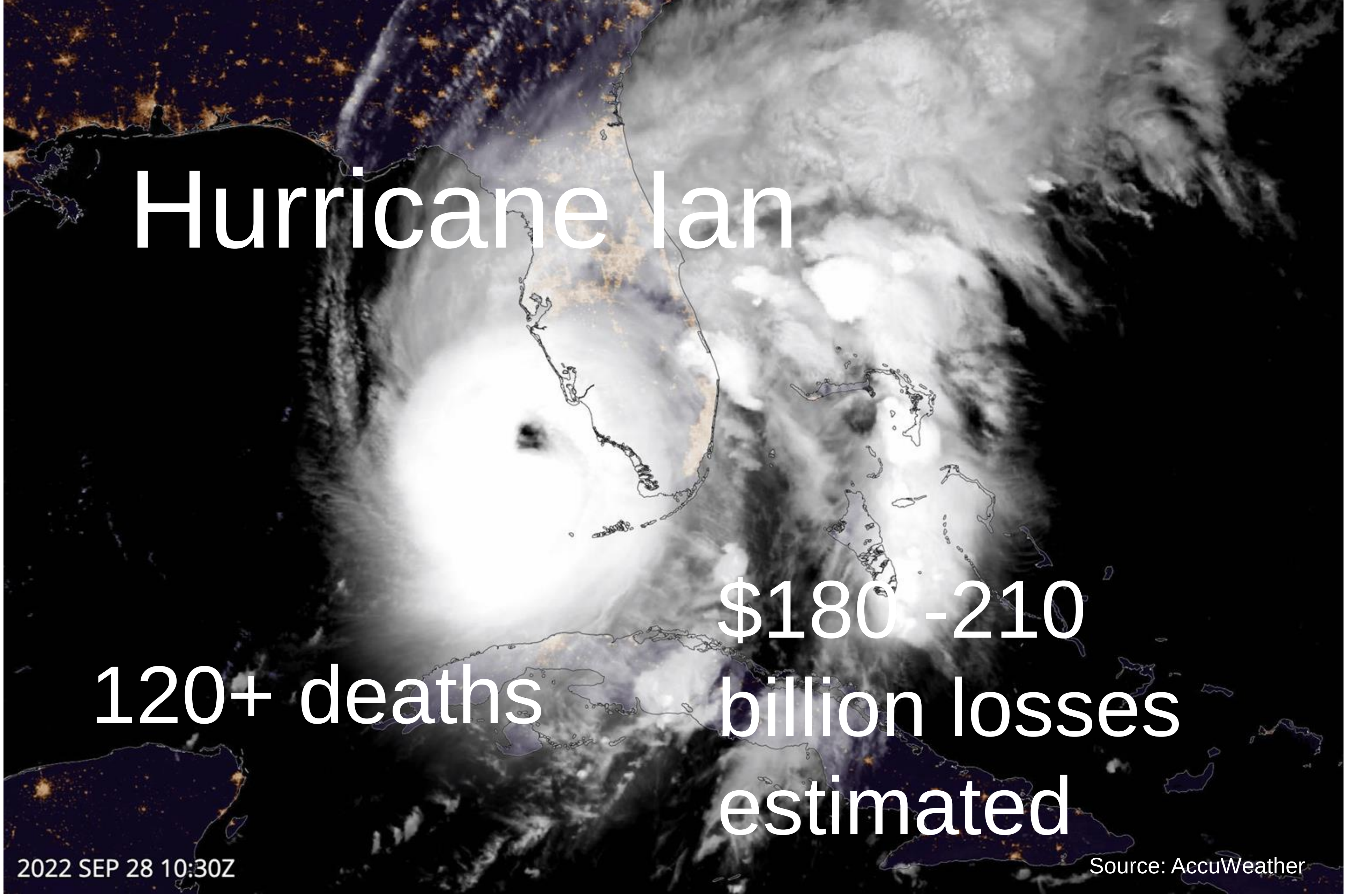
- Detecting **Domestic Abuse** at the Brigham and Women Hospital
- Detecting **Human Trafficking** at the Brigham and Women Hospital
- Predicting **Redcap Events** at University of Massachusetts Medical School, Worcester
- **Automatic Detection** of data from notes, scans, labs with STS (Society of Thorasic Surgents)
- Predicting **Edema** in the next 24-48 hours for stroke patients at Hartford hospital
- Early detection of various **Cancers** (gastric, colon, prostate) from MRIs/CT scans, lab results, and radiology reports

Holistic Artificial Intelligence for Huricanes

Hurricane Forecasting: A Novel Multimodal Machine Learning Framework

Leonard Boussioux, Theo Guenais, Cynthia Zeng and Dimitris Bertsimas

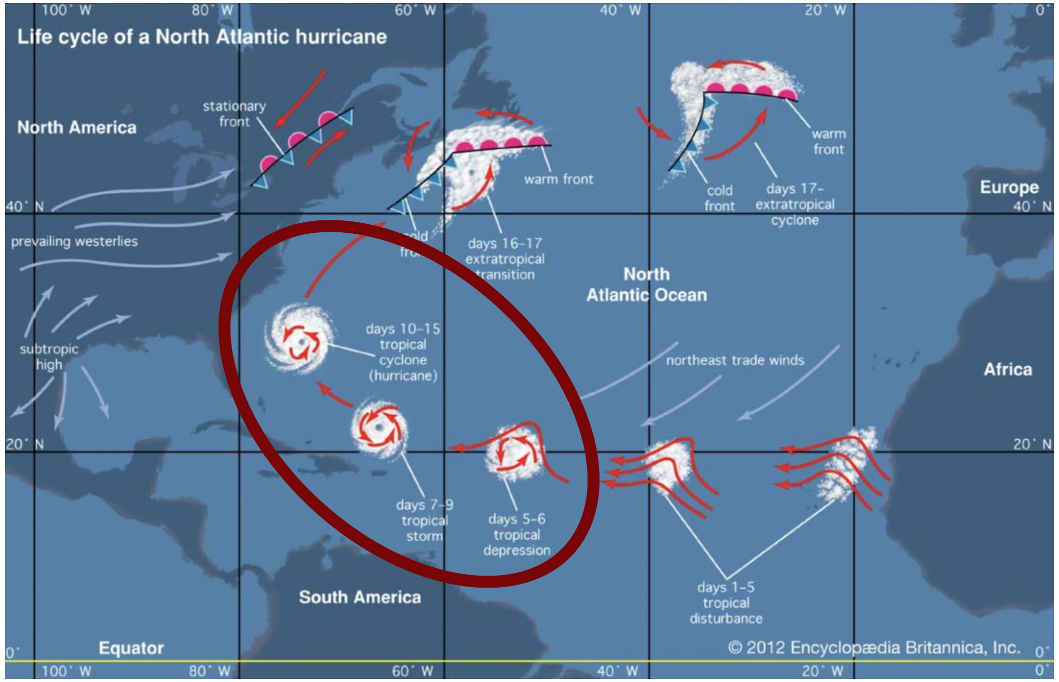
Weather and Forecasting, 37, 6, 817-831, 2022.


Hurricane Ian
120+ deaths
$180 -210 billion losses estimated
2022 SEP 28 10:30Z
Source: AccuWeather

The Problem of Hurricane Forecasting

Tropical Cyclones draw energy from warm ocean waters.

Track and Intensity forecasting tasks.



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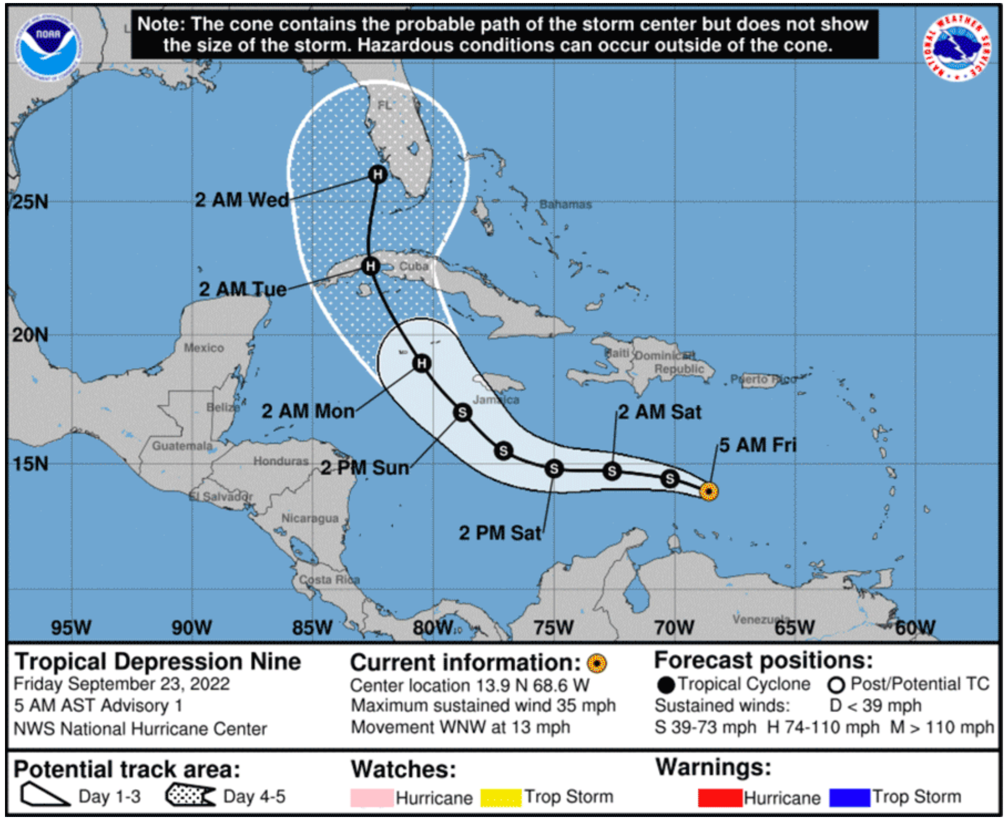
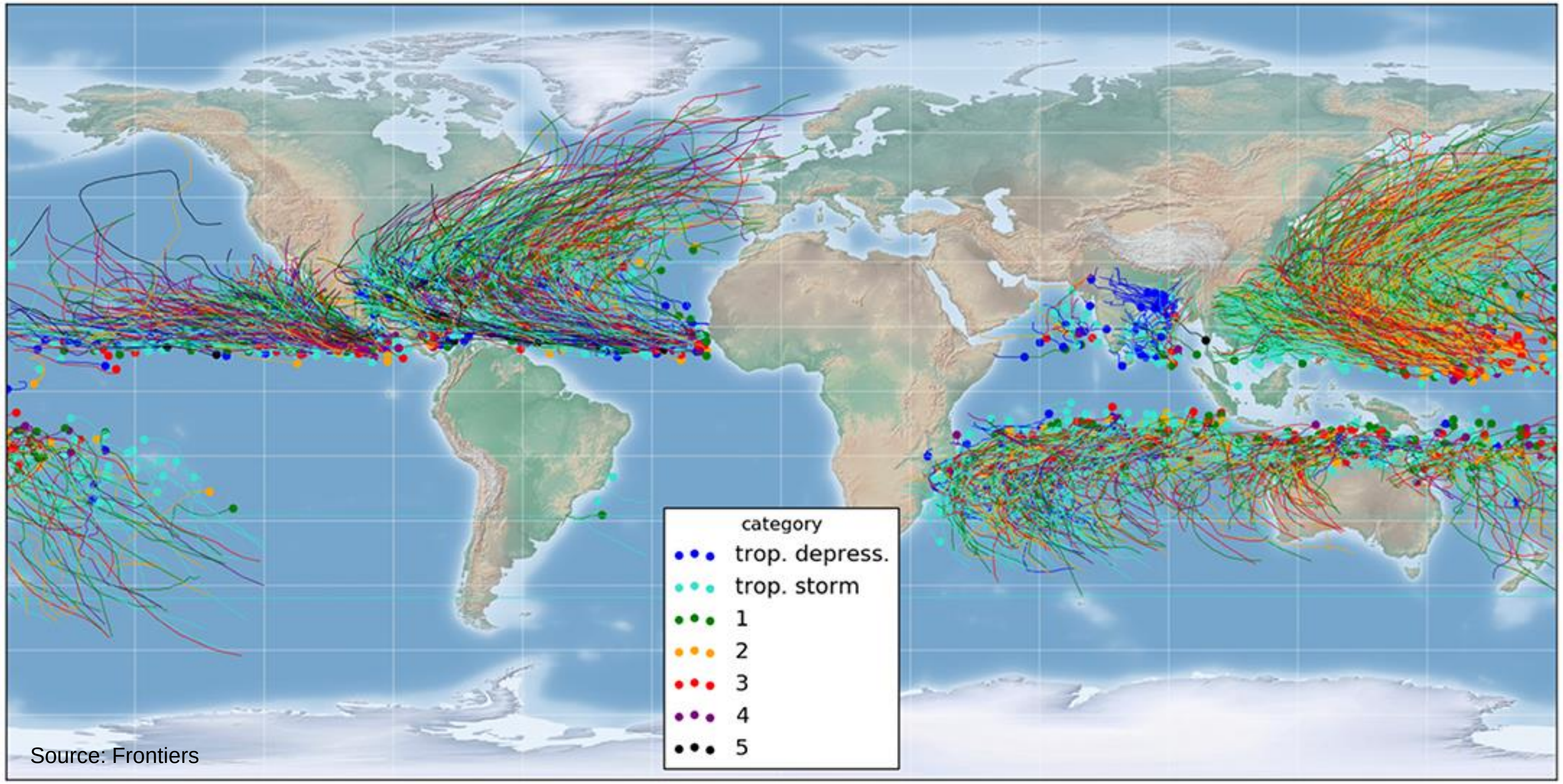


Data: Hurricanes since 1980

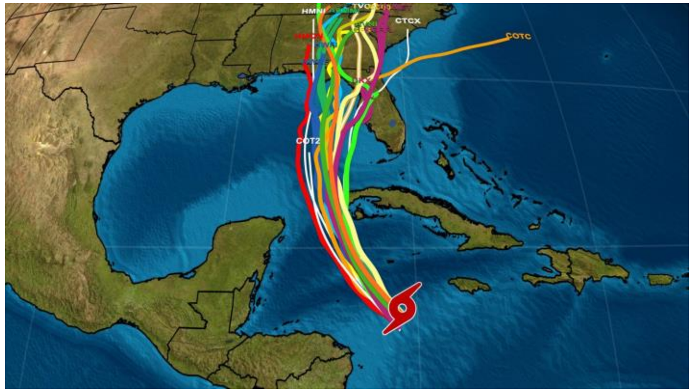


Multimodality: Three distinct data sources

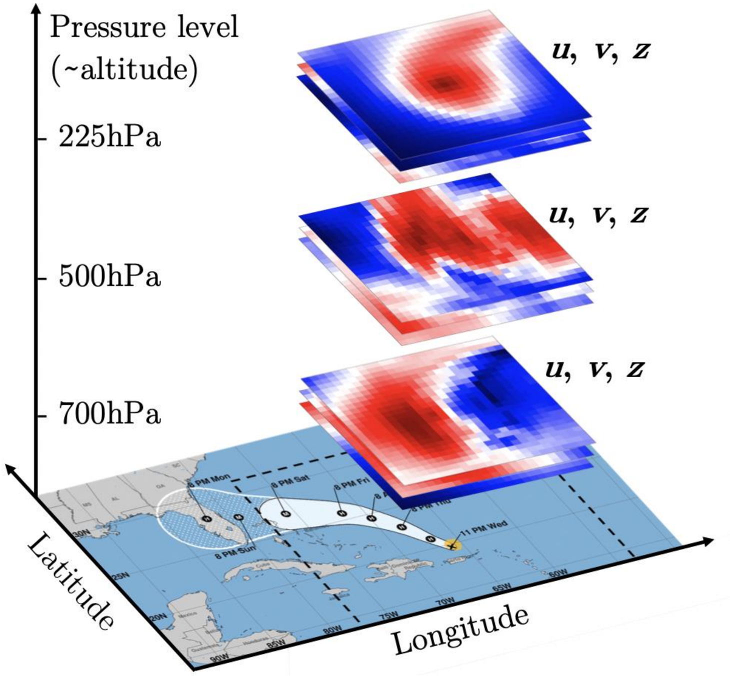
Historical storm features
(Time Series)

BASIN	ISO_TIME	LAT	LON	STORM_SPEED	STORM_DIR
		degrees_north	degrees_east	kts	degrees
EP	2016-01-05 06:00:00	2.00000	-173.500	3	73
EP	2016-01-05 09:00:00	2.04500	-173.353	3	71
EP	2016-01-05 12:00:00	2.10000	-173.200	3	67
EP	2016-01-05 15:00:00	2.17750	-173.042	4	56

Historical forecast data



Reanalysis maps
(Spatial-temporal vision data)



Intensity results

Simplified table of results for 24-hour lead-time, on 2016 – 2019 test set (results in knots)

Model type	MAE (Eastern Pacific)	MAE (North Atlantic)
Deep Learning only	10.7	11.4
Deep Learning + Multimodal framework	**10.3**	10.4
Best statistical model used by NHC (Decay-SHIPS)	11.7	10.2
Best dynamical model used by NHC (HWRF)	10.6	**9.7**

Takeaways:
1. Our multimodal framework with feature extraction is highly predictive.
2. Very competitive or better performance than the top statistical-dynamical and best dynamical models used by the NHC.

Key Results

- The multimodal model has a comparable performance with the best NHC models.

- Inclusion of the Multimodal model into an operational consensus model improves NHC's official forecast by **5% - 15%.**

Exciting applications of these methods

- Precise **Agriculture**
- **Wildfire** Management
- Monitor **climate change** affects
- **Weather** prediction

Other areas of application

- **Law**
- **Human Resources**
- **Drug Development**
- **Humanities**

Universities over Centuries

- Over Centuries, Universities are organized hierarchically and vertically
- MIT has been organized for almost 70 years in vertical five schools: Science, Engineering, Humanities, Management and Architecture.
- Each school has multiple departments (EECS and Mechanical Engineering, Mathematics, Physics, Philosophy, and Management, among many others)
- This reflects history and tradition
- Is this, however, the optimal structure or should be adapted?

Some further observations

- Real-world problems do not have labels.

- **Global warming** is not only a physics problem, or an engineering problem, or a mathematical problem.

- **Medicine** is not a biology problem, or a chemistry problem or a computer science problem.

- Given the available data in electronic form, both structured and unstructured, it makes sense to me to utilize all of the available data for better decision-making.

Some (Reasonably Safe) Predictions

- *Multimodal data will increasingly be used in science, engineering and medicine.*

- *Multimodal machine learning will be the predominant methodology for predictions and decision-making in all fields.*

- ***I expect that universities of the future will be organized horizontally.***

- *Classes in Multimodal ML and Optimization will be the core basis of many (all) fields augmented by specialized topics utilizing specific knowledge of the field.*

- *New fields will be (are) emerging: Digital Humanities, Digital Medicine, Digital Agriculture, Digital Metereology*

How should OR/MS adapt to these predictions?

- *OR/MS should embrace the change and lead rather than follow.*

- *We can take a leading/central role in this horizontal organization of universities, which has already started: At MIT it is called the Schwartzman College of Computing, but a better title is the College of AI.*

- *A significant challenge is that of lack of interpretability of deep learning. OR/MS can make progress.*

- *I was skeptical about deep learning as I felt it is too heuristic, not interpretable.*

- *It is undeniable that Deep learning is making significant problems in some of the most challenging problems of our times (Protein folding, matrix multiplication, drug development).*

What the unreasonable success of deep learning can teach us

- *Deep learning has had significant success by using a **huge** number of parameters (often more than data) and using **stochastic gradient** methods.*

- *We, in optimization, view the world as convex optimization is ``easy'', non-convex is ``hard''.*

- *I believe new phenomena emerge in very high dimensions:*

  areas for global optima become very flat

  stochastic methods avoid local optima (think of simulated annealing)

- *Opportunity to reconsider optimization in very high dimensions and algorithms that use randomness under this new lens.*

A Research and Education Agenda for the Future

- Make deep learning interpretable
- The mathematics of optimization in very high dimensions
- Change healthcare through analytics
- Change medicine through analytics
- Affect the training of medical doctors through digital medicine
- Joint education in analytics/medicine

Takeways

- *A new paradigm for science, engineering and medicine: **Multi-modality***

- *It will affect **universities** and our **field** to a first order in my opinion*

- *OR should adapt and embrace the positives of **Deep learning** while addressing its challenges (interpretability)*

- *Optimization can learn from the success of **Deep Learning***

- *Perhaps most importantly, we should broaden that what our field can do?*