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Scott Shearer, PhD, PE

Ohio State University

#MWBioinformatics

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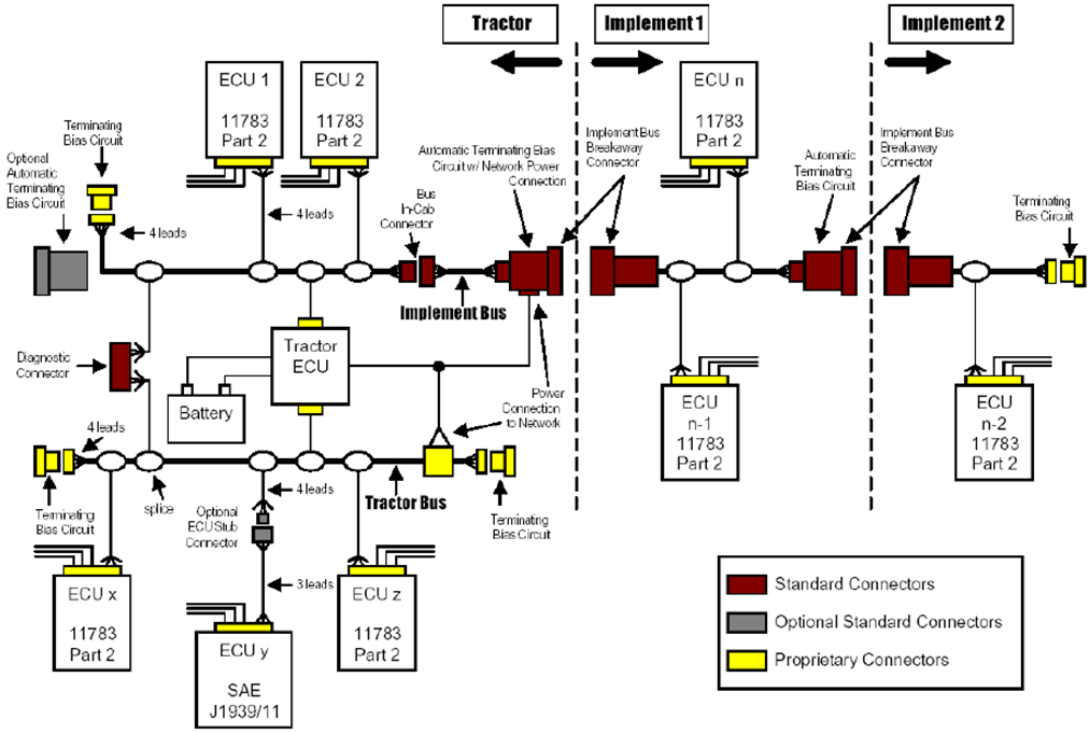
THE OHIO STATE UNIVERSITY

Digital Agriculture – Disruption or Distraction?

S.A. Shearer

Food, Agricultural and Biological Engineering

Controller Area Networks



CANbus Statistics:

- 500 kb/s asynchronous bus
- 132 bit messages (ISO 11783)
- 50% bus load
- 1,800 messages per second

CANbus on Deere 8R Tractor
(Source: wwwmanuals.deere.com)

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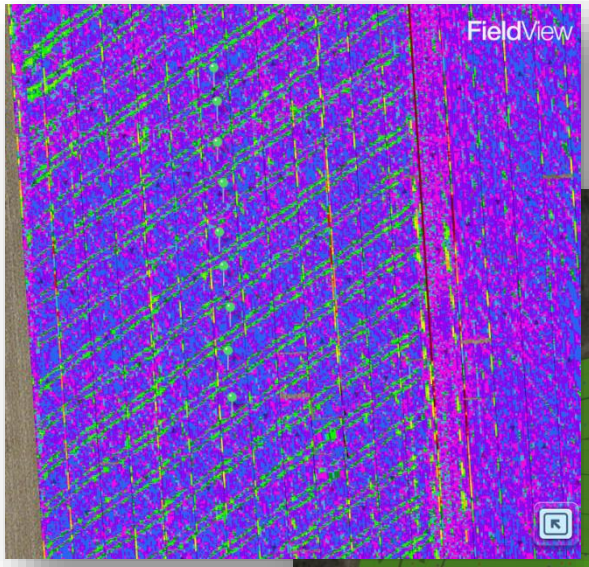
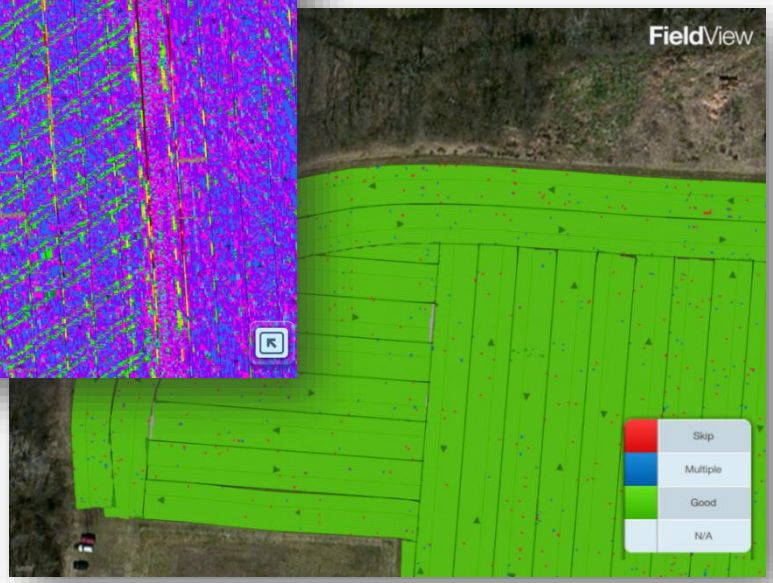
John Deere DB120 Planter

Machine Data

- As-Applied Files (.shp)
  - Spraying [0.3 MB/ac]
  - NH_3 application [4.3 MB/ac]
  - Planting [5.5 MB/ac]
- Yield Data [4.3 MB/ac]
- Prescription Files [0.01 MB/ac]
- Soil/Fertility Data [0.6 MB/ac]
- Total [0.5 KB/plant (corn)]
- If 35,000 plants/acre (corn)
  - 17.5 MB/acre
  - 42.7 GB for 2,500 acres



Applied Downforce



Seed Singulation

sUAS and Remote Sensing

24 bits per pixel

2.5 cm/pixel

17.2 MB/ac of image data

4.9 kB/plant (corn)/yr

If 35,000 plants/acre (corn)

429 GB for 2,500 acres

10 x data rate

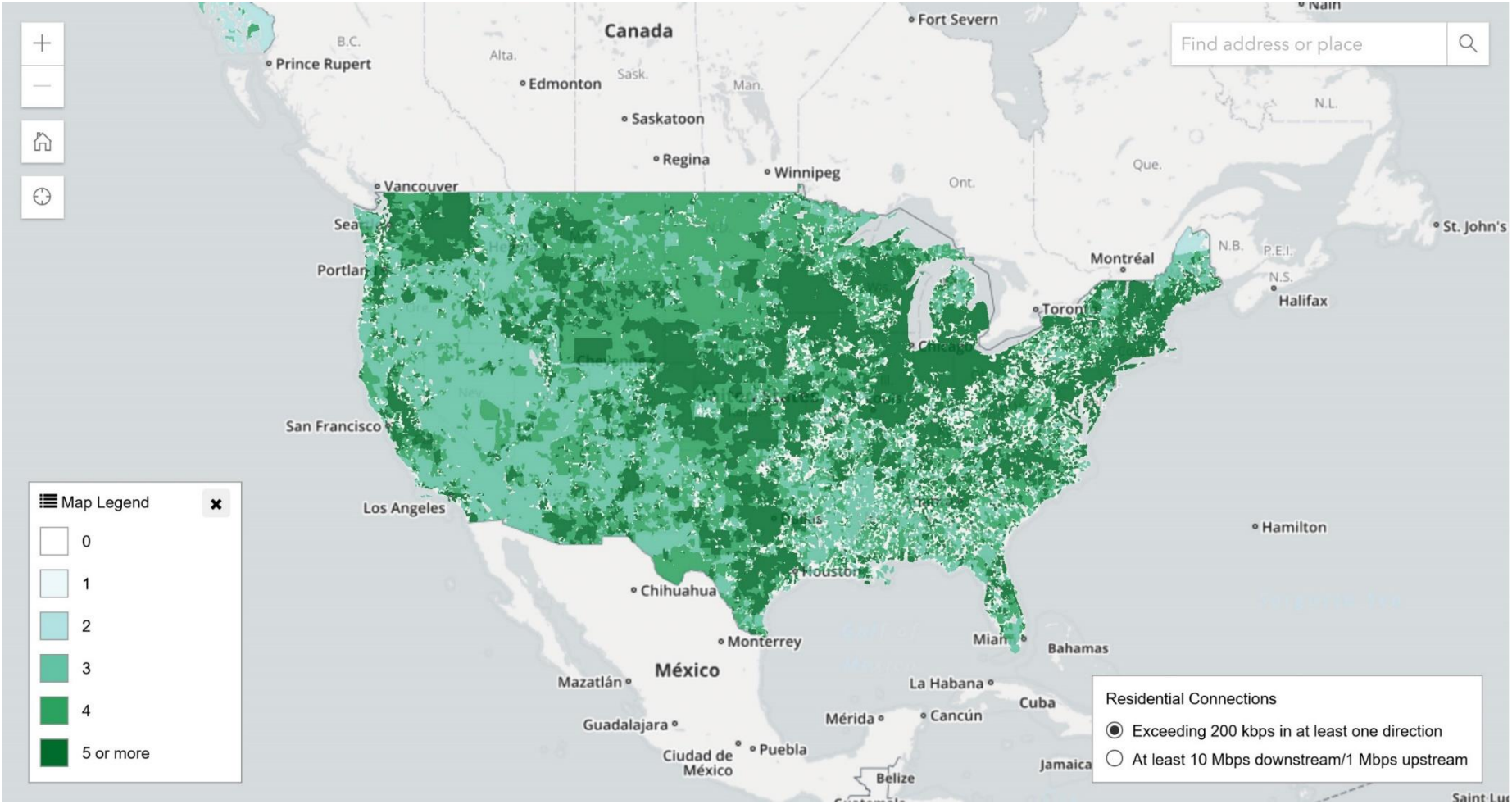
(Source: www.sensefly.com)

(Source: www.dji.com)

Evolving Data Ecosystems

(Source: Prassack Advisors)

Internet Access 200 kbps – FCC 2017



(Source: www.fcc.gov)

In-Field Sensor Networks

teralytic

(Source: www.blog.teralytic.com)

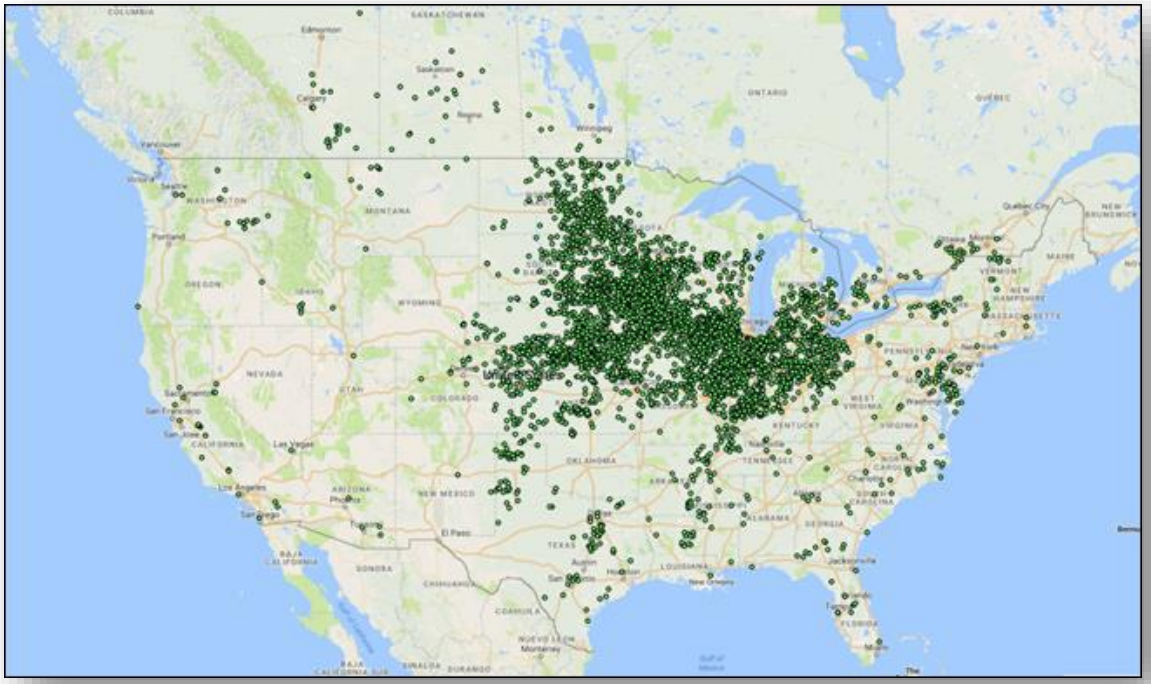
ONFARM GROW INFORMED

(Source: www.onfarm.com)

cropx

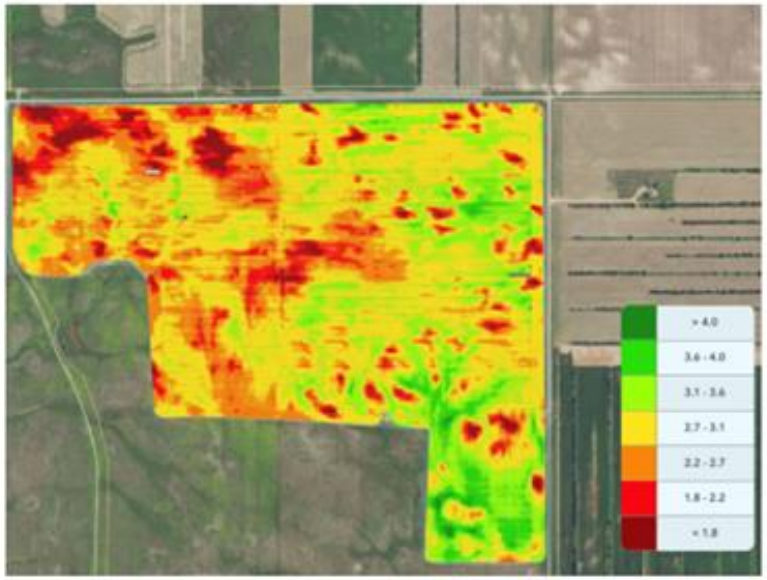
(Source: www.cropx.com)

DTN Weather Station Network

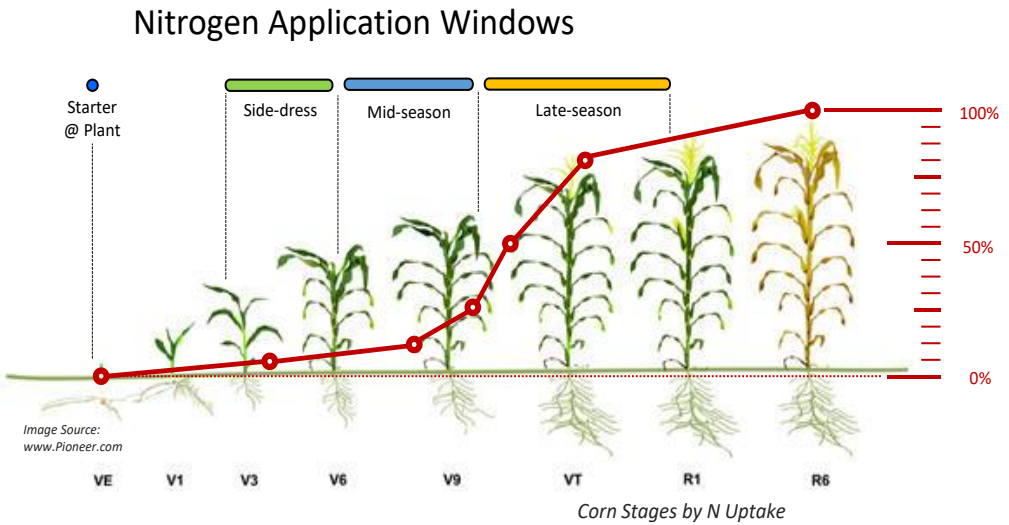


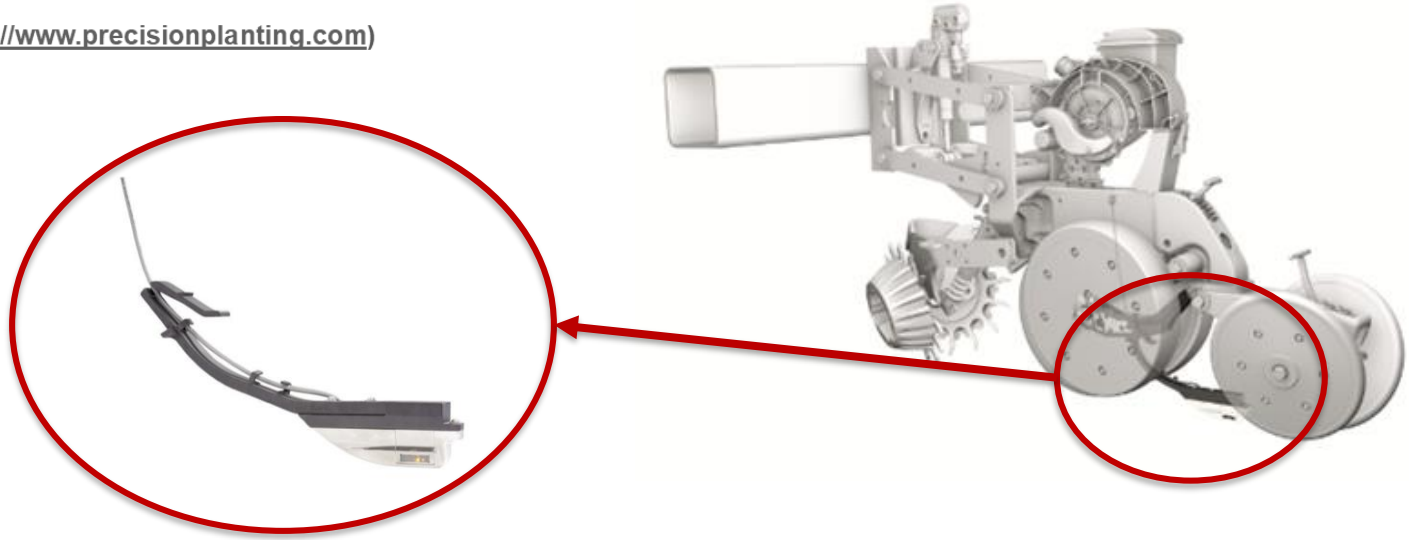
(Source: www.dtn.com)

Precision Planting SmartFirmer



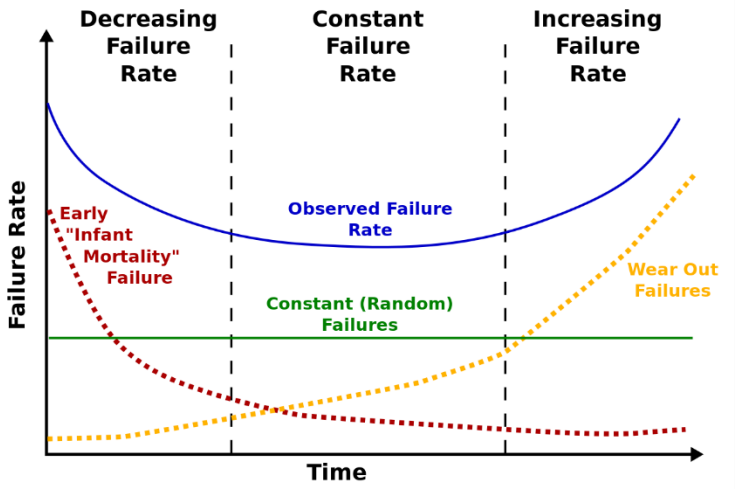
(Source: http://www.precisionplanting.com)

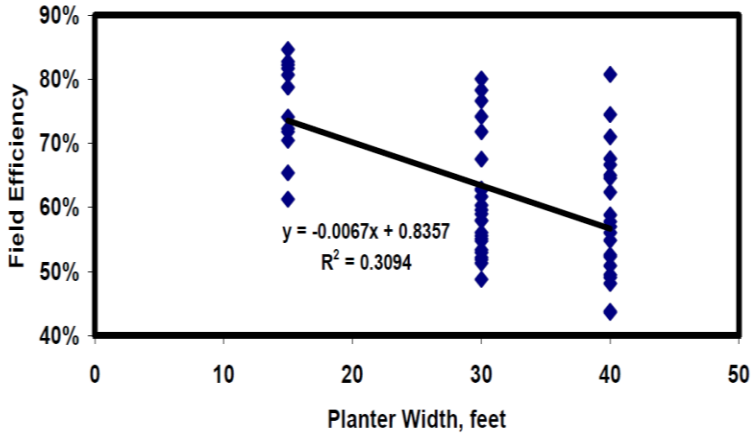




Reliability vs. Size

Planter Reliability		
Failure Rate	Width (Rows)	
	4	48
0.10%	99.6%	95.2%
1.00%	96.0%	52.0%

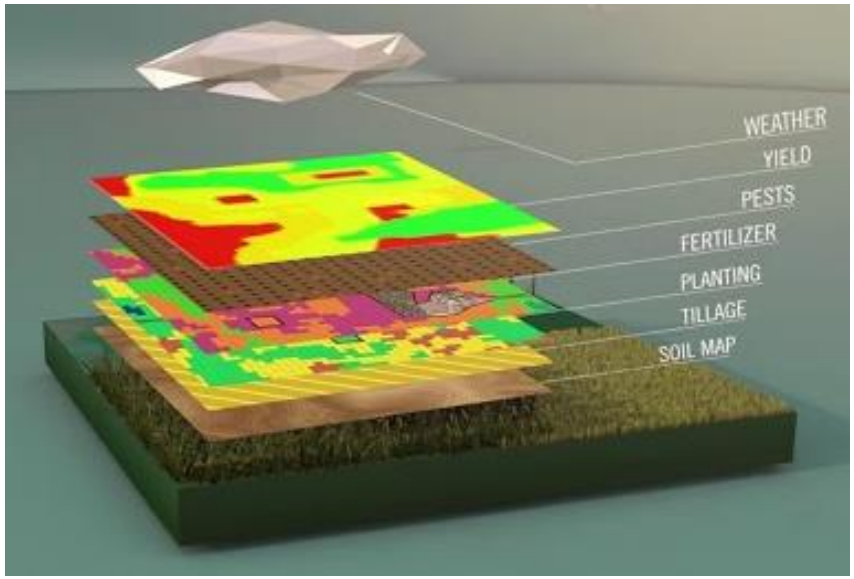




Source: Taylor, R.K., M.D. Schrock and S.A. Staggenborg. 2001. Using GPS Technology to Assist Machinery Management Decisions. Meeting Paper MC01-204, Mid-Central Conference of the ASAE.

Ag robot proliferation…

Future of Field Production

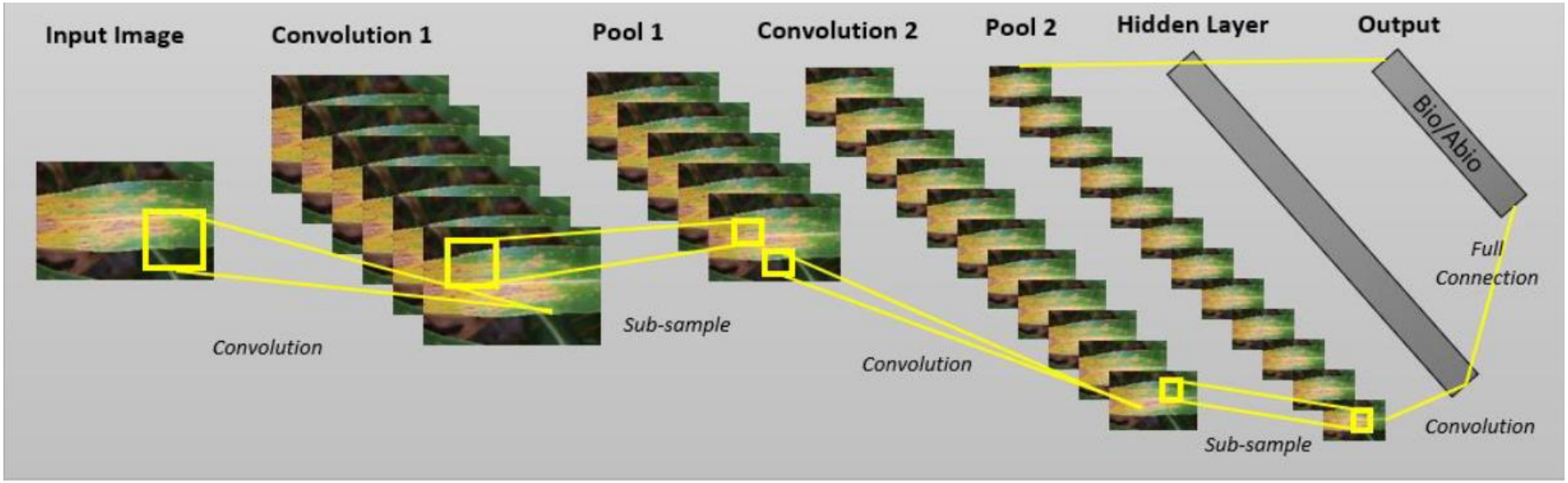


FARMERS BUSINESS NETWORK

amazon

Precision Livestock Systems

Deep Learning for Stress Diagnosis



- Convolution layers select features (lesions, lesion size, orientation, etc.)
- Fully connected layers calculate classification output (i.e. stress class)

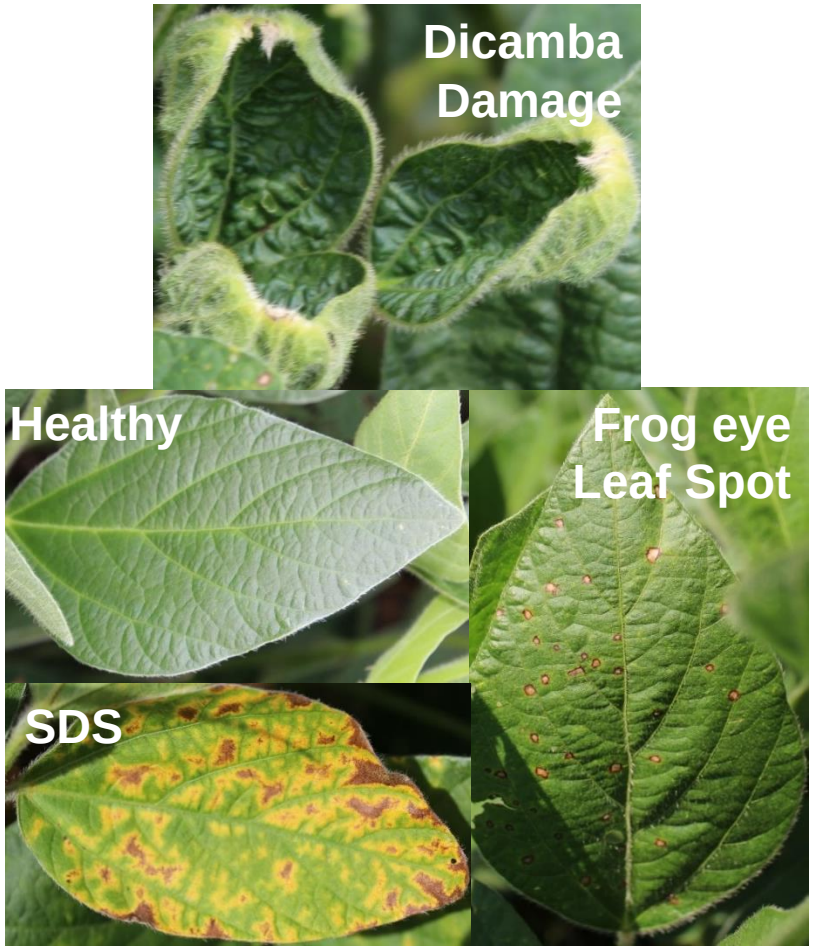
Imaging Payload

Fabricated Camera Head

Raspberry Pi Camera Module V2 w/
Sony IMX219 8-Megapixel Sensor

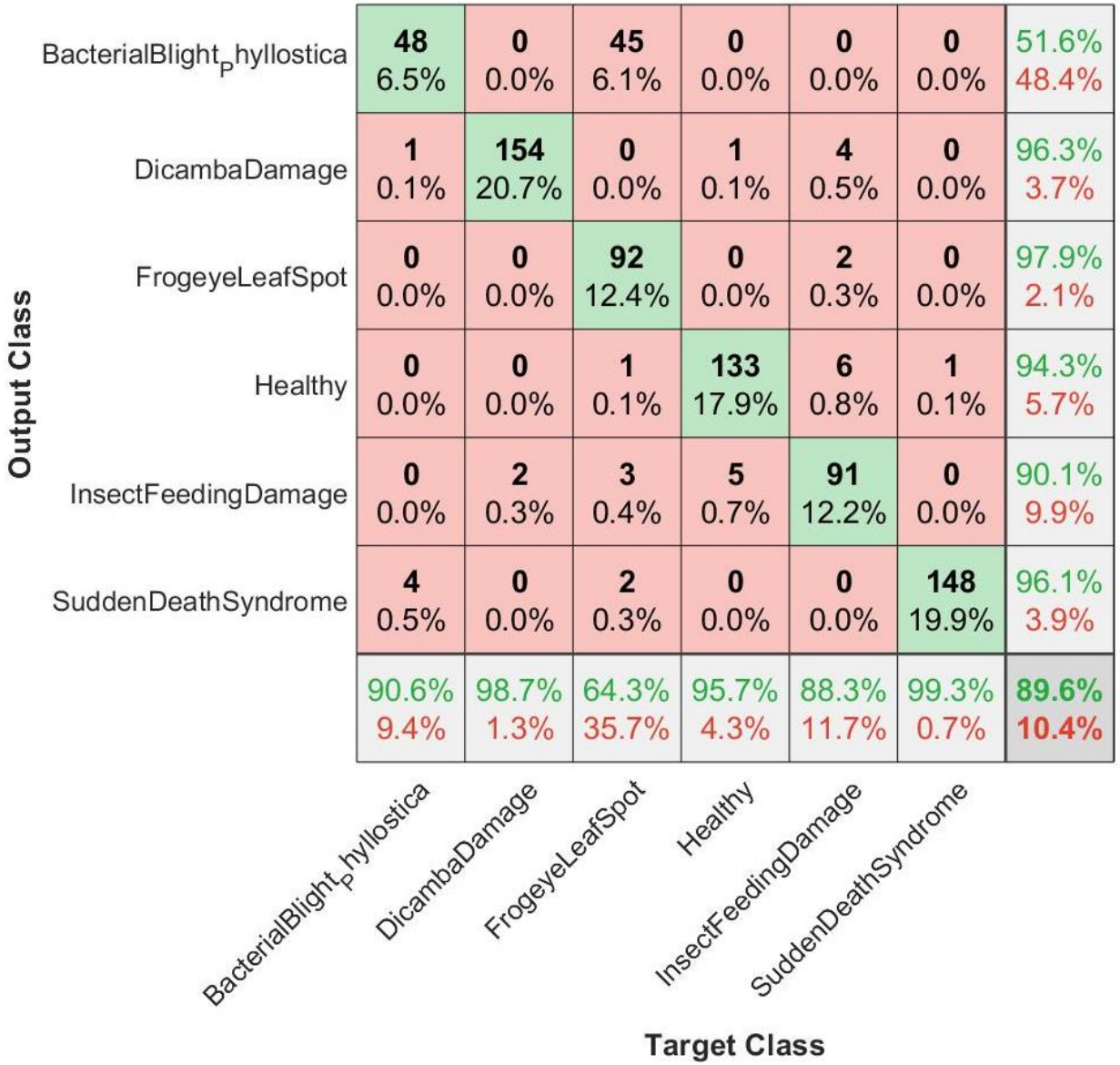
sUAS with Payload

Soybean Reference Library



Stress Category	No. of Images
Dicamba Damage	780
Frogeye Leaf Spot	704
Insect Damage	517
Sudden Death Syndrome	748
Healthy	695
Phyllosticta/Bacterial Blight	268
Total	**3,712**

Soybean CNN Classifier Results

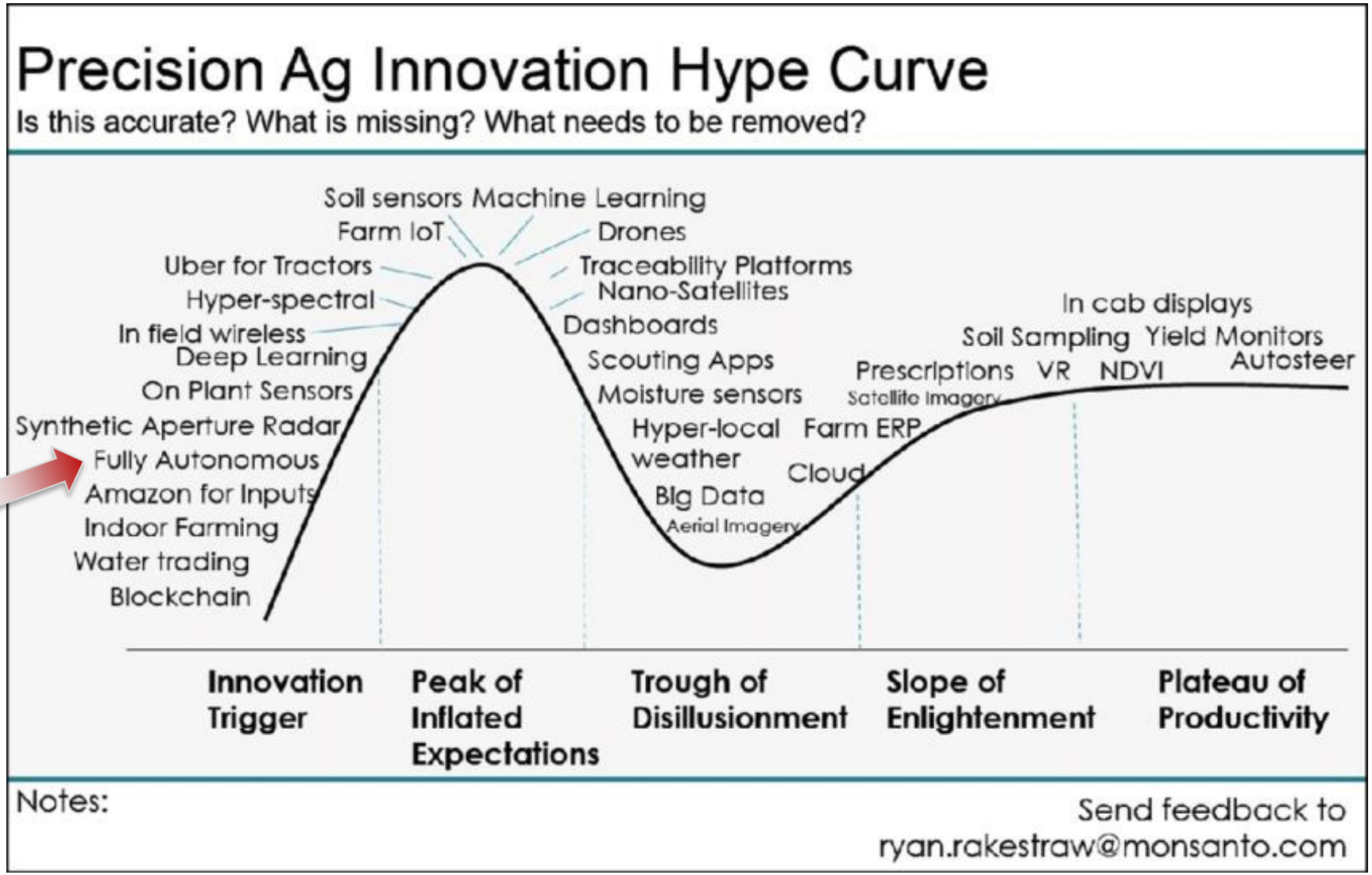


See and Spray Technology

John Deere/Blue River Targeted Application (Vision Systems and AI)

(Source: https://www.theverge.com)

Gartner Hype Curve



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Student Presentation:

Kathryn Kyler

Children's Mercy

#MWBioinformatics

@BioNexusKC

Drug dosing variation increases with weight in children hospitalized with asthma

Kate Kyler, MD
Fellow (PGY-6), Pediatric Hospital Medicine
Children's Mercy Kansas City

Collaborators/Mentors: Jessica L. Bettenhausen, MD[1]; Matt Hall, PhD[2]; Mark Hoffman, PhD[1,3]; Kim Smolderen, PhD[3]

[1]Children's Mercy Kansas City, [2]Children's Hospital Association, [3]University of Missouri-Kansas City

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Background – Obesity and Asthma

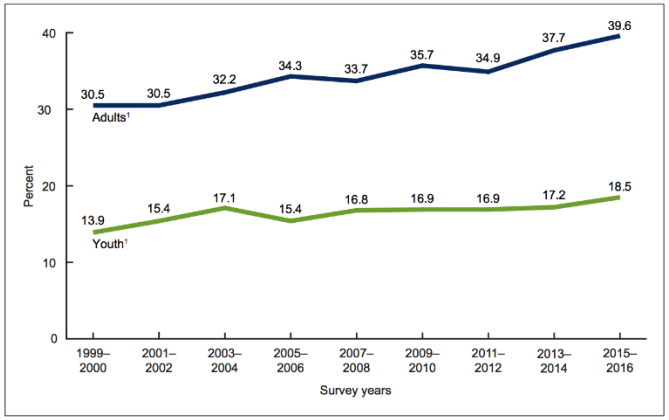
CHILDHOOD OBESITY

- Obesity affects approximately 18.5% of children aged 2-19 years
- Rates continue to increase
- These trends hold true in hospitalized children
  - 16-20% of hospitalized children have obesity

OBESITY & ASTHMA

- Asthma is one of the most common reasons for hospitalization in children
  - A substantial proportion have obesity
- Children with obesity at increased risk of developing asthma
  - Associated with worse outcomes

Figure 5. Trends in obesity prevalence among adults aged 20 and over (age adjusted) and youth aged 2–19 years: United States, 1999–2000 through 2015–2016



¹Significant increasing linear trend from 1999–2000 through 2015–2016.
NOTES: All estimates for adults are age adjusted by the direct method to the 2000 U.S. census population using the age groups 20–39, 40–59, and 60 and over.
Access data table for Figure 5 at: https://www.cdc.gov/nchs/data/databriefs/db288_table.pdf#5.
SOURCE: NCHS, National Health and Nutrition Examination Survey, 1999–2016.

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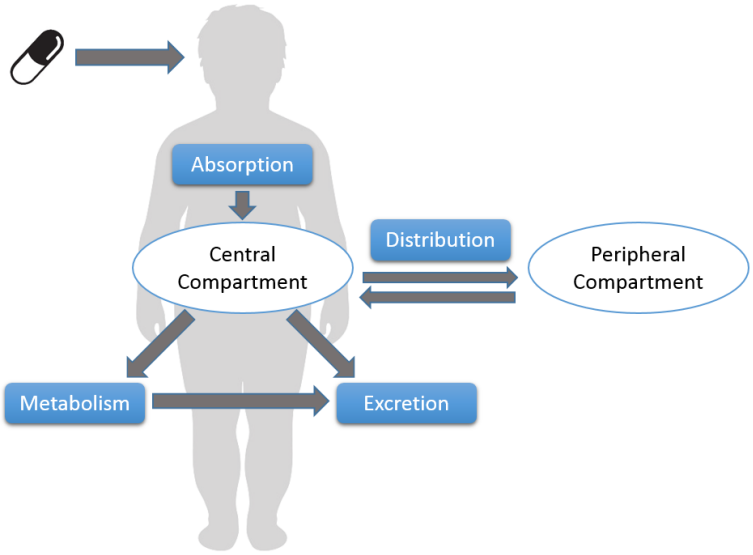
Obesity and Drugs

- All children hospitalized with asthma exacerbations are being prescribed drugs to treat their illness
  - Steroids
- Obesity causes physiologic changes that affect drug disposition in the body
  - Organ blood flow, increased cardiac output
  - CYP enzyme activity
  - Volume of distribution, clearance
- **Standard total body weight-based dosing may put children at risk for unwanted toxicities or therapeutic failures**



Obesity and Drugs

NO prescribing guidelines exist specifically for children with obesity hospitalized with asthma

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Study Question and Objectives

Does drug dosing variability INCREASE as weight INCREASES for children hospitalized with an asthma exacerbation?

Objectives:

1) To utilize a large dataset to examine the rates of steroid prescriptions that do not adhere to available dosing guidelines for asthma exacerbations by weight category
2) To determine which patient- and hospital-level factors are associated with non-adherence to dosing guidelines for asthma exacerbations

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Methodology

- **DESIGN**: Retrospective cohort analysis using the Cerner Health Facts® Database
- **POPULATION**: Children aged 2-17 years hospitalized with asthma exacerbation during the years 2010-2017
- **MEASURES**:
  - Outcome variable: proportion of non-guideline adherent doses
  - Independent variables:
    - Weight category: underweight, healthy weight, overweight, class I/II/III obesity
    - Demographics
    - Hospital-level characteristics: census region, teaching facility designation, urban/rural location

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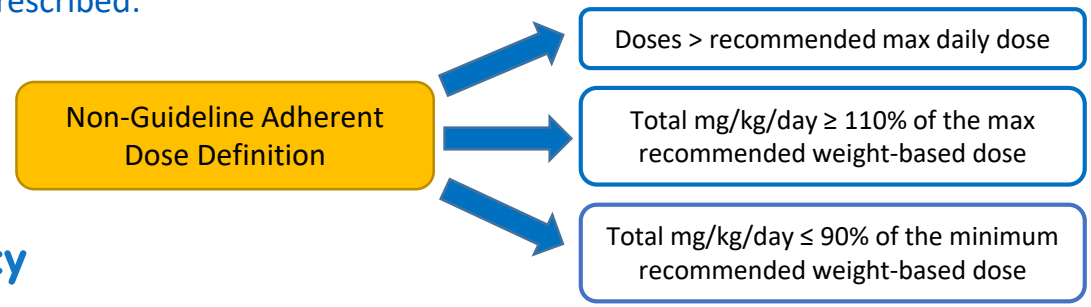
Methodology

- **DEFINITIONS**:
  - Weight categories determined according to CDC age- and sex- specific BMI percentile guidelines
  - Determination of drug doses as either guideline adherent or non-guideline adherent based on national asthma guidelines from the NHLBI:

Drug	Total Body Weight Based Dosing	Maximum Daily Dose
Prednisone	1-2 mg/kg/day	80 mg
Prednisolone	1-2 mg/kg/day	80 mg
Methylprednisolone	1-2 mg/kg/day	80 mg
Dexamethasone	0.6 mg/kg/dose	16 mg

  - Each drug dose determined to be guideline adherent or non-guideline adherent based on total daily dose prescribed:



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Methodology – Statistical Analysis

Chi square tests and multivariable logistic regression models

were used to determine statistical differences in non-guideline adherent prescriptions of all included steroid drugs between:

1) Weight categories

2) Demographic characteristics

3) Hospital-level characteristics

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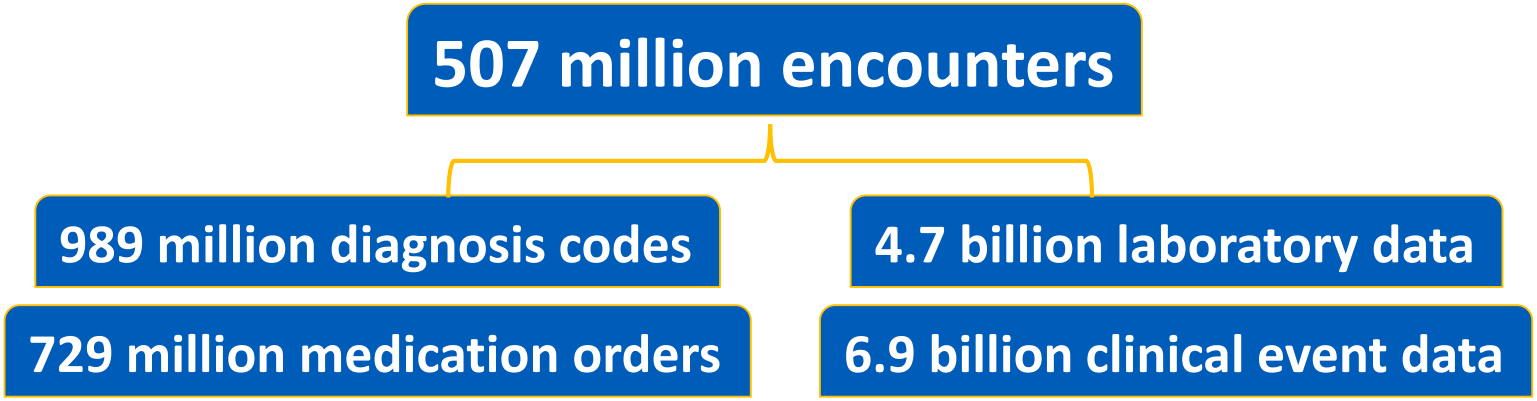
Cerner Health Facts® Database

- Large, national-level, de-identified data source
- Contains detailed longitudinal patient-level pharmacy, laboratory, clinical, and billing data



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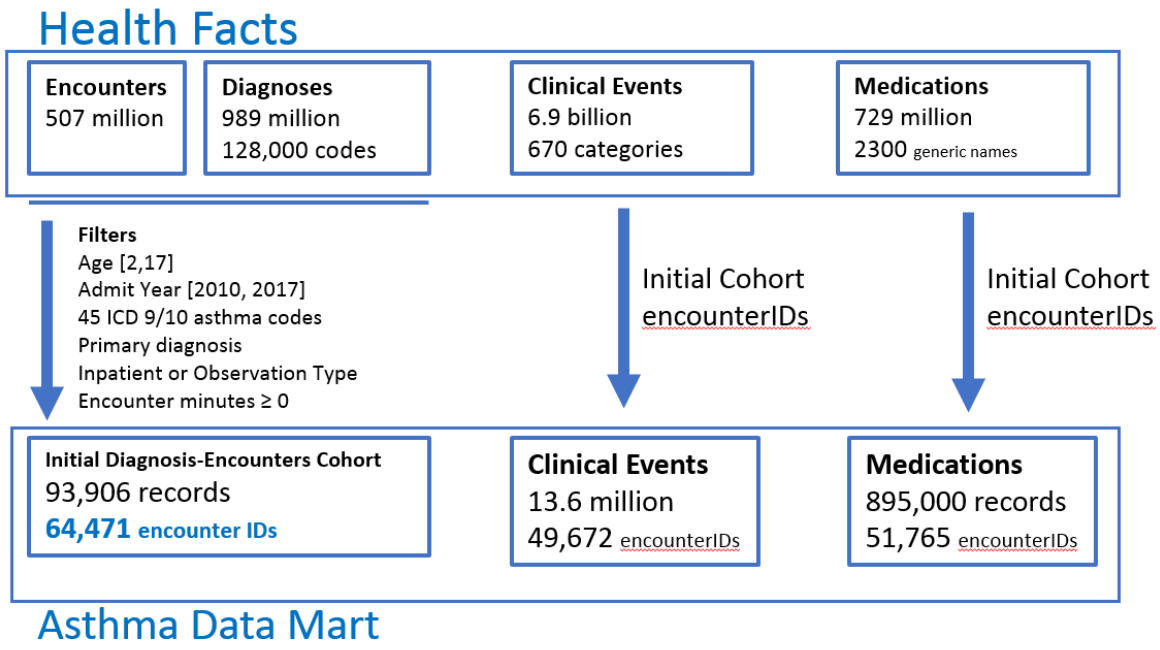
Data Retrieval Process

Data Flow Summary



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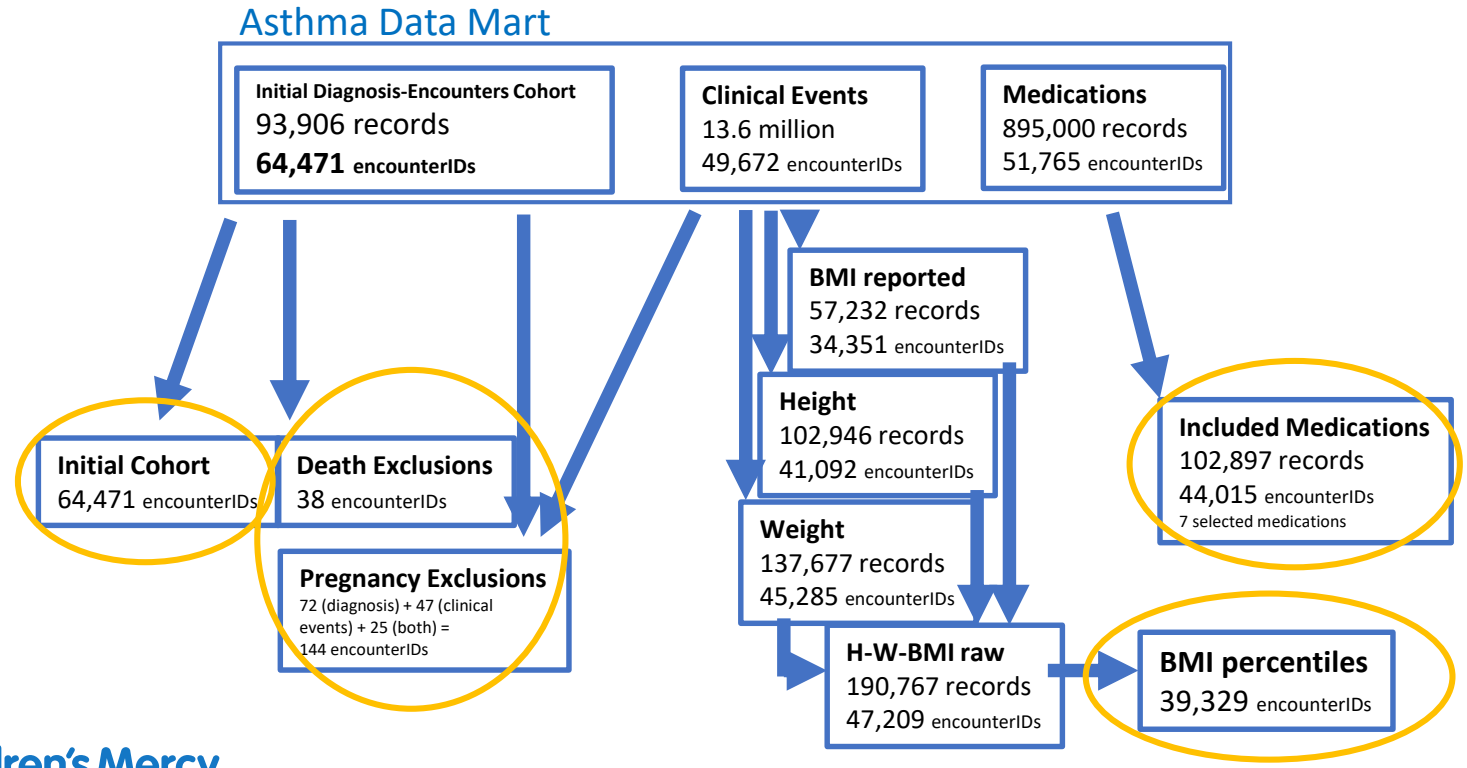
Data Retrieval Process



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Final Cohort

24,155 Encounters

34,235 Steroid prescriptions

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Results

Demographic Characteristics

		Overall
	Overall	**24155**
Age	2-5 years	8656 (35.8)
	6-10 years	10822 (44.8)
	11-14 years	3234 (13.4)
	15-17 years	1443 (6)
Gender	Male	14451 (59.8)
	Female	9704 (40.2)
Race	Non-Hisp White	71925 (29.8)
	Non-Hisp Black	12308 (51.0)
	Other	1647 (6.8)
	Unknown	3008 (12.5)
Payer	Government	13475 (55.8)
	Private	4681 (19.4)
	Other	2977 (12.3)
	Unknown	3022 (12.5)

Hospital-level Characteristics

		Overall
Region	South	11965 (49.5)
	Northeast	4929 (20.4)
	Midwest	4725 (19.6)
	West	2536 (10.5)
Academic Center	Yes	17750 (86.5)
	No	2760 (13.5)
Rural vs Urban	Urban	20016 (82.9)
	Rural	4139 (17.1)

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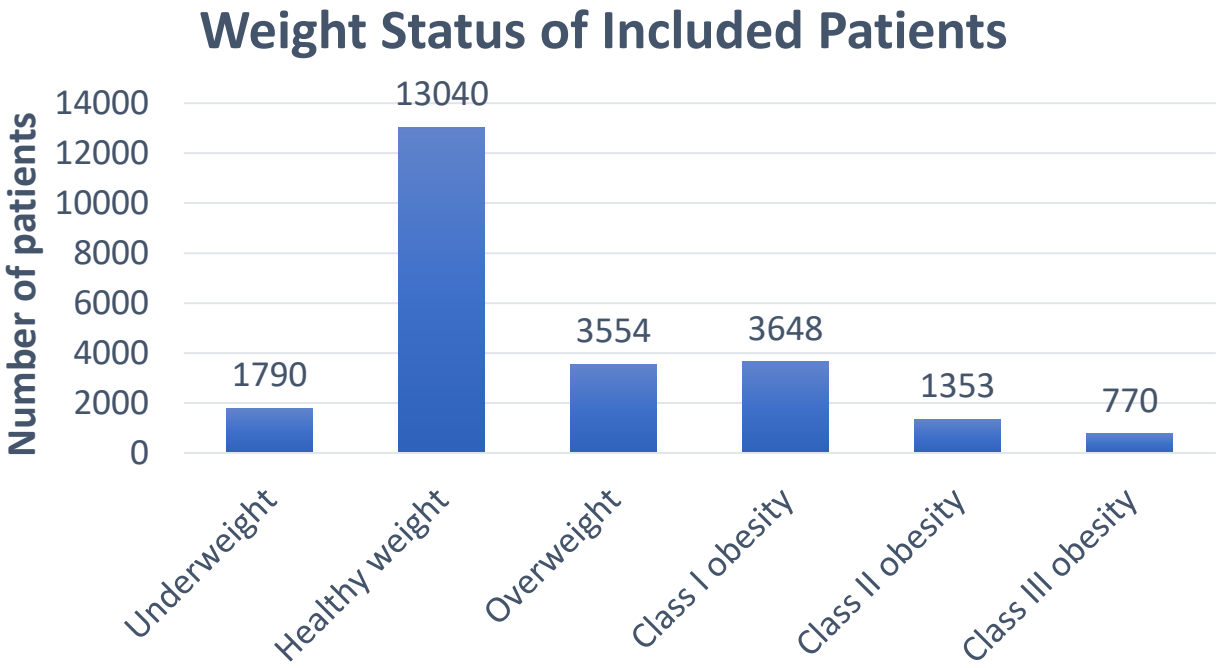
Results



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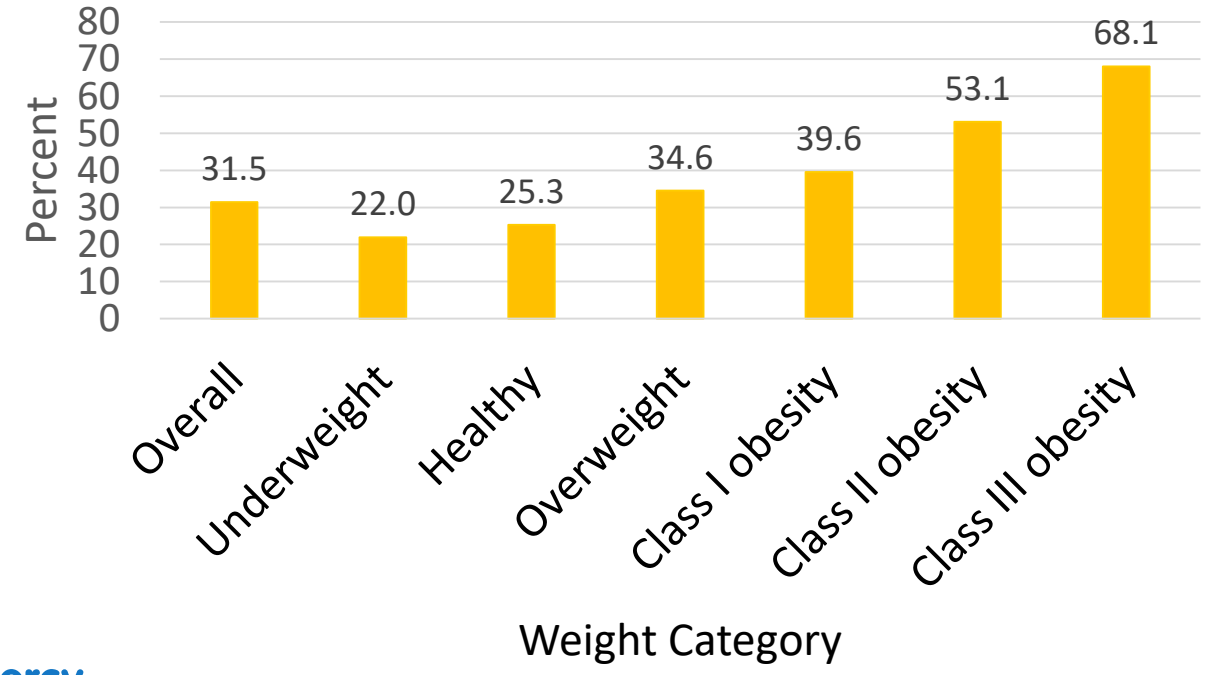
Results

Proportion of encounters receiving non-guideline adherent drug prescriptions (unadjusted)



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Results

- Other characteristics associated with receiving a non-guideline adherent prescription (all $p<0.0001$):
  - Type of steroid prescribed
  - Age
  - Sex
  - Race
  - Insurance payer
  - Census region
  - Teaching facility vs not
  - Urban/rural location

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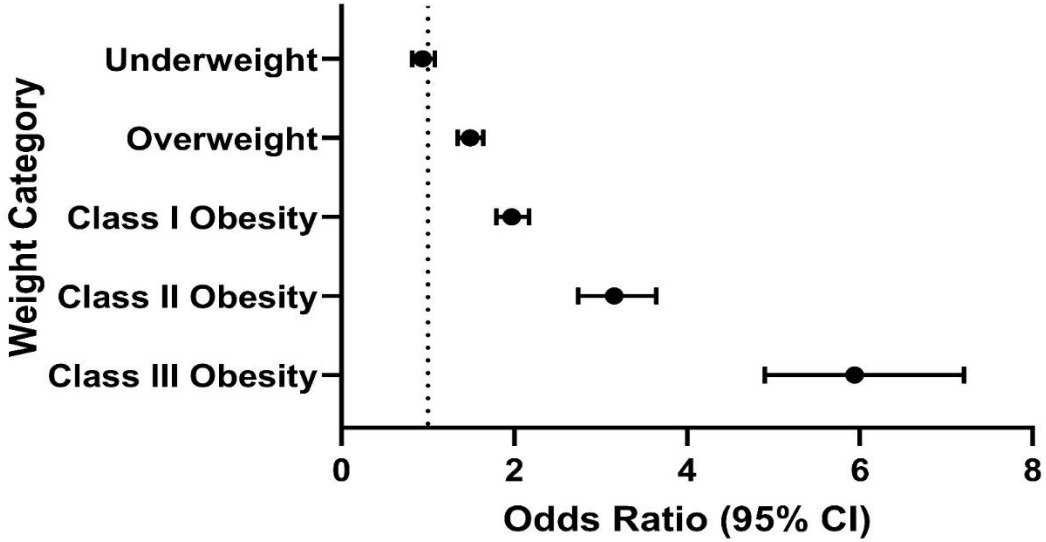
Results

Figure 2. Adjusted likelihood of receiving non-guideline adherent steroid dose by weight category



*Model adjusted for all other significant variables associated with receiving non-guideline adherent doses: age, gender, race, payer, drug received, census region, teaching facility, and urban/rural location

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Conclusions

- The likelihood of being prescribed a non-guideline adherent steroid dose increases with increasing weight category
- Many other factors were associated with receiving a non-guideline adherent dose
- The creation of drug dosing guidelines specifically aimed at patients with obesity may help mitigate the risk of receiving drug over- or under-doses

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IMAGE ANALYSIS

Moderator:

Devin Koestler, PhD

University of Kansas Medical Center

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Doina Caragea, PhD

Kansas State University

#MWBioinformatics

@BioNexusKC

Root Anatomy based on Root Cross-Section Image Analysis with Deep Learning

Doina Caragea[1], Chaoxin Wang[1], Xukun Li[1], Raju Bheemanahalli[2] and S.V. Krishna Jagadish[2]

[1]Department of Computer Science
[2]Department of Agronomy

Kansas State University

Midwest Bioinformatics Conference

Deep Learning in Agriculture

Computers and Electronics in Agriculture 147 (2018) 70–90

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Review

Deep learning in agriculture: A survey

Andreas Kamilaris*, Francesc X. Prenafeta-Boldú

Institute for Food and Agricultural Research and Technology (IRTA), Spain

ARTICLE INFO

Keywords:
Deep learning
Agriculture
Survey
Convolutional Neural Networks
Recurrent Neural Networks
Smart farming
Food systems

ABSTRACT

Deep learning constitutes a recent, modern technique for image processing and data analysis, with promising results and large potential. As deep learning has been successfully applied in various domains, it has recently entered also the domain of agriculture. In this paper, we perform a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. We examine the particular agricultural problems under study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study. Moreover, we study comparisons of deep learning with other existing popular techniques, in respect to differences in classification or regression performance. Our findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques.

Image-based Plant Phenotying

Kansas State University | Department of Computer Science

OXFORD (GIGA)n SCIENCE

GigaScience, 6, 2017, 1–10

doi: 10.1093/gigascience/gix083
Advance Access Publication Date: 23 August 2017
Research

RESEARCH

Deep machine learning provides state-of-the-art performance in image-based plant phenotyping

Michael P. Pound[1], Jonathan A. Atkinson[2], Alexandra J. Townsend[2], Michael H. Wilson[3], Marcus Griffiths[2], Aaron S. Jackson[1], Adrian Bula Georgios Tzimiropoulos[1], Darren M. Wells[2], Erik H. Murchie[2], Tony P. Pridmore[1] and Andrew P. French[1,2,*]

[1]School of Computer Science, University of Nottingham, Jubilee Campus, Wollaton Road, Nottingha 1BB, UK, [2]School of Biosciences, University of Nottingham, Sutton Bonington Campus, Nr Loughbo 5RD, UK and [3]Centre for Plant Sciences, Faculty of Biological Sciences, University of Leeds, Leeds, L

*Correspondence address. Andrew P. French, School of Computer Science, University of Nottingham, Jubilee Campus, Wollaton Road, No 1BB, UK. Tel: 0115 9516374; E-mail: andrew.p.french@nottingham.ac.uk

OXFORD (GIGA)n SCIENCE

GigaScience, 8, 2018, 1–12

doi: 10.1093/gigascience/giy153
Advance Access Publication Date: 6 December 2018
Review

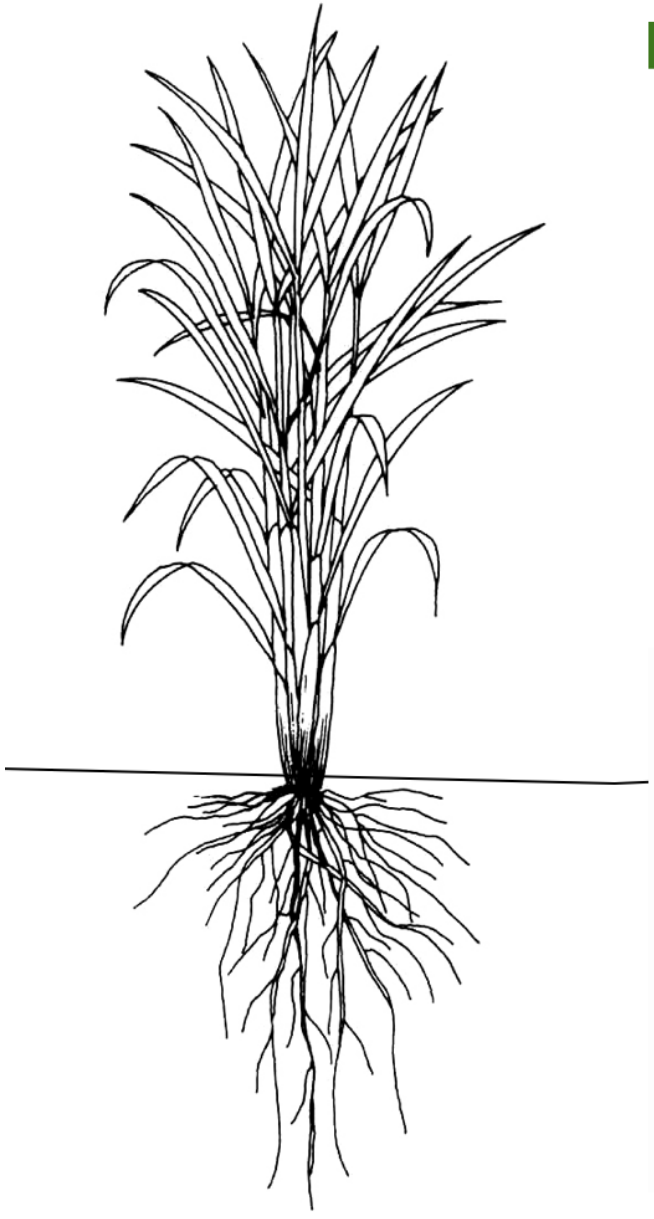
REVIEW

Computer vision-based phenotyping for improvement of plant productivity: a machine learning perspective

Keiichi Mochida [1,2,3,4,5,*], Satoru Koda [6], Komaki Inoue [1], Takashi Hirayama [3], Shojiro Tanaka [7], Ryuei Nishii [8] and Farid Melgani [9]

[1]Bioproductivity Informatics Research Team, RIKEN Center for Sustainable Resource Science, 1-7-22 Suehiro-cho, Tsurumi-ku, Yokohama, Kanagawa 230-0045, Japan, [2]Microalgae Production Control Technology Laboratory, RIKEN Baton Zone Program, RIKEN Cluster for Science, Technology and Innovation Hub, 1-7-22

Need for Belowground Analysis



nature plants

Comment | Published: 04 August 2015

The hidden half of crop yields

Anthony Bishopp & Jonathan P. Lynch

Nature Plants **1**, Article number: 15117 (2015) | Download Citation

The tremendous gains in crop yields seen over the twentieth century were underpinned by fertilizer use and manipulation of the aboveground parts of the plant. To meet the food demands of the twenty-first century, plant scientists must turn their attention belowground.

Plant Physiology

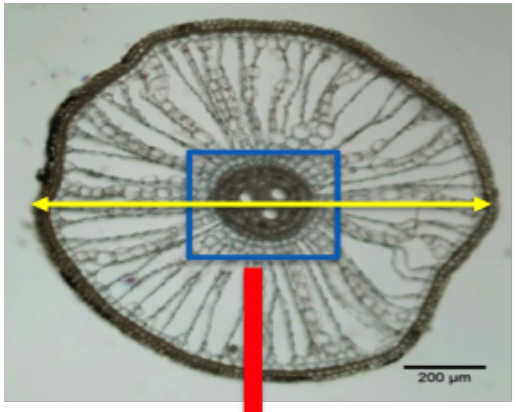
Research Article | Articles

Genetic Control of Plasticity in Root Morphology and Anatomy of Rice in Response to Water Deficit

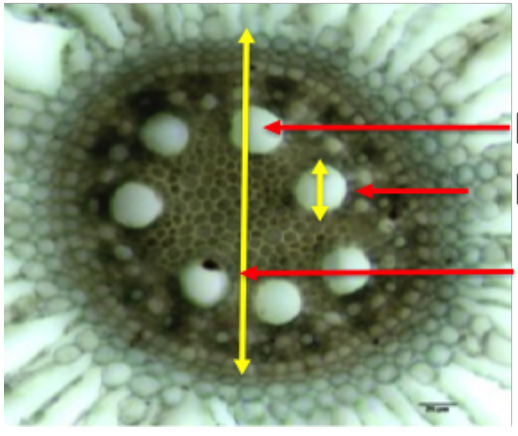
Niteen N. Kadam, Anandhan Tamilselvan, Lovely M.F. Lawas, Cherryl Quinones, Rajeev N. Bahuguna, Michael J. Thomson, Michael Dingkuhn, Raveendran Muthurajan, Paul C. Struik, Xinyou Yin, S.V. Krishna Jagadish

Published August 2017. DOI: https://doi.org/10.1104/pp.17.00500 Altmetric 6

Root Anatomical Traits Correlated with Water Deficit



Root diameter (RD, µm)



Late metaxylem number (LMXN)

Late metaxylem diameter (LMXD, µm)

Stele diameter (SD, µm)

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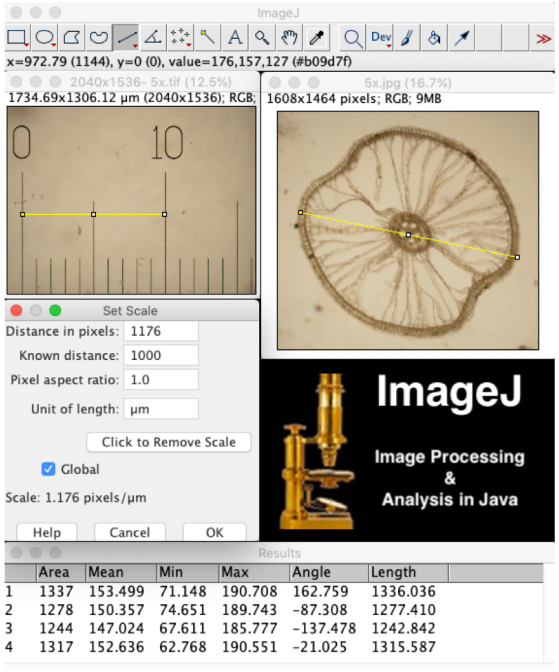
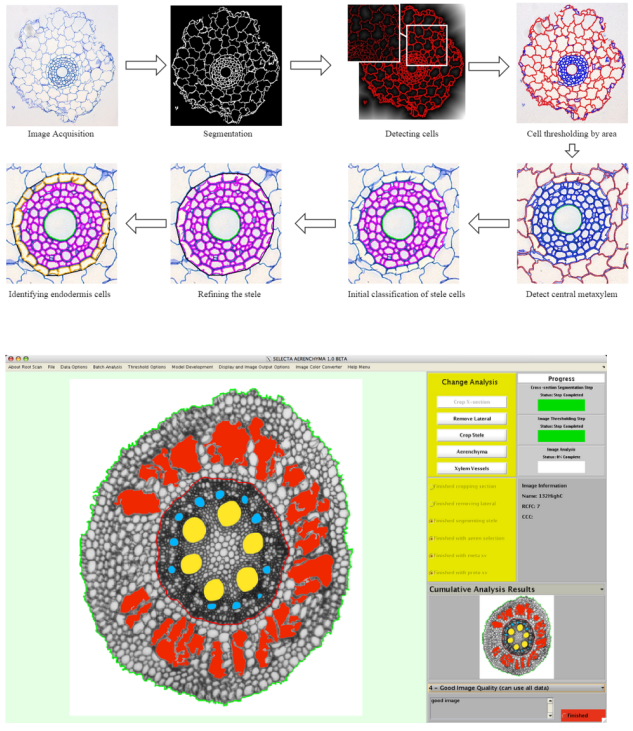
Existing Approaches for Root Anatomy

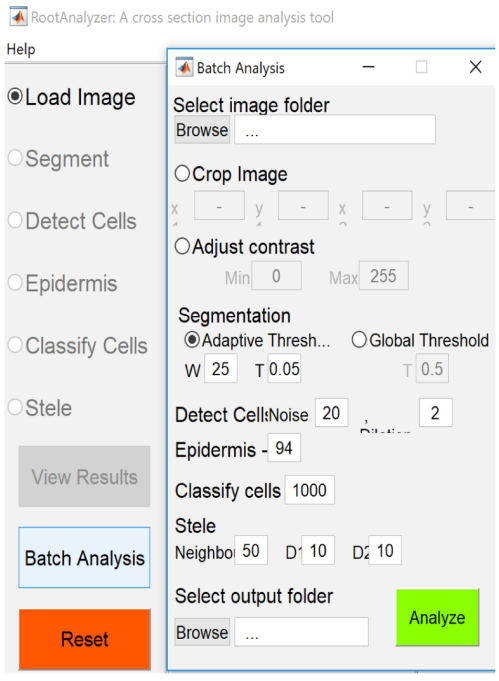
- ImageJ - manual approach
- RootScan - semi-automated approach
- RootAnalyzer - automated approach



ImageJ (Schneider et al., 2012)



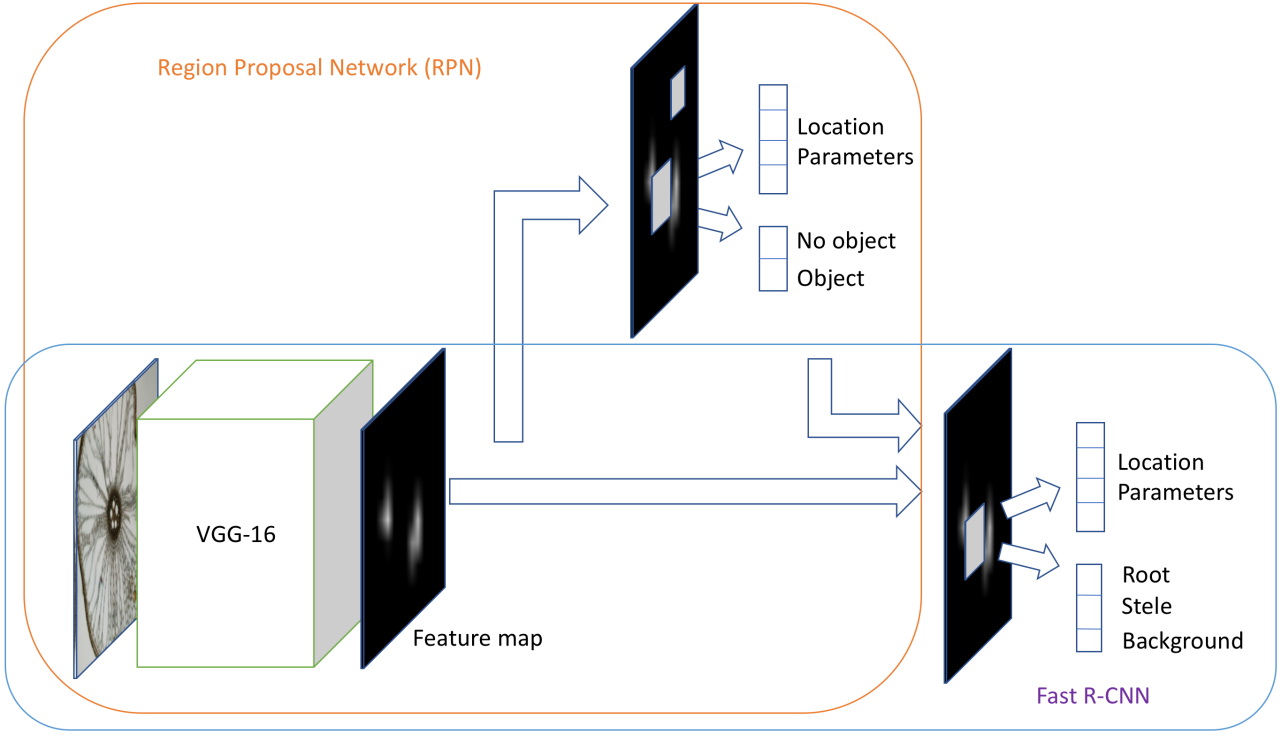
RootScan (Burton et al., 2012)



RootAnalyzer (Chopin et al., 2015)

Proposed Deep Learning Approach

- Detect root, stele and late metaxylem using a model for object detection, specifically, Faster R-CNN (Ren et al., 2015)
- Estimate RD, SD, LMXD and LMXN based on the bounded boxes corresponding to the detected objects

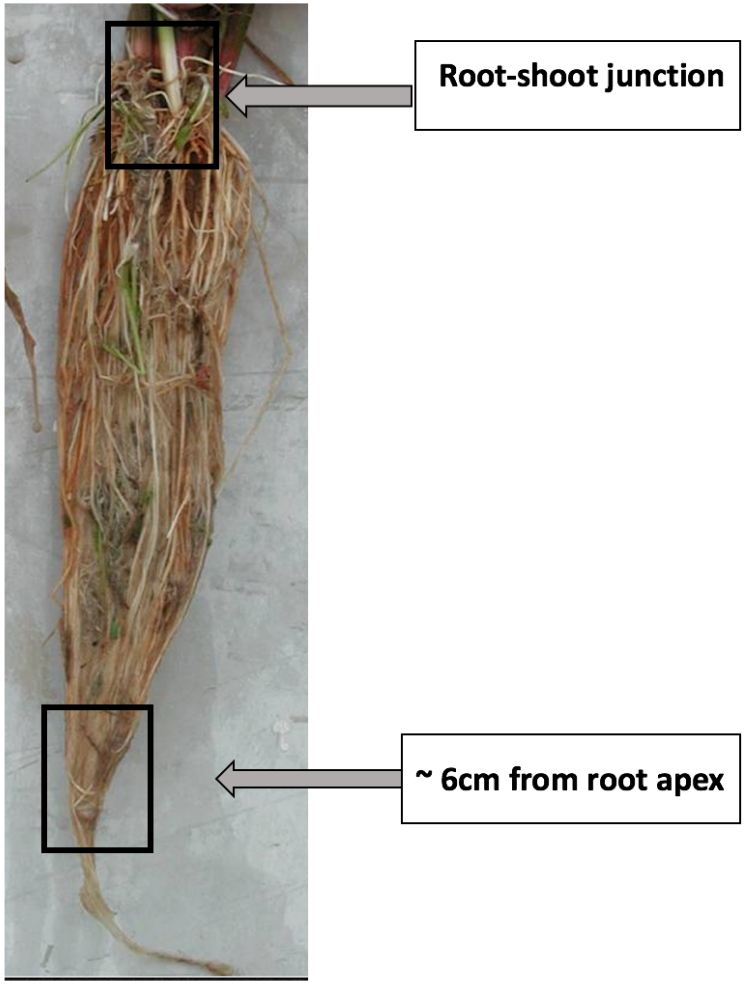


Research Questions

- Can the Faster R-CNN models accurately detect objects of interest and their corresponding bounding boxes?
- How does the performance vary with the number of training images?
- How accurate are the measurements obtained automatically from the bounded boxes?
- How does the Faster R-CNN based approach compare with the existing approaches?

Dataset

- Twenty-five accessions of Oryza species were grown in plastic pots.
- For each species, there were three biological replicates.
- For each replicate, 2-3 images were collected from the root-shoot junction, and 2-3 images at $\approx$ 6 cm from the root apex.
- The total number of images in the dataset is 388. Most images have a 50$\times$ magnification version and a 100$\times$ magnification version.
- All images were manually annotated with respect to RD, SD, LMXD and LMXN.



Experimental Setup

- Trained Faster R-CNN models
  - Model to detect root/stele objects
  - Model to detect late metaxylem (LMX) objects
    - Trained from 50× and 100× magnification images, respectively
- Training, development, and test datasets
  - Performed 5-fold cross-validation (where we split based on accession)
  - Used three folds for training, one fold for development and one fold for test
  - Averaged results over the five folds

Evaluation Metrics

- **Intersection-over-Union (IoU)** - Used to evaluate how well the predicted bounded boxes overlap with the ground bounding boxes for root/stele objects
- **Mean Average Precision (mAP)** - Used to evaluate the ability of the models to correctly detect the LMX objects
- **Root Mean Square Error (RMSE)** - Used to evaluate how well the measurements estimated based on detected bounding boxes match the ground truth measurements for RD, SD, LMXD, and LMXN, respectively

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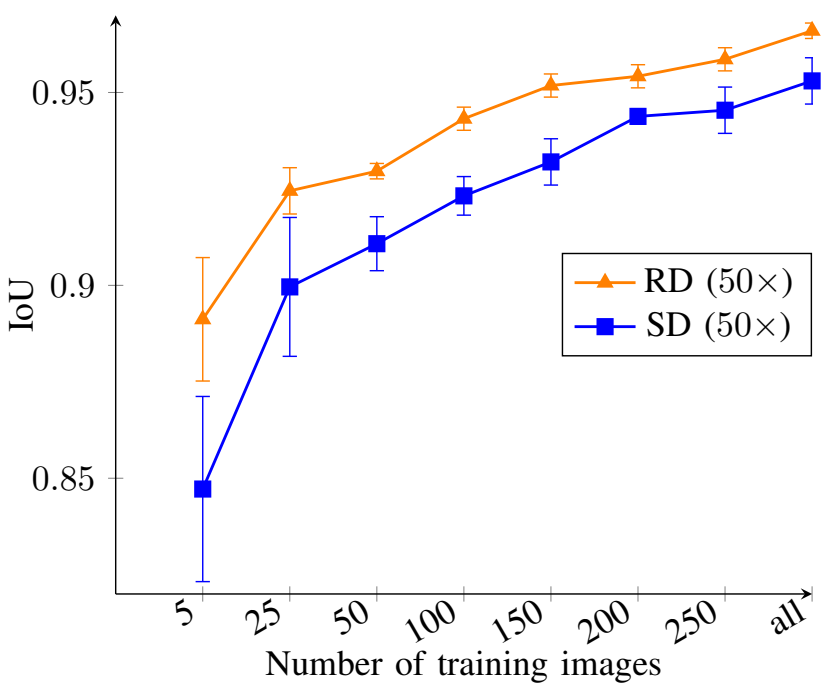
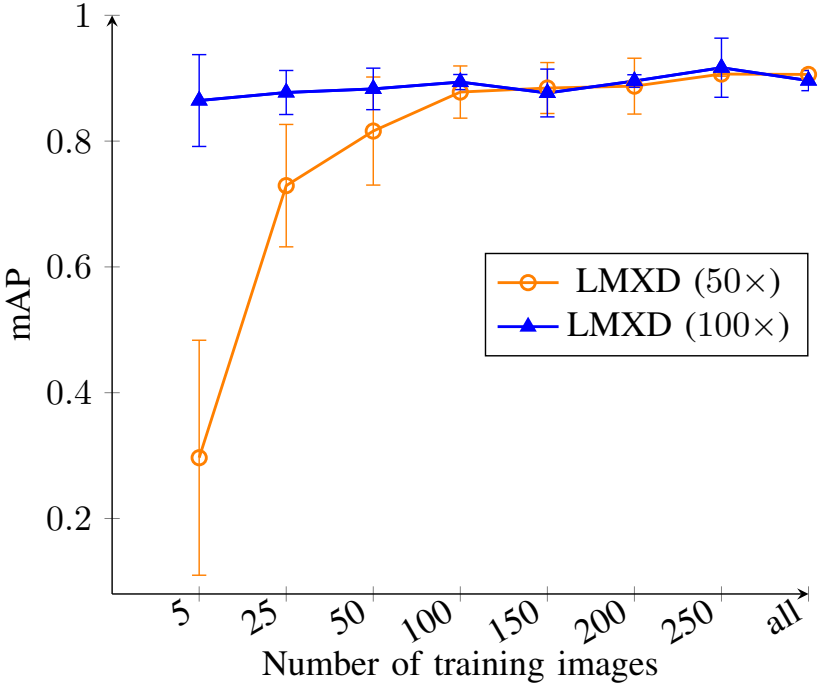
Variation of Performance with Training Data





- Accurate root/stele and LMX models can be learned from a relatively small number of images

RMSE Results

Split (Test Fold)	RD (50×)	SD (50×)	LMXD (50×)	LMXD (100×)	LMXN (50×)	LMXN (100×)
Split 1 (Fold 5)	62.77	21.93	3.67	2.45	0.81	1.37
Split 2 (Fold 4)	32.18	17.54	3.77	3.13	0.71	0.45
Split 3 (Fold 3)	61.19	21.96	3.53	3.22	0.91	0.83
Split 4 (Fold 2)	33.12	20.01	3.58	3.56	1.90	0.63
Split 5 (Fold 1)	43.67	20.94	2.43	1.61	0.74	0.25
Average	46.59	20.39	3.40	2.79	1.02	0.71
Standard dev.	14.77	1.81	0.55	0.77	0.50	0.43

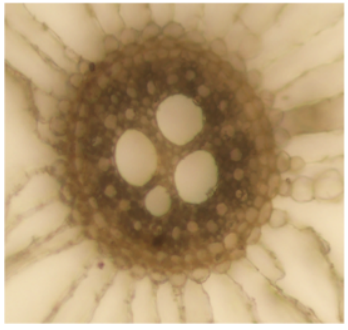
- The predicted bounding boxes lead to accurate estimates for RD, SD, LMXD, LMCN.
- Higher resolution images are better for estimating LMX measurements.

Comparison with Existing Tools

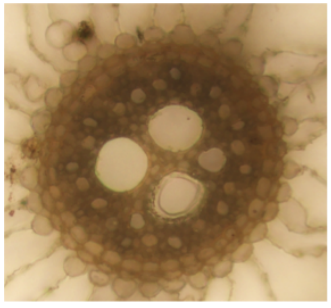
Method	RD	SD	LMXD	LMXN
RootAnalyzer	208.44 ± 22.40	172.21 ± 20.65	32.89 ± 10.62	4.01 ± 0.54
RootScan	66.82 ± 20.86	42.27 ± 25.54	6.26 ± 2.39	0.72 ± 0.23
DL-RootAnatomy (50×)	**43.67 ± 16.80**	**20.51 ± 1.84**	3.58± 0.57	1.13 ± 0.43
DL-RootAnatomy (100×)	N/A	N/A	**2.79 ± 0.93**	**0.64 ± 0.31**

- A subset of the images is used in this experiment
- RootAnalyzer was run in batch mode with tuned parameters
- RootScan was run in semi-automated mode; the original segmentation was corrected as needed
- Our approach gives the best results overall

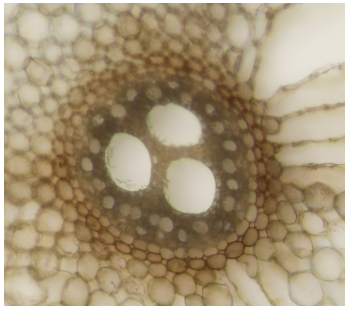
Error Analysis Revealed Noisy Ground Truth



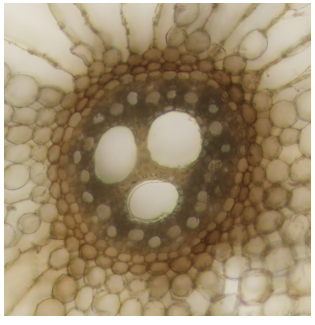
(a) LMXN=4



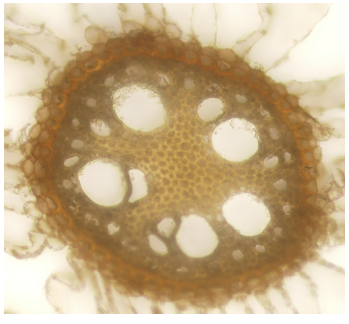
(b) LMXN=3



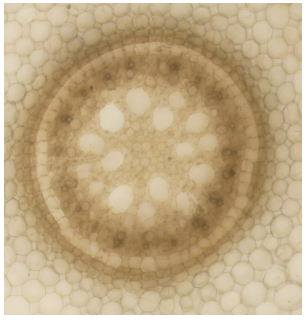
(c) LMXN=4



(d) LMXN=3



(e) LMXN=12



(f) LMXN=11

Conclusions

- Presented a fully automated approach for processing root cross-section images to extract anatomical root features.
- The approach makes use of state-of-the-art Faster R-CNN object detection networks.
- Predicted bounding boxes are used to obtain numeric measurements, such as RD, SD, LMVD, LMXN.
- The trained models produce accurate and consistent annotations, when trained on a relatively small number of training image.
- Further improvements expected for larger/less noisy training sets.

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Andrés Bur, MD

University of Kansas Medical Center

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Clinical applications of deep neural network-based image classification in oncology

Andrés M. Bur, MD

Assistant professor

Head and neck oncologic surgery

Department of Otolaryngology – Head and Neck Surgery

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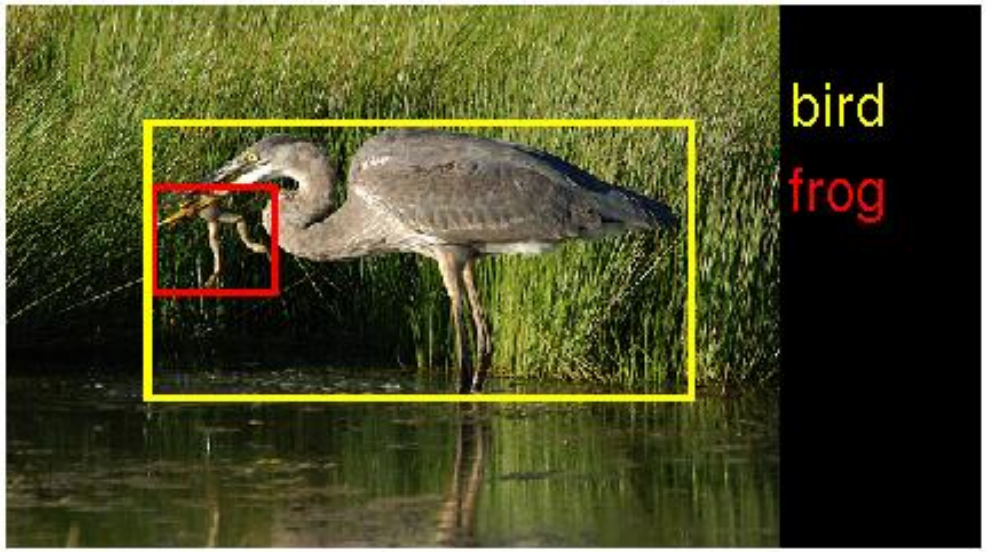
Computer vision

A subfield of artificial intelligence focused on training computers to interpret and understand the visual world.



Russakovsky O, Jia Deng, Hao Su, et al. ImageNet Large Scale Visual Recognition Challenge. *IJCV,* 2015.

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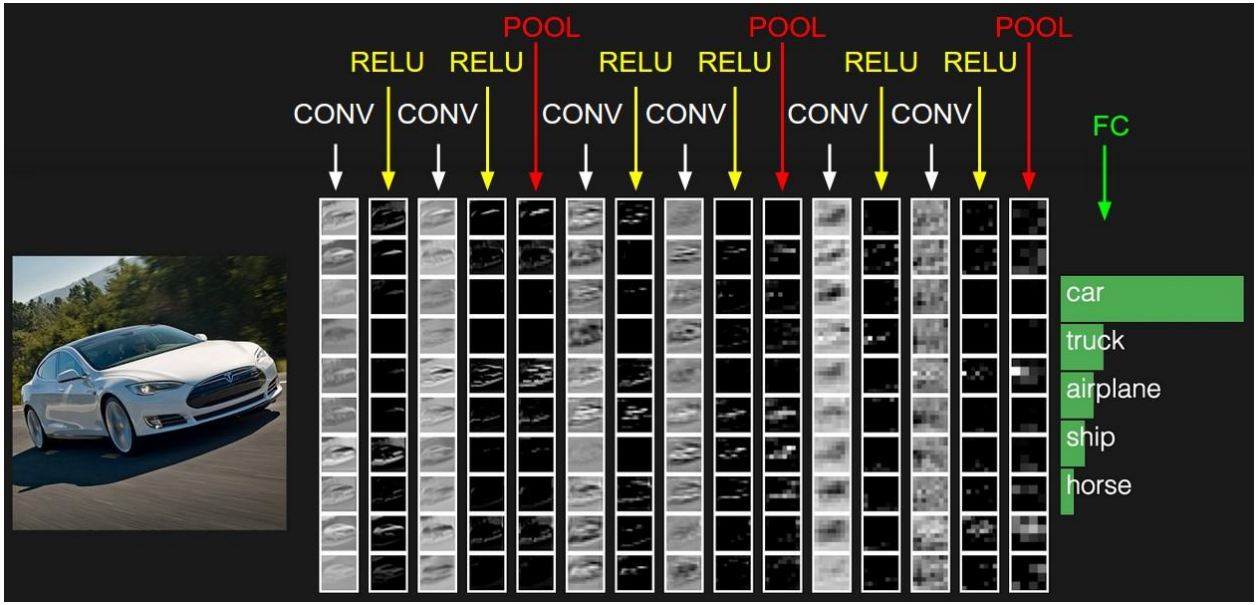
Convolutional neural networks

A type of multilayer artificial neural network that is well-suited for image and video classification tasks



Li F. Convolutional neural networks for visual recognition. Available online at: http://cs231n.stanford.edu/

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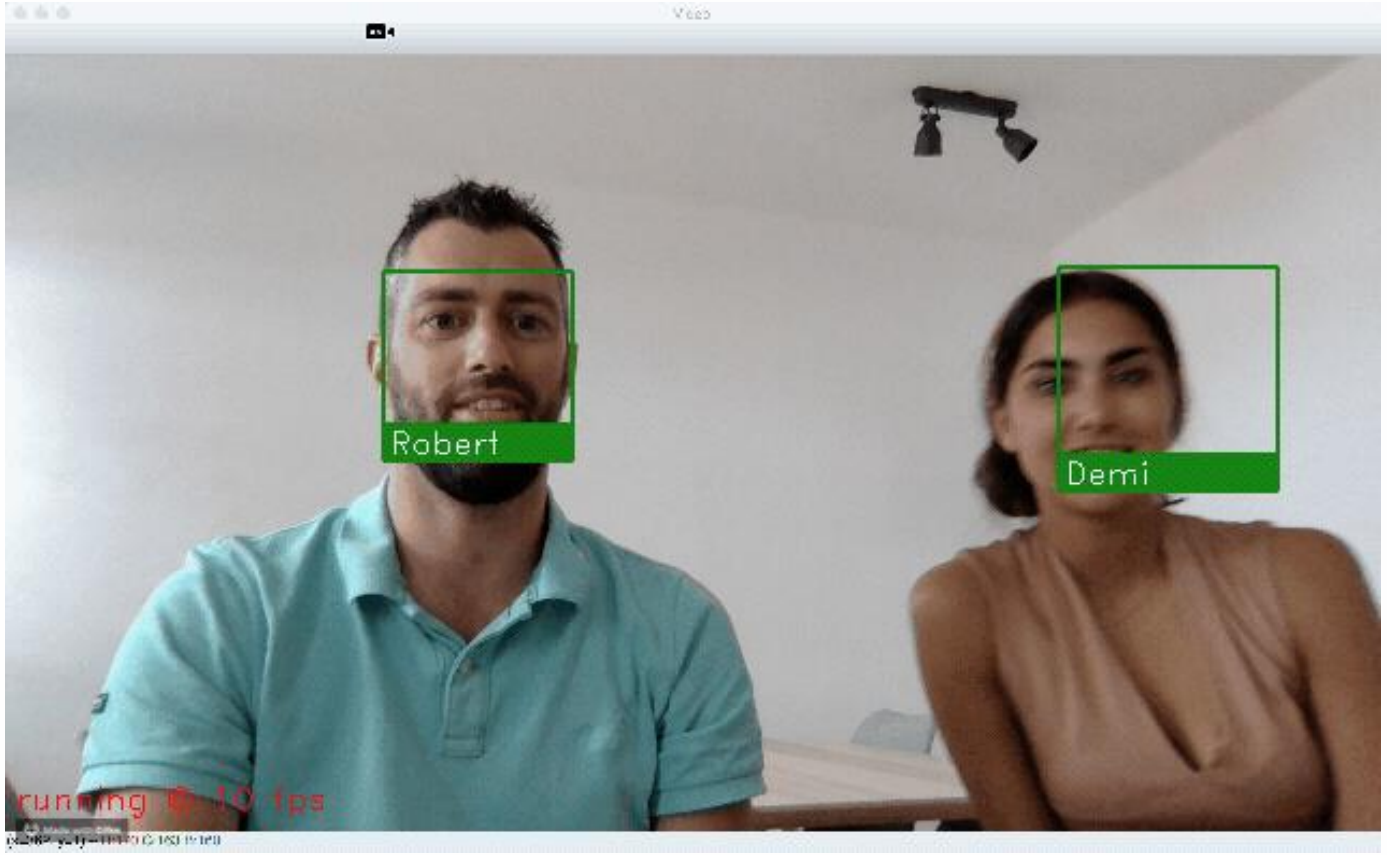
CNNs for facial recognition



van Straalen R. Facial recognition with python in an hour (or two). https://medium.com/data-science-lab-amsterdam/face-recognition-with-python-in-an-hour-or-two-d271324cbeb3

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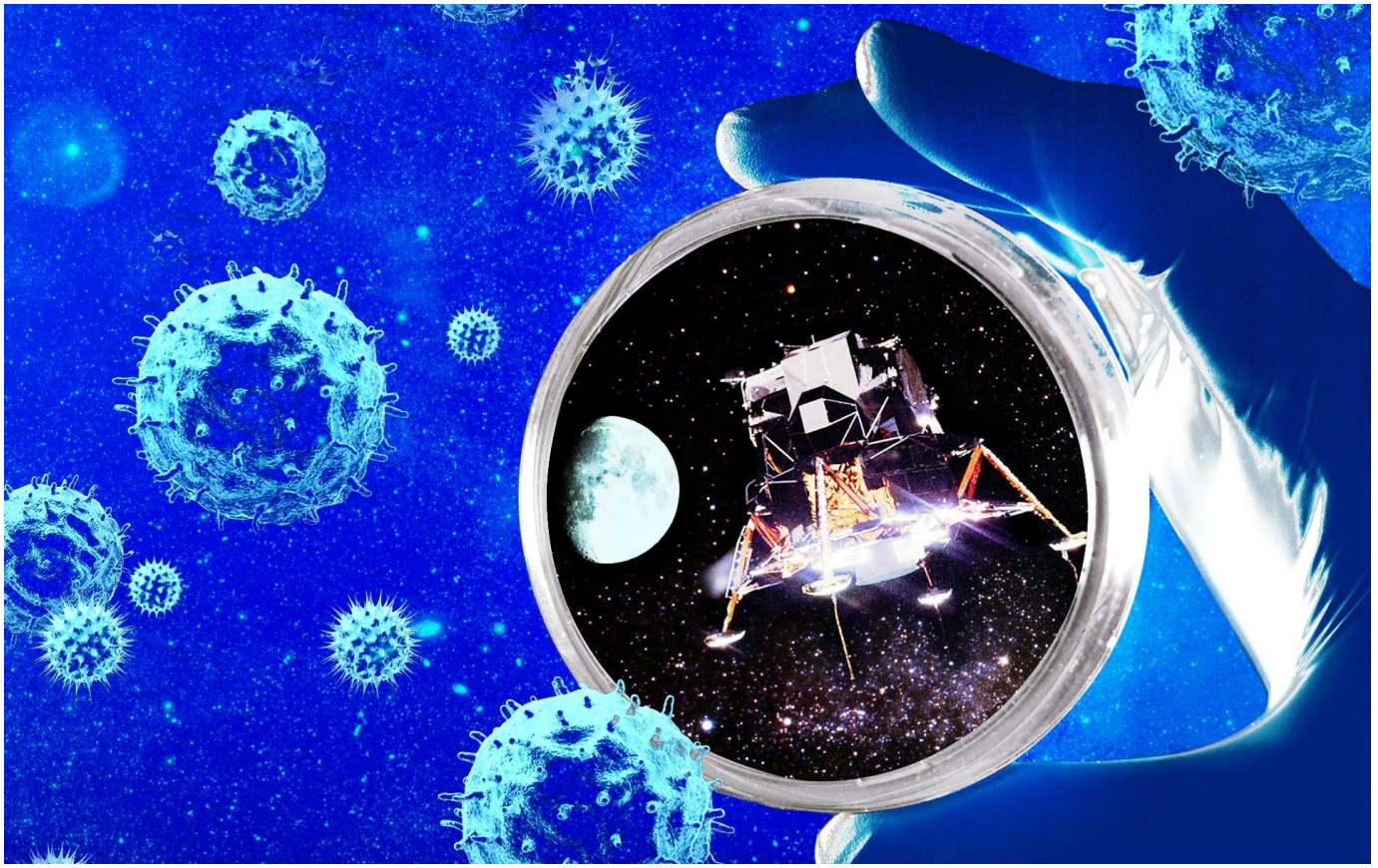
Can CNNs be applied to cancer care?



Newkirk VR. Cancer: the Final Frontier. https://www.theatlantic.com/politics/archive/2016/04/cancer-the-final-frontier/478962/

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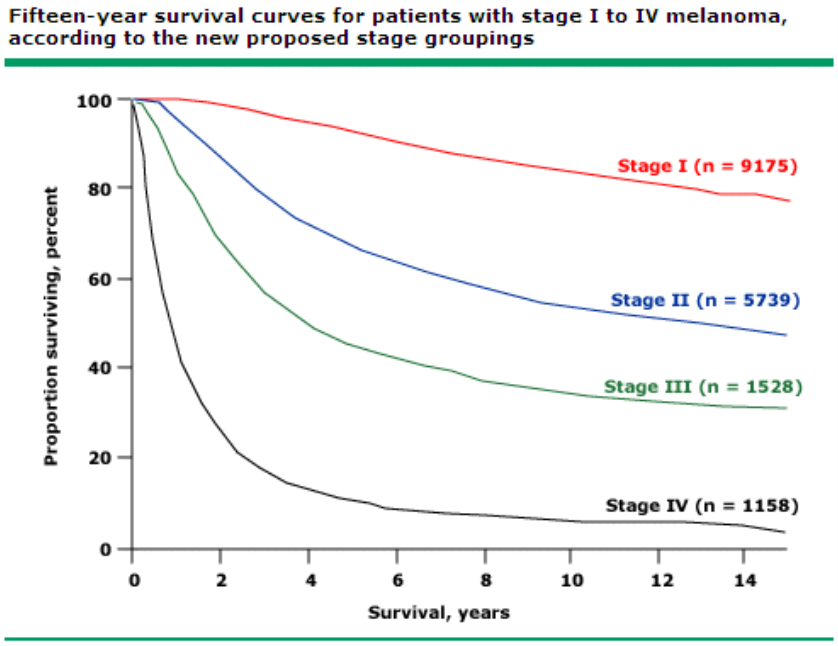
Lymph nodes in cancer

- Whether or not a cancer has spread to the lymph nodes is important for staging, prognosis and treatment
- Unfortunately, this is not obvious in many cases



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Lymph nodes in cancer

- Options for patients at risk of lymph node metastasis:
  - Option 1: Observe and treat if needed
  - Option 2: Treat/remove at risk lymph nodes

The NEW ENGLAND JOURNAL of MEDICINE

ORIGINAL ARTICLE

Elective versus Therapeutic Neck Dissection in Node-Negative Oral Cancer

Anil K. D'Cruz, M.S., D.N.B., Richa Vaish, M.S., Neeti Kapre, M.S., D.N.B., Mitali Dandekar, M.S., D.N.B., Sudeep Gupta, M.D., D.M., Rohini Hawaldar, B.Sc., D.C.M., Jai Prakash Agarwal, M.D., Gouri Pantvaidya, M.S., D.N.B., Devendra Chaukar, M.S., D.N.B., Anuja Deshmukh, M.S., D.L.O., D.O.R.L., Shubhada Kane, M.D., Supreeta Arya, M.D., D.N.B., D.M.R.D., Sarbani Ghosh-Laskar, M.D., D.N.B., Pankaj Chaturvedi, M.S., F.A.I.S., Prathamesh Pai, M.S., D.N.B., D.O.R.L., Sudhir Nair, M.S., M.Ch., Deepa Nair, M.S., D.N.B., D.O.R.L., and Rajendra Badwe, M.S., for the Head and Neck Disease Management Group

D'Cruz AK, Vaish R, Kapre N, et al. Elective versus therapeutic neck dissection in node-negative oral cancer. N Engl J Med 2015;373:521–9.

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Contents lists available at ScienceDirect

Oral Oncology

journal homepage: www.elsevier.com/locate/oraloncology

Machine learning to predict occult nodal metastasis in early oral squamous cell carcinoma

Andrés M. Bur[a,*], Andrew Holcomb[a], Sara Goodwin[a], Janet Woodroof[b], Omar Karadaghy[a], Yelizaveta Shnayder[a], Kiran Kakarala[a], Jason Brant[c], Matthew Shew[a]

[a] Department of Otolaryngology – Head and Neck Surgery, University of Kansas School of Medicine, 3901 Rainbow Boulevard M.S. 3010, Kansas City, KS, USA
[b] Department of Pathology and Laboratory Medicine, University of Kansas School of Medicine, 3901 Rainbow Boulevard, Kansas City, KS, USA
[c] Department of Otolaryngology – Head and Neck Surgery, Hospital of the University of Pennsylvania, 3400 Spruce Street, Philadelphia, PA, USA

Classifier	Sensitivity	Specificity	AUC
DOI (d_t = 4 mm)	0.750	0.458	0.657
Kernel SVM	0.833	0.559	0.776
Gradient boosting	0.917	0.525	0.798
Logistic regression	0.917	0.627	0.821
Decision forest	0.917	0.576	0.840

Bur AM, Holcomb A, Goodwin S, et al. Machine learning to predict occult nodal metastasis in early oral squamous cell carcinoma. Oral Oncol. 2019;92:20-25

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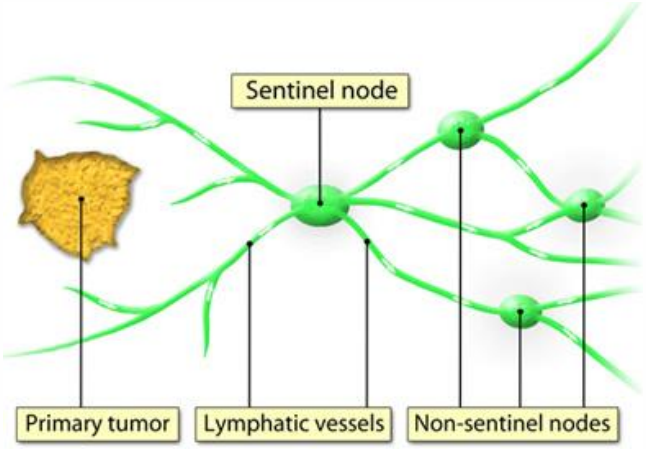
Sentinel lymph node biopsy

- The *sentinel lymph node* is the first node to which cancer cells are likely to spread from a primary tumor
- If *any* cancer cells are identified in the sentinel lymph node, it is considered positive and additional treatment is warranted



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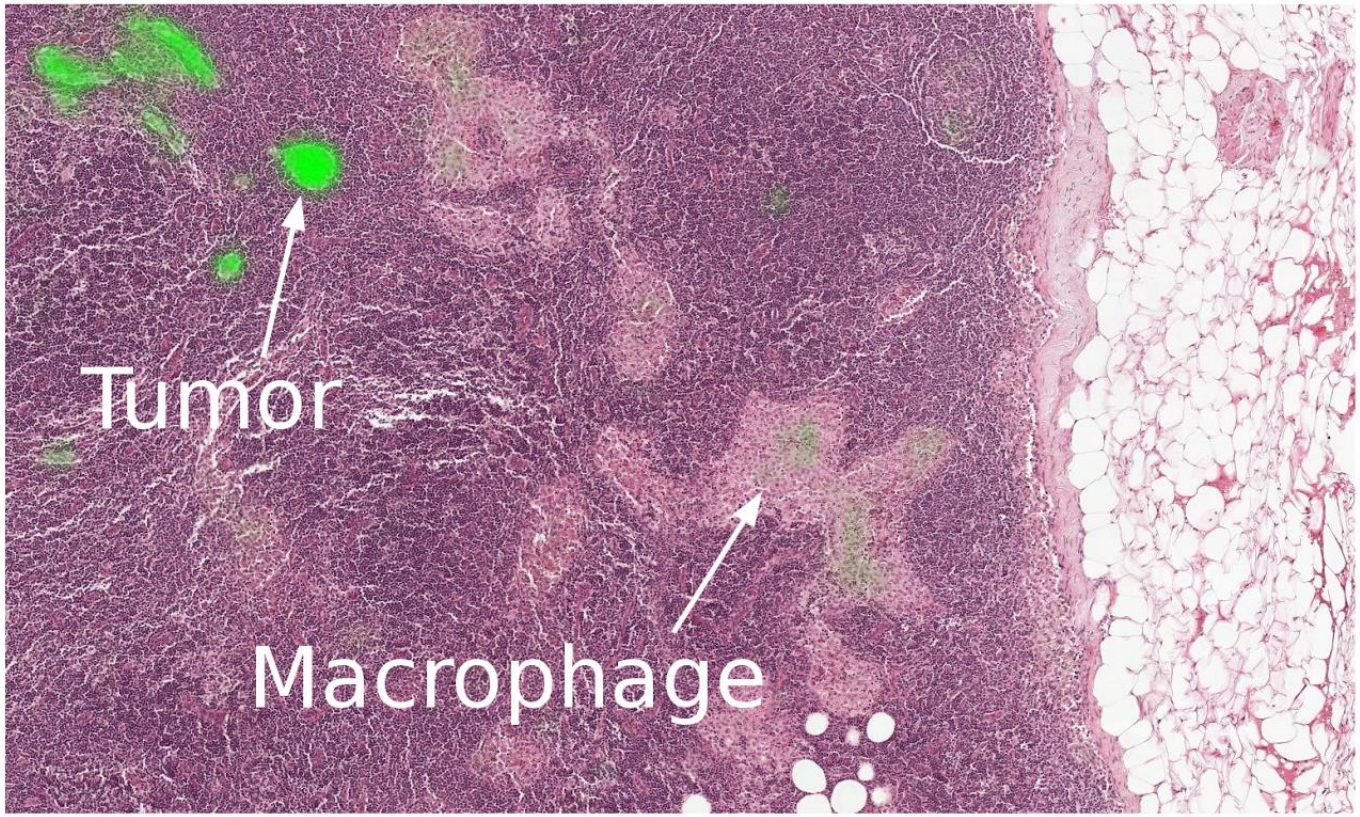
Positive or negative?



Litjens G, Bandi P, Bejnordi BE, et al. 1399 H&E-stained sentinel lymph node sections of breast cancer patients: the CAMELYON dataset. GigaScience, giy065, DOI: 10.1093/gigascience/giy065

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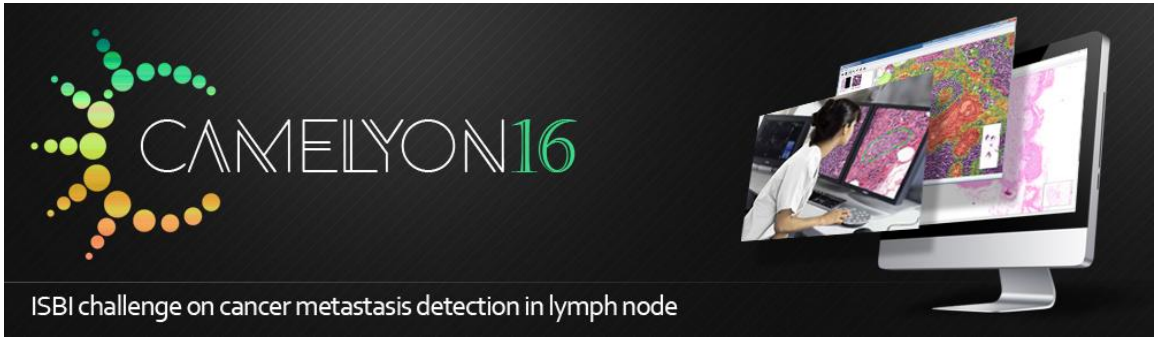

"The goal of this challenge is to evaluate new and existing algorithms for automated detection of metastases in hematoxylin and eosin (H&E) stained whole-slide images of lymph node sections."

The CAMELYON16 challenge:

- Contained 400 whole-slide images of sentinel lymph nodes from patients with breast cancer
- Spanned 2 years (2014-2016)
- Received 32 submissions

Litjens G, Bandi P, Bejnordi BE, et al. 1399 H&E-stained sentinel lymph node sections of breast cancer patients: the CAMELYON dataset. GigaScience, giy065, DOI: 10.1093/gigascience/giy065

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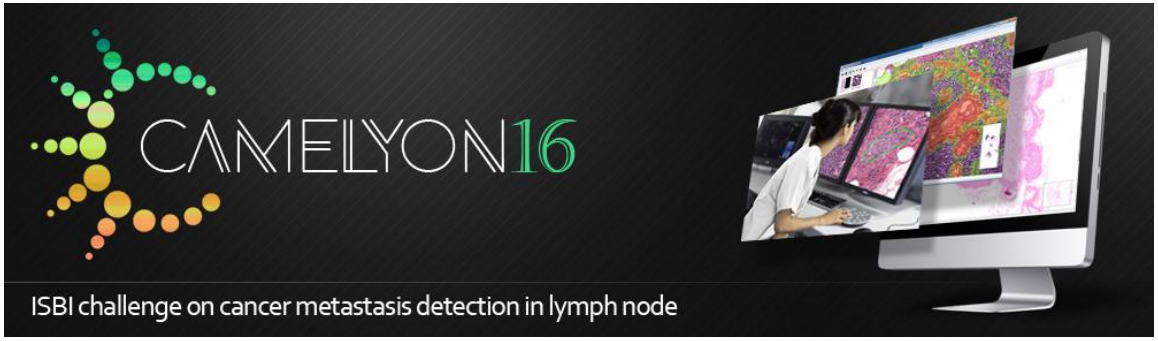

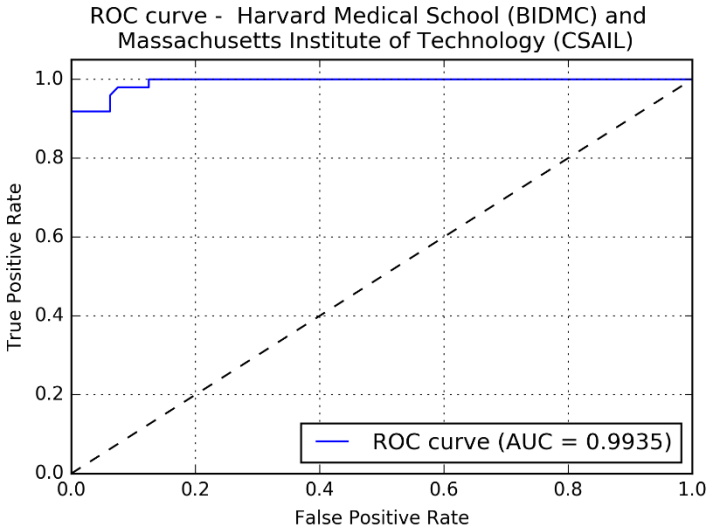

"A pathologist independently reviewed the same images, obtaining a whole slide image classification AUC of 0.966 and a tumor localization score of 0.733. Combining our deep learning system's predictions with the human pathologist's diagnoses increased the pathologist's AUC to 0.995, representing an approximately 85 percent reduction in human error rate."

Wang D, Khosla A, Gargeya R, Ishad H, Beck AH (2016). Deep learning for identifying metastatic breast cancer. https://arxiv.org/abs/1606.05718.

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SCIENTIFIC REPORTS

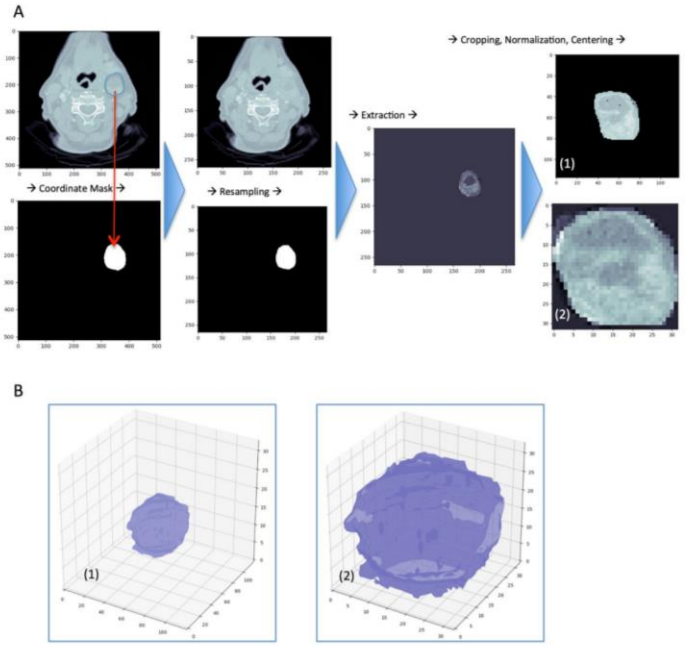
OPEN

Pretreatment Identification of Head and Neck Cancer Nodal Metastasis and Extranodal Extension Using Deep Learning Neural Networks

Received: 25 May 2018
Accepted: 7 September 2018
Published online: 19 September 2018

Benjamin H. Kann[1], Sanjay Aneja[1], Gokoulakrichenane V. Loganadane[1], Jacqueline R. Kelly[1], Stephen M. Smith[2], Roy H. Decker[1], James B. Yu[1], Henry S. Park[1], Wendell G. Yarbrough[3], Ajay Malhotra[4], Barbara A. Burtness[5] & Zain A. Husain[1]

- Trained a 3-dimensional CNN using a set of nearly 3,000 CT-segmented lymph node samples with corresponding labels
- Validated on a blinded test set of 131 samples



Kann BH, Aneja S, Loganadane GV, et al. Pretreatment identification of head and neck cancer nodal metastasis and extranodal extension using deep learning neural networks. Sci Rep. 2018;8:14036.

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Pretreatment Identification of Head and Neck Cancer Nodal Metastasis and Extranodal Extension Using Deep Learning Neural Networks

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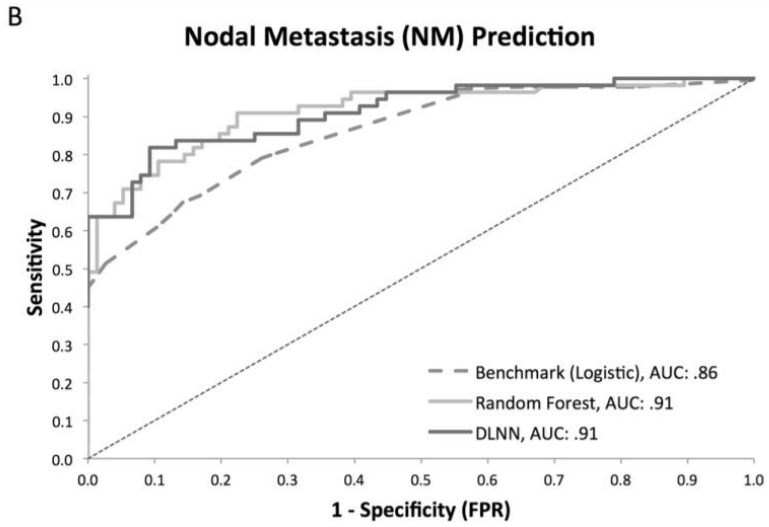

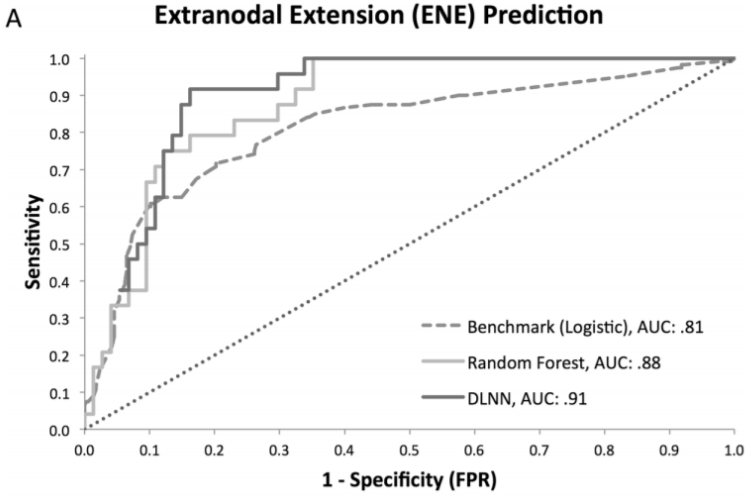

Kann BH, Aneja S, Loganadane GV, et al. Pretreatment identification of head and neck cancer nodal metastasis and extranodal extension using deep learning neural networks. Sci Rep. 2018;8:14036.

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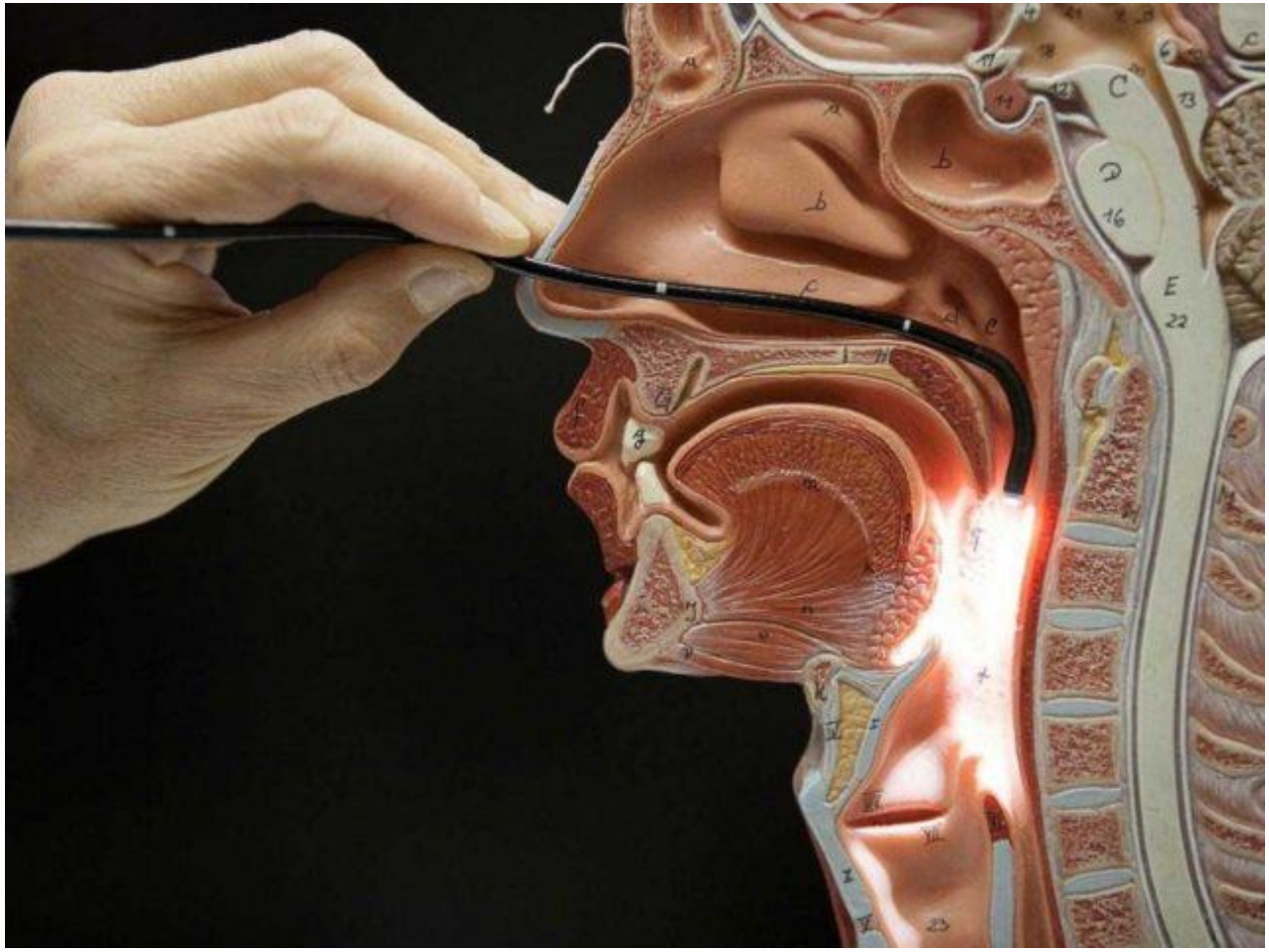
Identification of laryngeal cancer



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Identification of laryngeal cancer

Label

Normal

Cancer

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Identification of laryngeal cancer

Actual	Normal	Normal	Cancer	Cancer
Probability(Normal)	1.00	0.98	<0.001	0.17
Probability (Cancer)	<0.001	0.02	1.00	0.83
Prediction	Normal	Normal	Cancer	Cancer

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Conclusions

- A recent explosion in the digitization of medical data, including pathologic and radiographic images, has enabled development of deep learning in oncology
- Deep learning has not yet transformed patient care in oncology but a growing body of research showing its potential has garnered interest
- High quality data is key to developing clinically useful algorithms to improve patient care

Bur AM, Shew M, New J. Artificial intelligence for the otolaryngologist: a state of the art review. Otolaryngol Head Neck Surg 2019.

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DATA APPLICATION

Moderator:

Mark Nichols, PhD

University of Missouri – Kansas City

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Mark Clements, MD, PhD

University of Missouri – Kansas City

Children's Mercy

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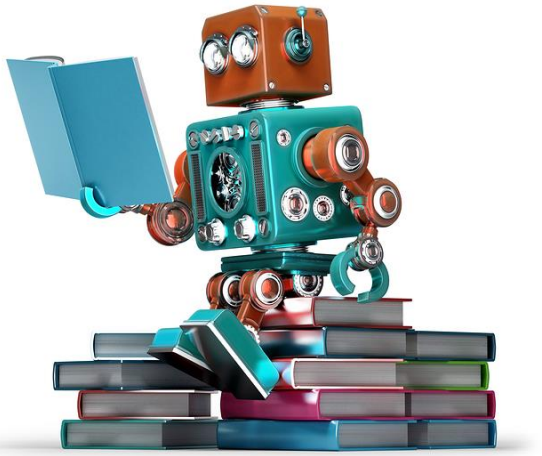
Improving Type 1 Diabetes Care

with advanced machine learning and quality improvement methods



Not this kind of machine learning!

UMKC School of Medicine

Children's Mercy HOSPITALS & CLINICS
www.childrensmercy.org

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Conflicts of Interest

Glooko

Eli Lilly

Medtronic

Health Information Technology

Children's Mercy, Joslin Diabetes Center to use machine learning for diabetes management

Written by Julie Spitzer | June 12, 2017 | Print | Email

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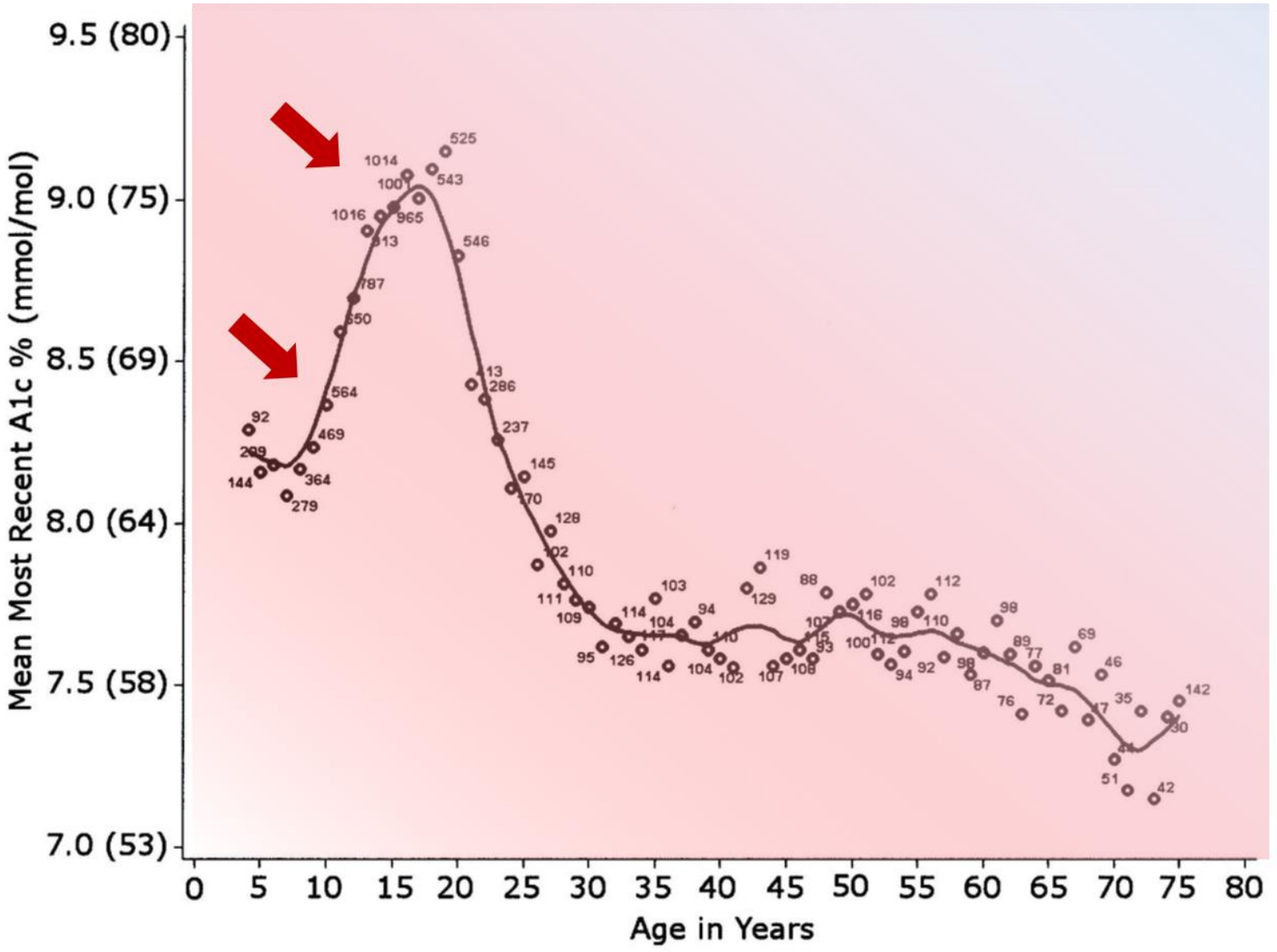
Children's Mercy Kansas City (Mo.) and Boston-based Joslin Diabetes Center will deploy predictive models for Type 1 diabetes management using technology from Cambridge, Mass.-based Cyft.

Cyft technology uses machine learning and natural language processing to analyze disparate data sources — including patients' EMRs — to create predictive models for health professionals. Children's Mercy and Joslin Diabetes Center will deploy the models to detect at-risk patients in need of intervention.

The three-year project, funded by a grant from the Helmsley Charitable Trust, will begin at Children's Mercy and Joslin Diabetes Center mid-2017.

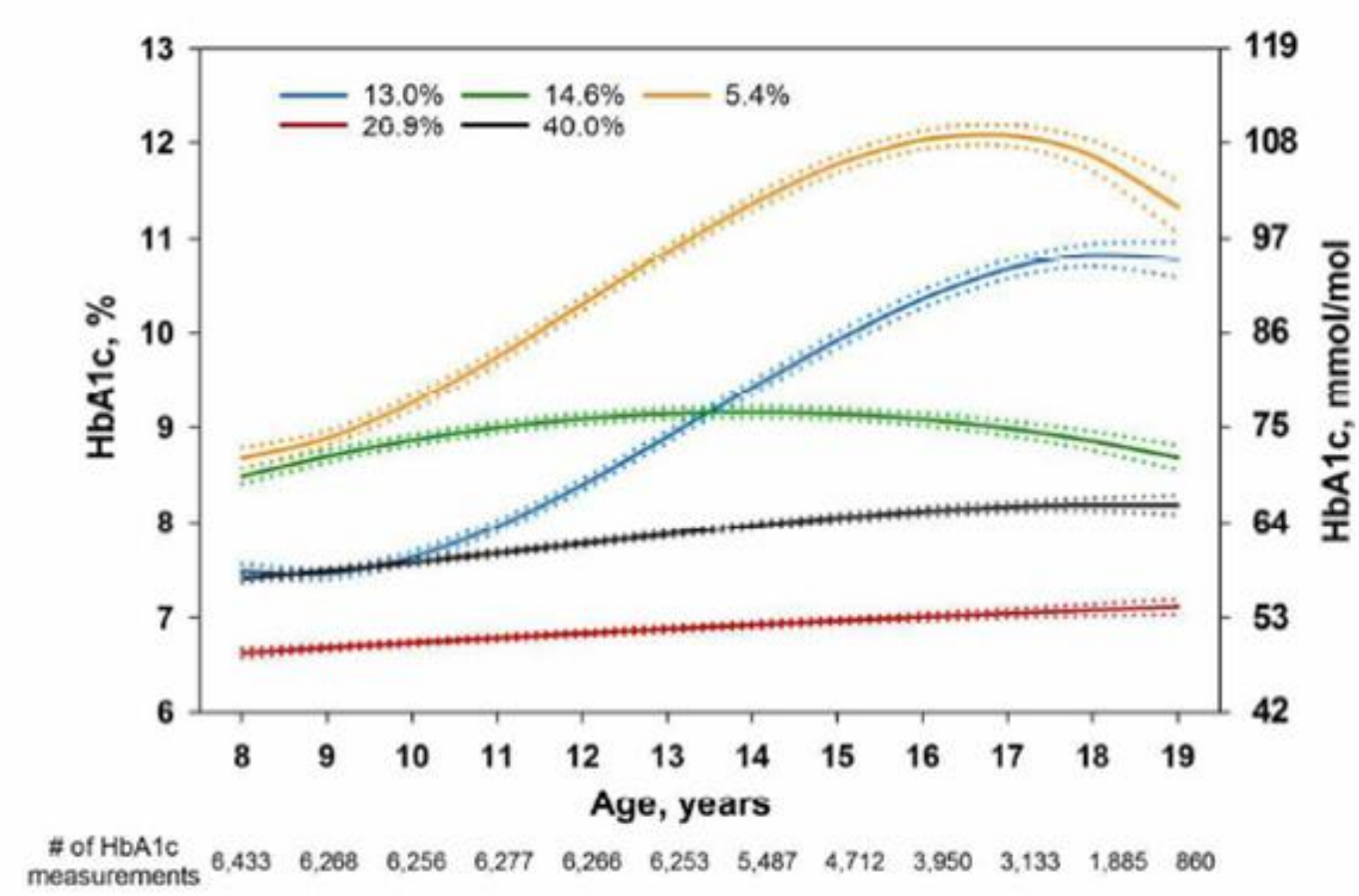
3-year, $3.15 million award from the
Leona M. and Harry B. Helmsley Charitable Trust

Glycemic control across the life span



Miller et al., Diabetes Care. 2015. 38(6):971-8

Why consider machine learning to make predictions? Example: Youth have varying trajectories of HbA1c and we can predict them

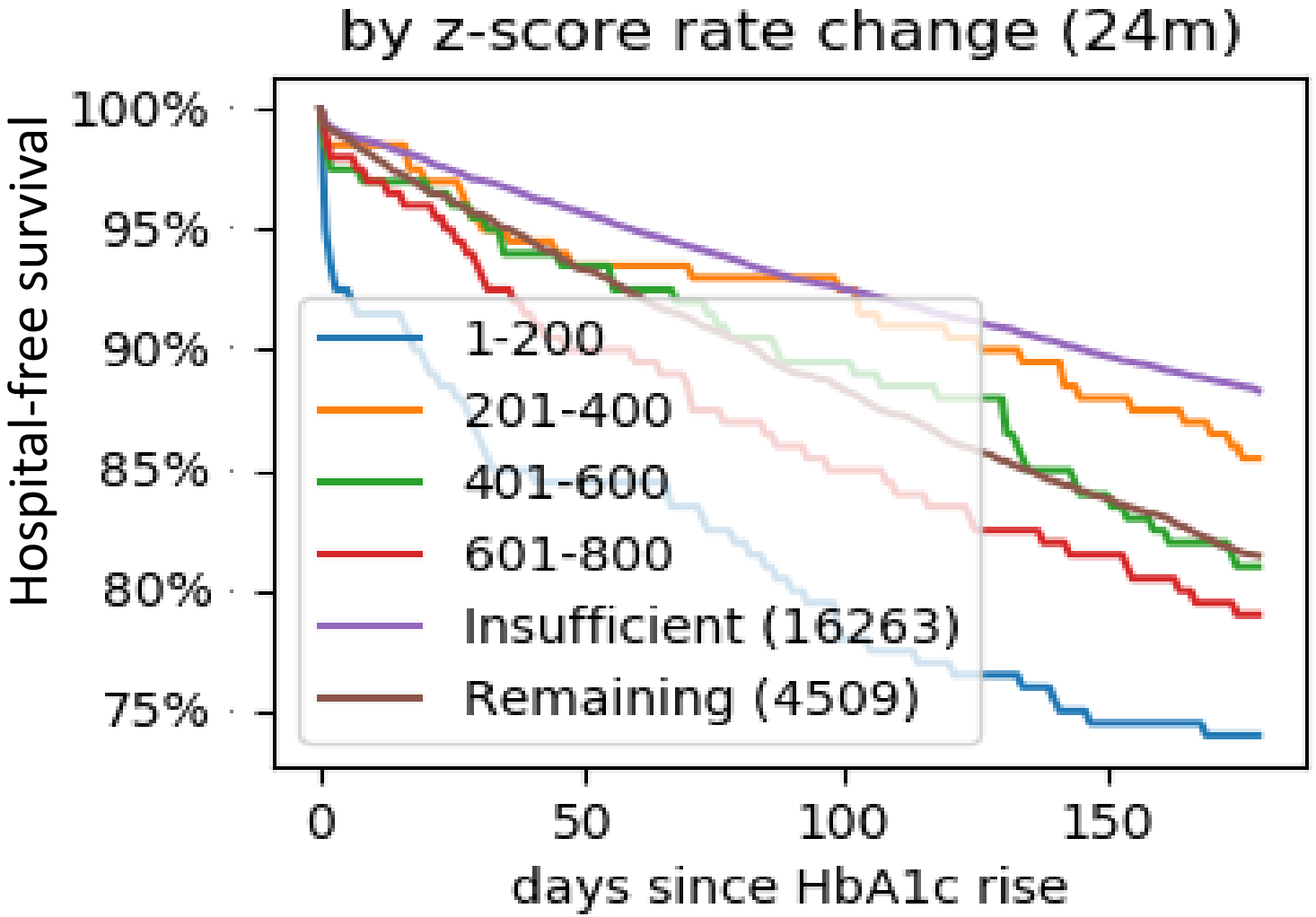


But statistical models are time consuming and difficult to run every day

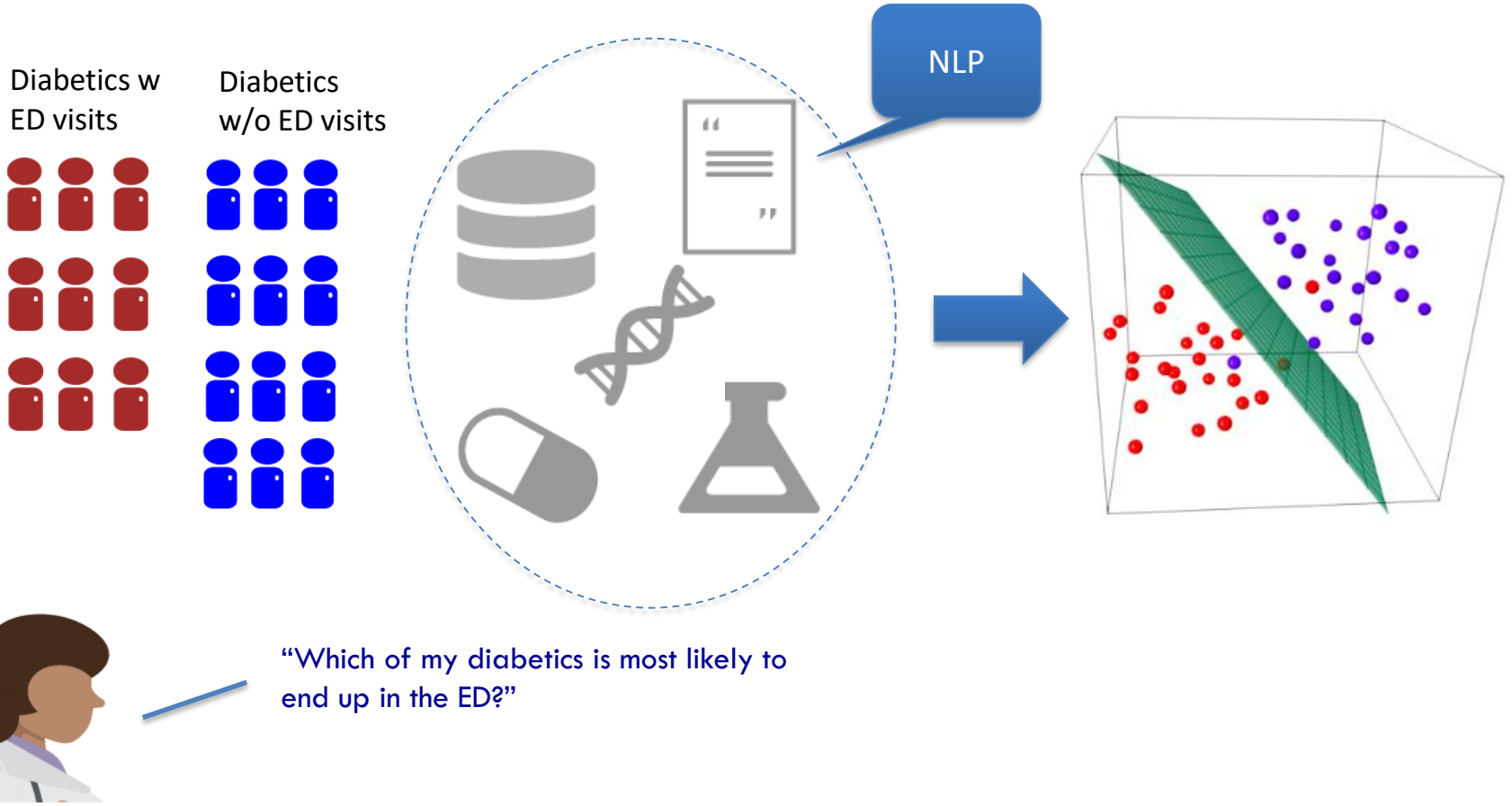
Schwandt et al., Diabetes Care. 2017; 40(3):309-16

Why predict rate of A1c rise?

The case of hospital admissions



This strategy can be applied to other outcomes as well
Example: hospital admission for diabetic ketoacidosis



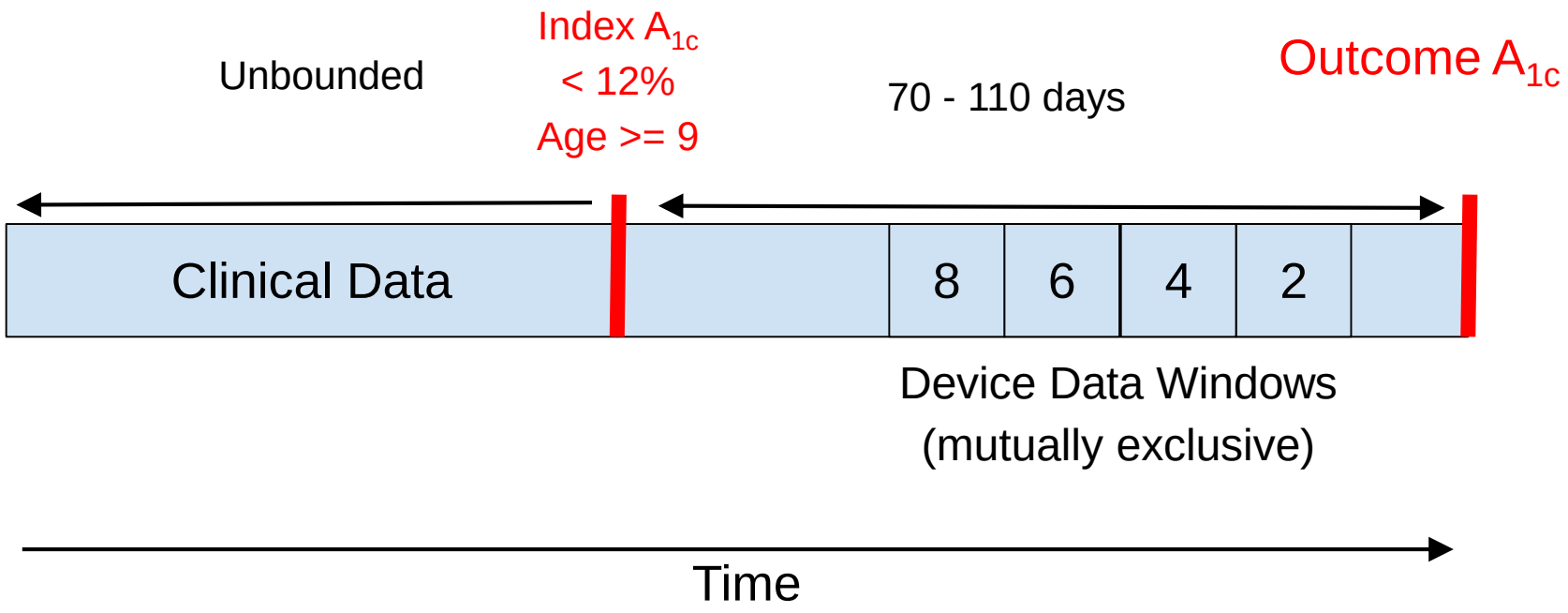
Machine Learning and NLP use the EMR's dirty, messy, raw, partly missing/reliable data

Problem statement:

Can we use machine learning to understand and reduce the percent of patients with large rises in HbA1c

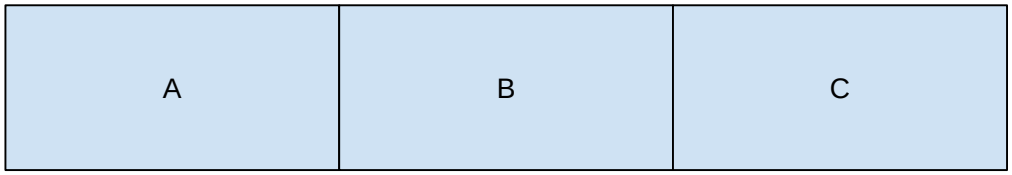
Data model for predicting rise in A1c

A single case of HbA_{1c} change



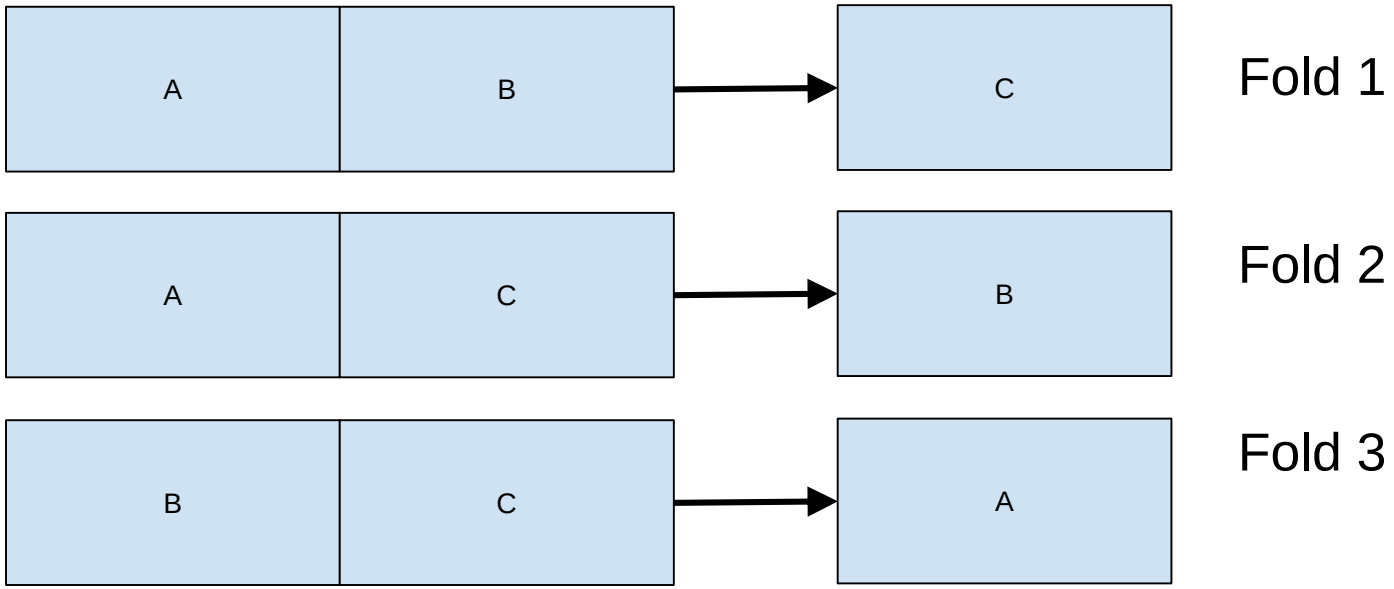
Model training & validation with 5 years of clinical data

Divide available cases



Fit Model

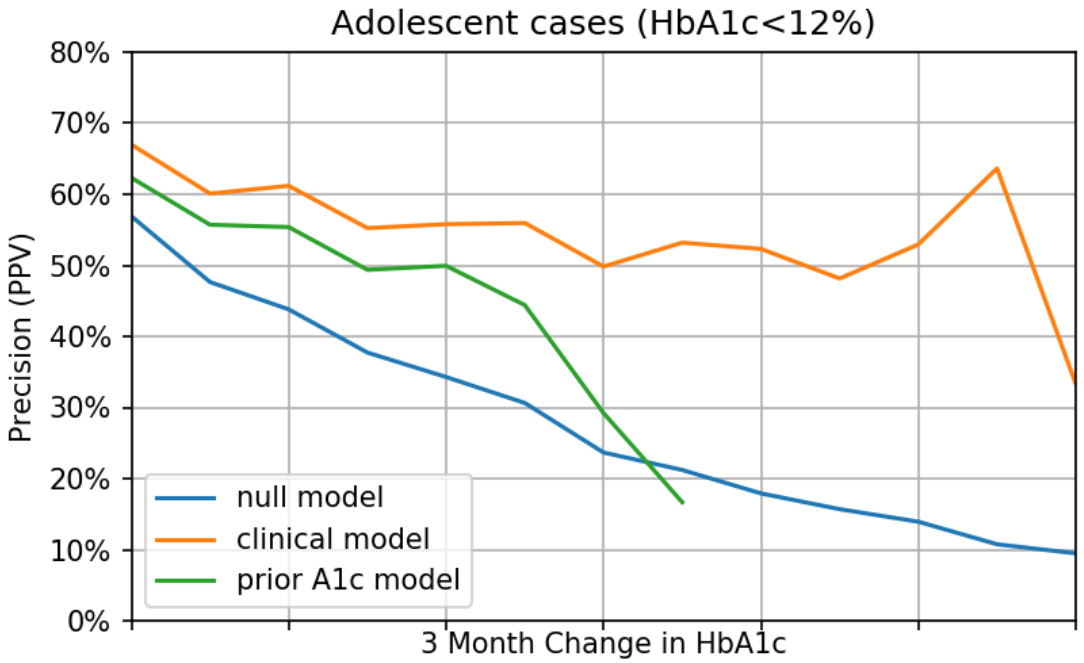
Evaluate

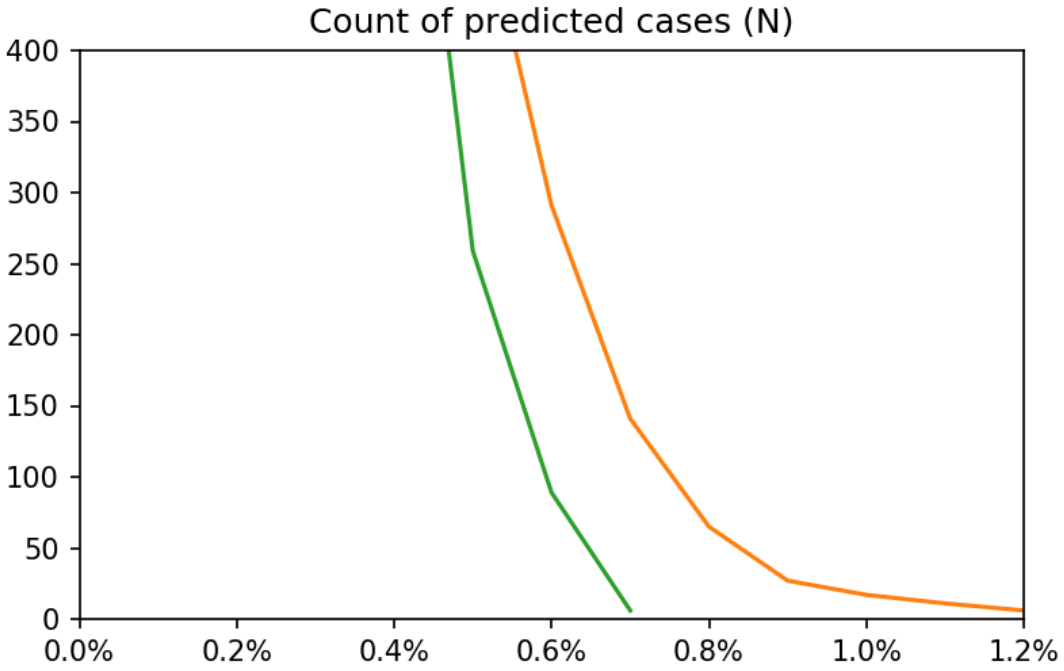


Features included in model

Features (total)	17,466
Features used in any fold	1,630
Features used in all folds	305

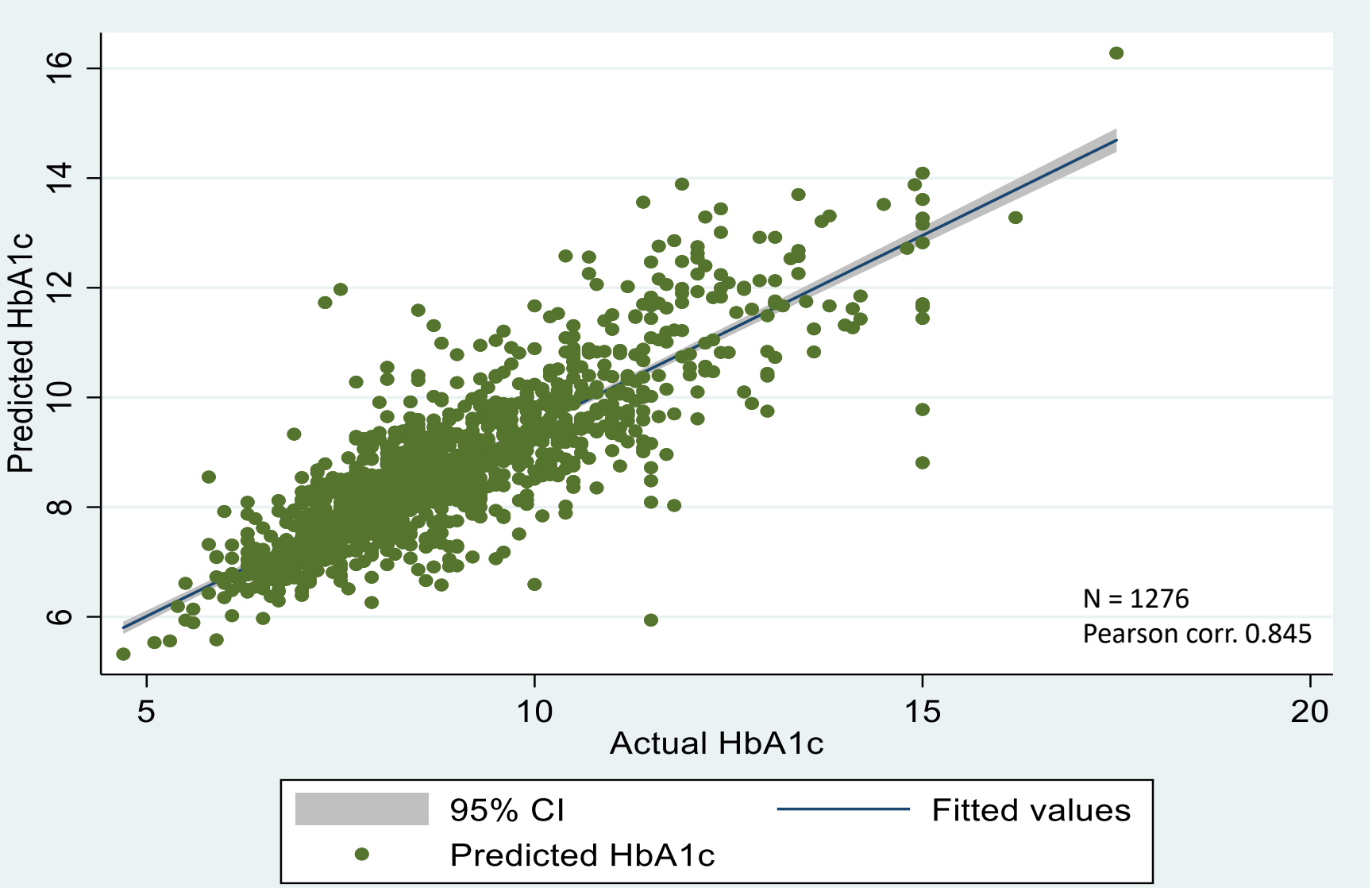
Precision of machine learning model





Hundreds of cases

Clinical deployment: Positive correlation of Predicted versus Actual HbA1c values



Demographic characteristics of cohort

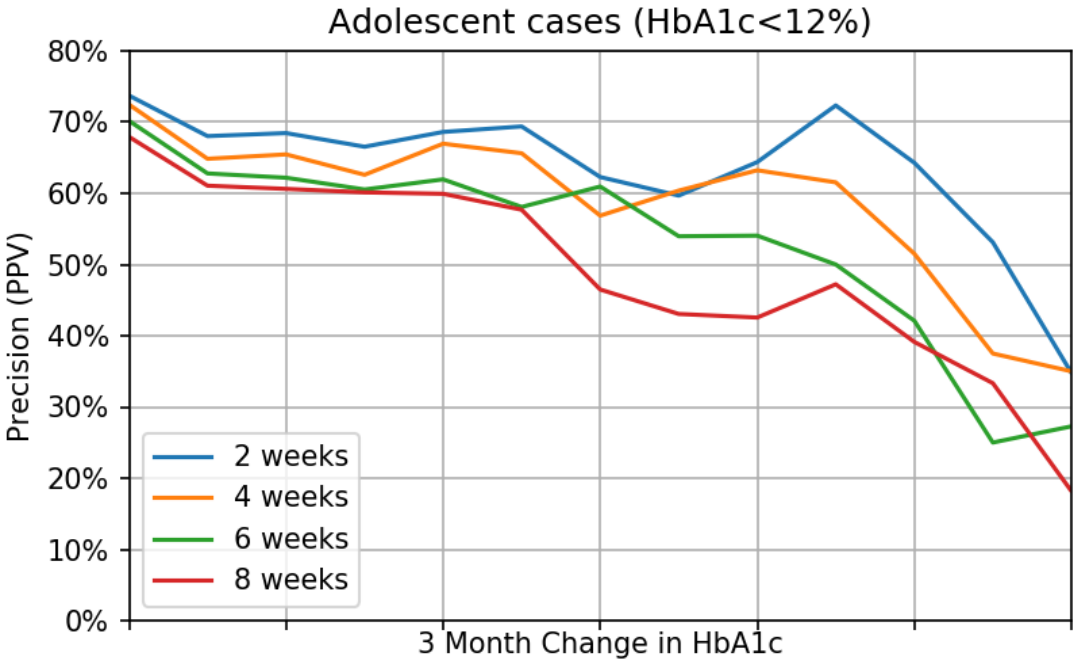
	Frequency (%)
Sex	
Female	648 (51%)
Male	627 (49%)
Race	
White	1063 (83.4%)
Black or African American	80 (6.3%)
Hispanic	52 (4.1%)
Multiracial	51 (4.0%)
Asian	11 (0.9%)
American Indian or Alaska Native	6 (0.5%)
Native Hawaiian or Pacific Islander	3 (0.2%)
Other	4 (0.3%)
Declined/Refused	3 (0.2%)
Unknown to Respondent	1 (0.1%)
Respondent Not Available	1 (0.1%)
Ethnicity	
Non-Hispanic/Non-Latino	1190 (93.3%)
Hispanic/Latino	82 (6.4%)
Declined/Refused	2 (0.2%)
Unknown to Respondent	1 (0.1%)
Insulin delivery and glucose monitoring type (n=942)	
CGM	445 (47%)
Pump	497 (53%)
Age [Median (IQR)]	14.1 (10.8,16.5)

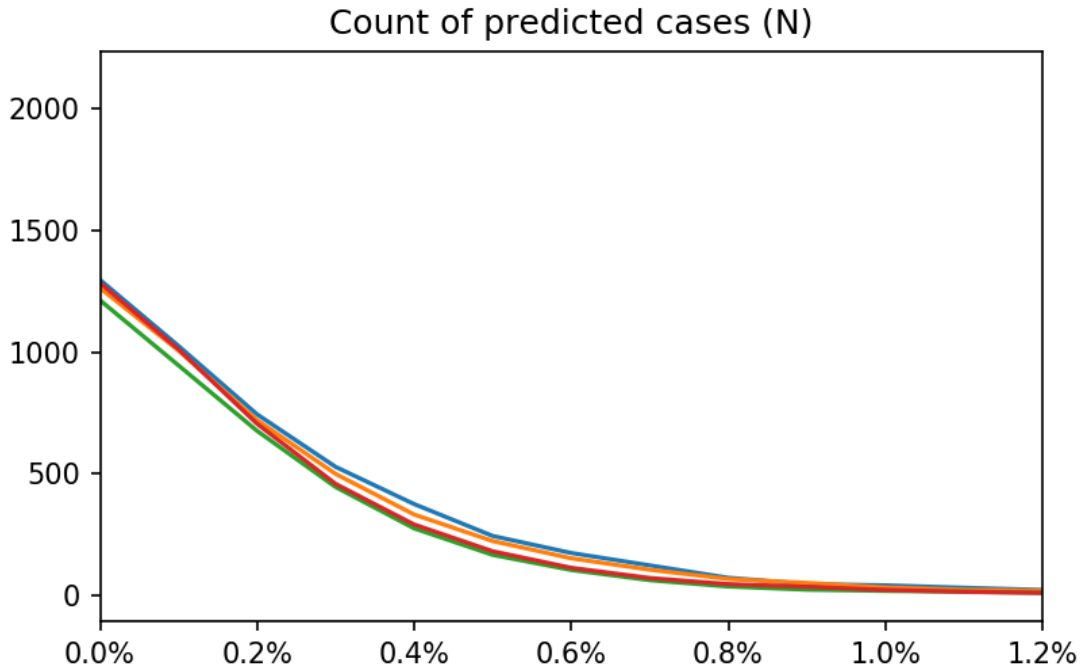
What happens if we select different thresholds for taking action on the predicted HbA1c?

	Estimate (%)	95% Confidence Interval
Less than 0.3 vs Greater than or equal to 0.3		
Sensitivity	21.3%	18%, 24.9%
Specificity	86.1%	83.3%,88.5%
PPV	55.5%	48.6%,62.1%
NPV	57.3%	54.2%,60.3%
Less than 0.4 vs Greater than or equal to 0.4		
Sensitivity	11.7%	9.05%,14.9%
Specificity	93.5%	91.6%,95.2%
PPV	54.1%	44.3%,63.7%
NPV	62%	59.1%,64.7%
Less than 0.5 vs Greater than or equal to 0.5		
Sensitivity	6.45%	4.33%,9.19%
Specificity	97.3%	95.9%,98.3%
PPV	54.9%	40.3%,68.9%
NPV	66.9%	64.1%,69.5%
Less than 0.6 vs Greater than or equal to 0.6		
Sensitivity	2.67%	1.29%,4.86%
Specificity	98.8%	97.8%,99.4%
PPV	47.6%	25.7%,70.2%
NPV	71%	68.4%,73.5%

Precision of machine learning model

With device data added





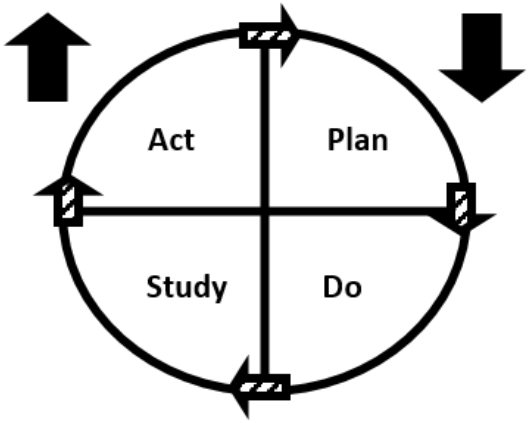
Model for improvement

Design an integrated research and care delivery system to improve the care of families / patients with T1D

What are we trying to accomplish?

How will we know that a change is an improvement?

What changes can we make that will result in improvement?



Diabetes Center Key Driver Diagram

Outcomes/Aim

diabetes center will improve clinical outcomes and patient experience by:

- Decreasing % patients with rising A1c
- Decreasing % of patients with A1c >9%
- No increase in rate of severe hypoglycemia

IOM Triple Aim

- Improve patient experience: advance quality of life; reduce burden
- Improve population health: decrease acute and chronic complications
- Decrease per capita cost of care: fewer hospitalizations, co-morbidites

Key Drivers

Partnership with accessible, prepared, coordinated multi-disciplinary team
% completed Pre-Visit Planning
% >4 visits/year (or dec. loss to FU)
% annual CDE visit
(% annual screening labs)

Effective self-management
% patients using CGM and/or testing > 4x/day, % blousing optimally

Evidence based and patient-preference driven treatment regimen
% patients setting, documenting, reviewing goals

Efficient integration of technology and application of data to support care
% patients reviewing data between visits
% patients with telehealth contact between vsits

Psychosocial supports
% eligible pts with mental health screening & action

Psychosocial supports
% eligible pts with mental health screening & action

Interventions

Use of advanced machine learning to predict those with greatest A1c rise
Clinical systems to support care
- Data Warehouse
- Population Management

Apply QI methods to enhance Patient-Centered and Personalized Care
- Shared Decision Making
- High-risk management protocols

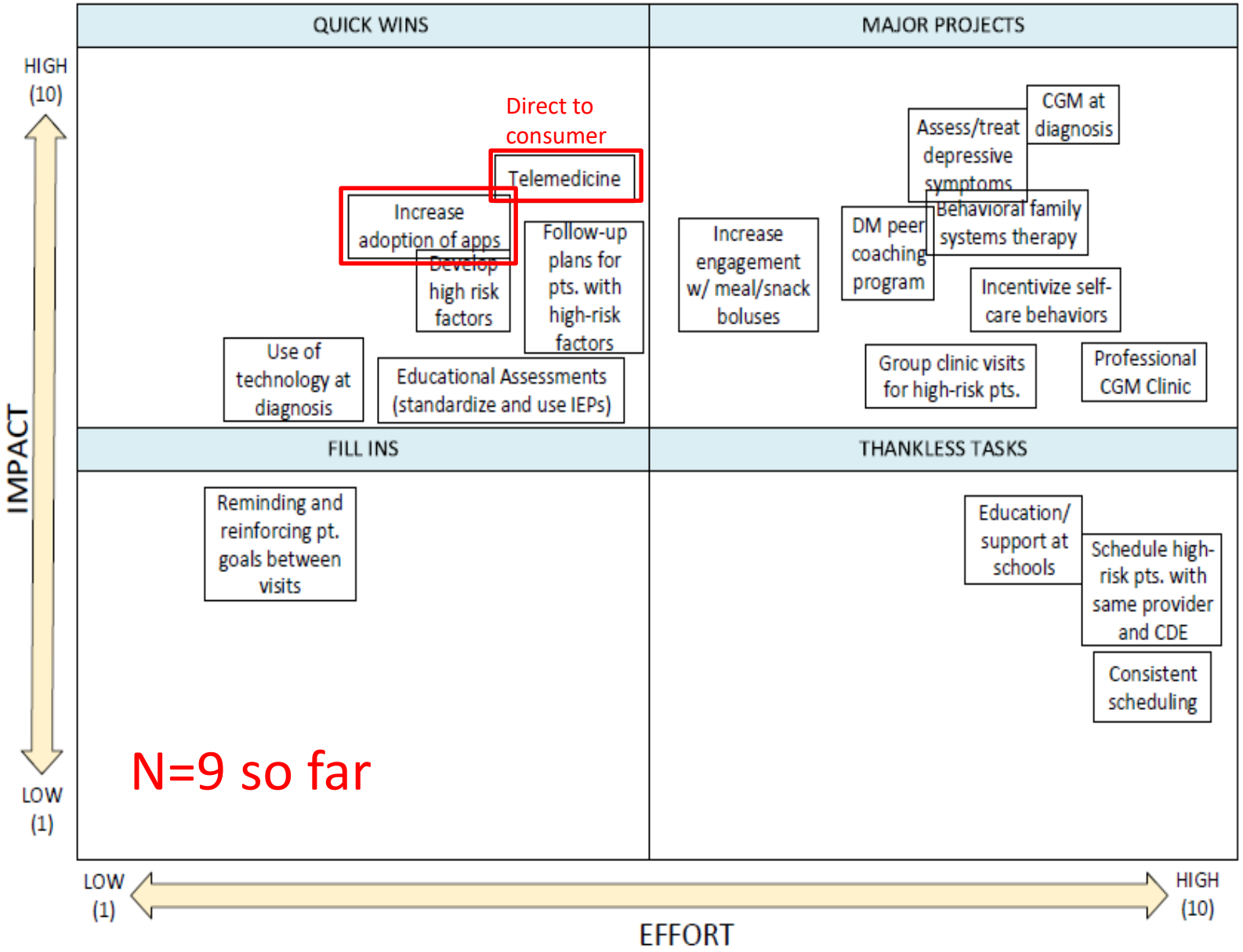
Monitoring Protocol

Insulin Adjustment Protocol

Adherence Protocol

Case Management Protocol

Improving T1D Care Grant Prioritization Matrix

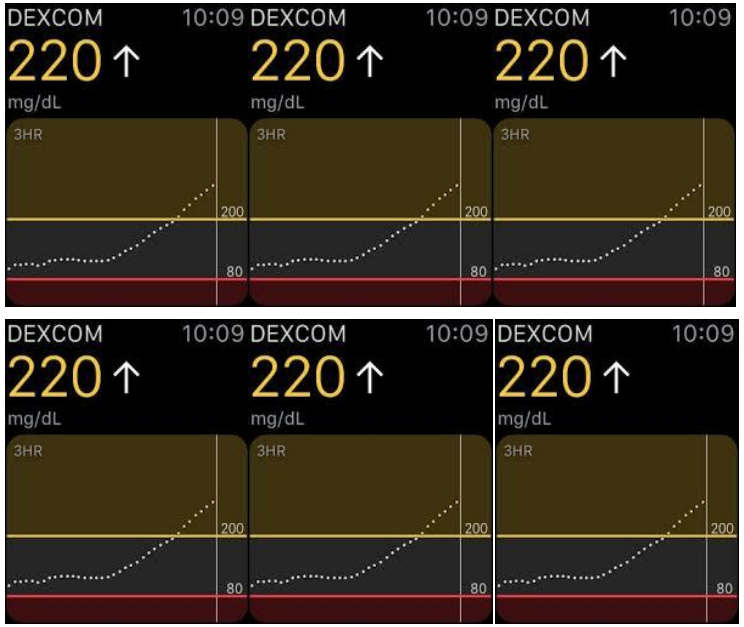


New interventions to reduce rise in HbA1c?

KLUE

dexcom®
CONTINUOUS GLUCOSE MONITORING

Group Follow application



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School of Medicine
University of Missouri Health

Overcoming resistance to immune based therapy in Colorectal Cancer

Jonathan B. Mitchem, MD

Harry S. Truman VA Medical Center

Department of Surgery

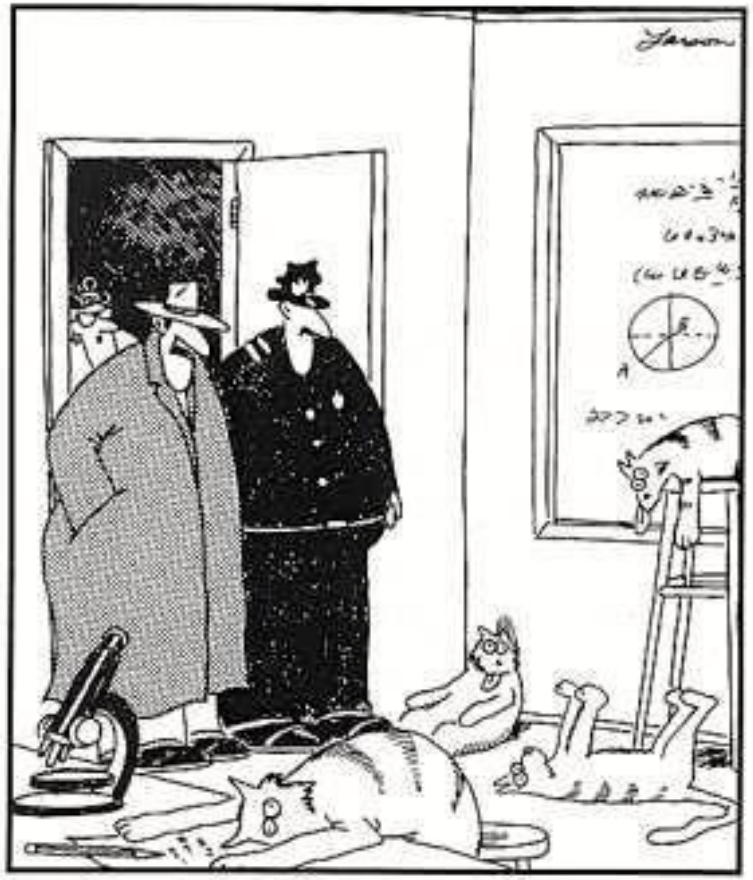
University of Missouri School of Medicine

Disclosures

- None

- **Why is this important?**
  - **140,000- the number of people diagnosed with colorectal cancer each year**
  - **50,000- the number of people who die from colorectal cancer each year**
  - **15%- the percent of patients with stage IV disease alive at 5 years**

• How we can do better?



"Notice all the computations, theoretical scribblings, and lab equipment, Norm. … Yes, curiosity killed these cats."

- **What do we already know?**

- **Better Immune Response = better response to therapy, lower recurrence rate, longer survival**

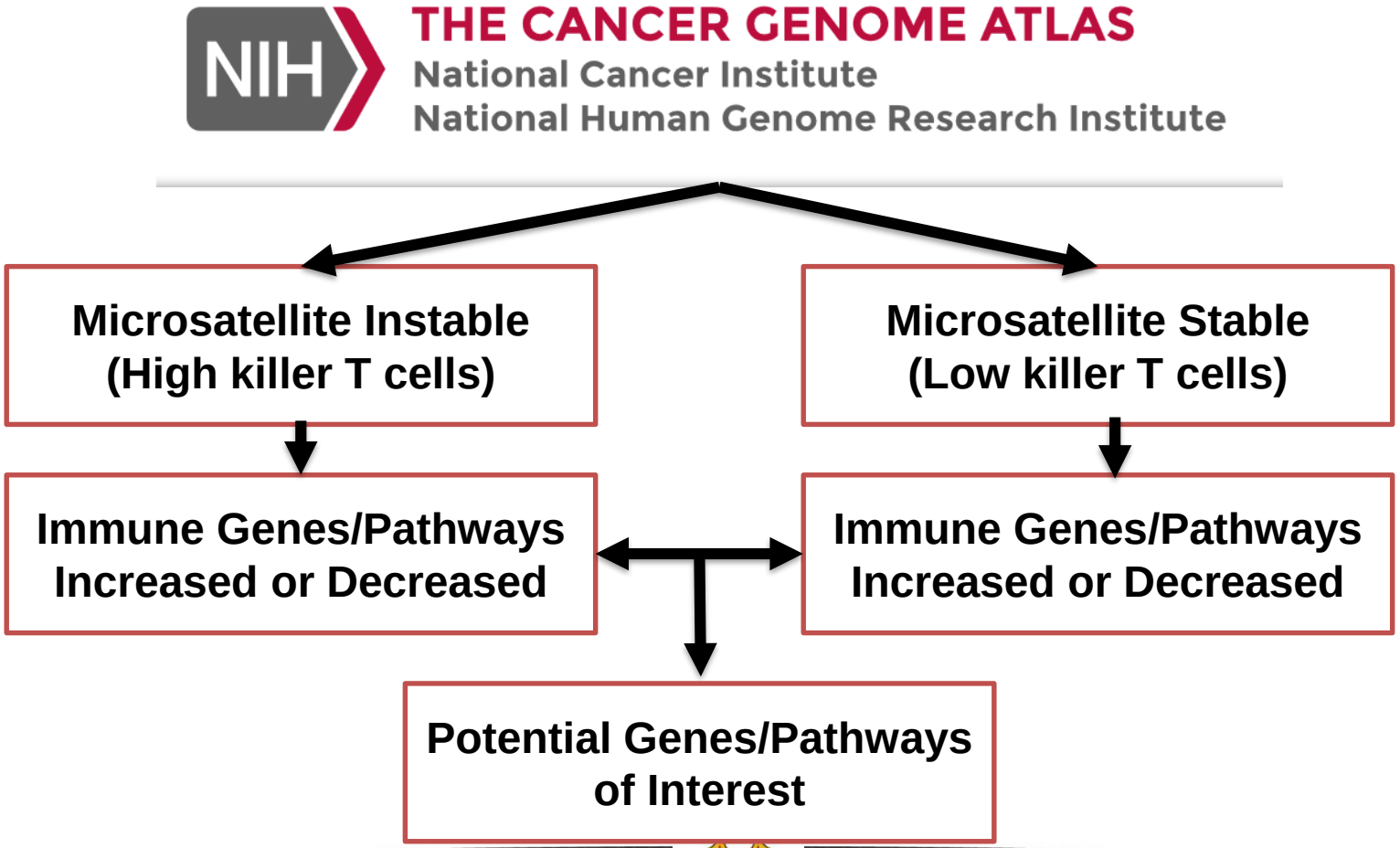
- **But, immune based therapy does not work for the majority of CRC patients**

- **Why?**

Are there patients that immune based therapy works for?

- Microsatellite instability or MSI
- ~13-15% of all CRC patients
- Leads to large number of mutations→ higher number of aberrant proteins→ increased novel antigens→ better immune response

Why do MSI patients have more T cells?



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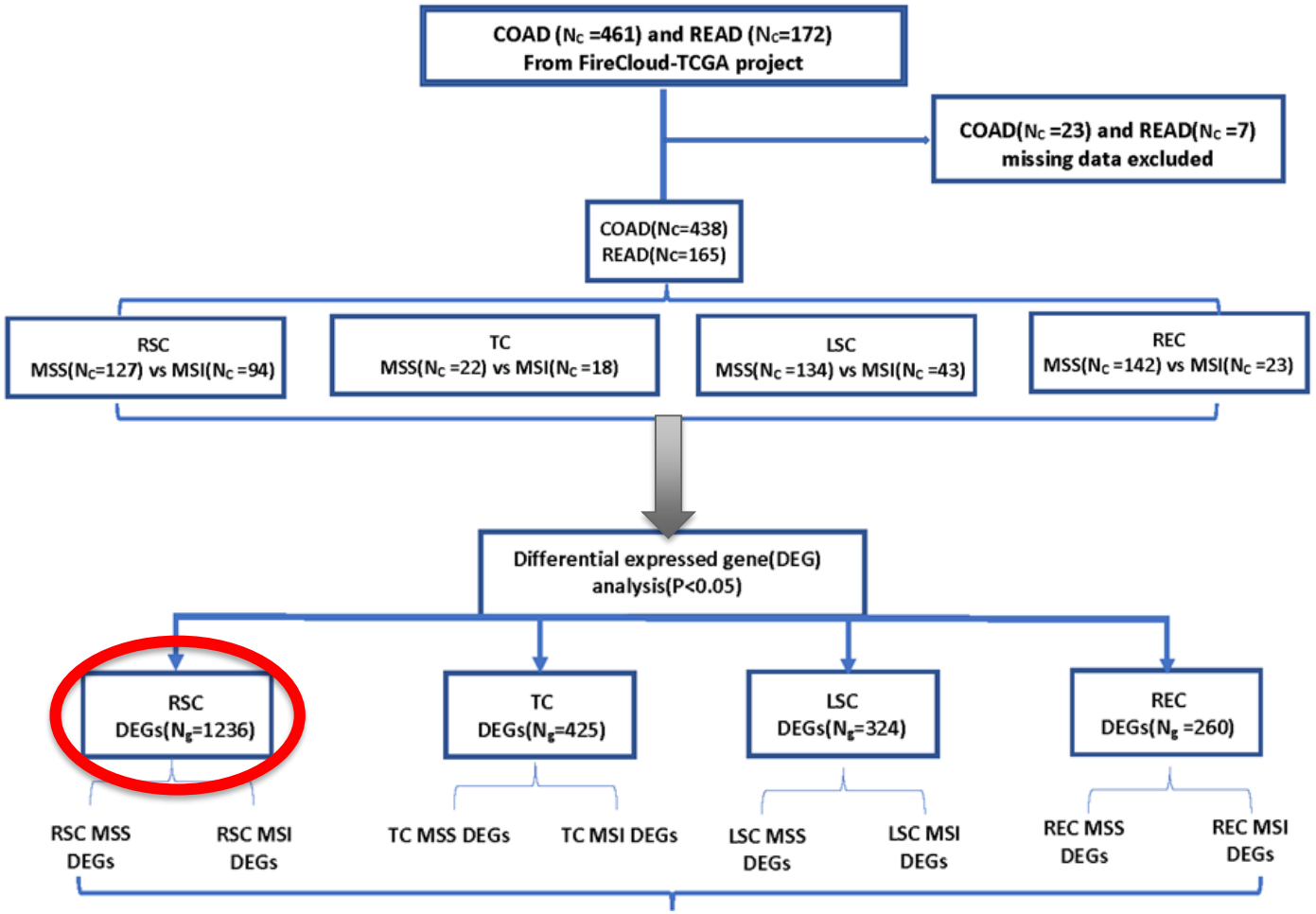
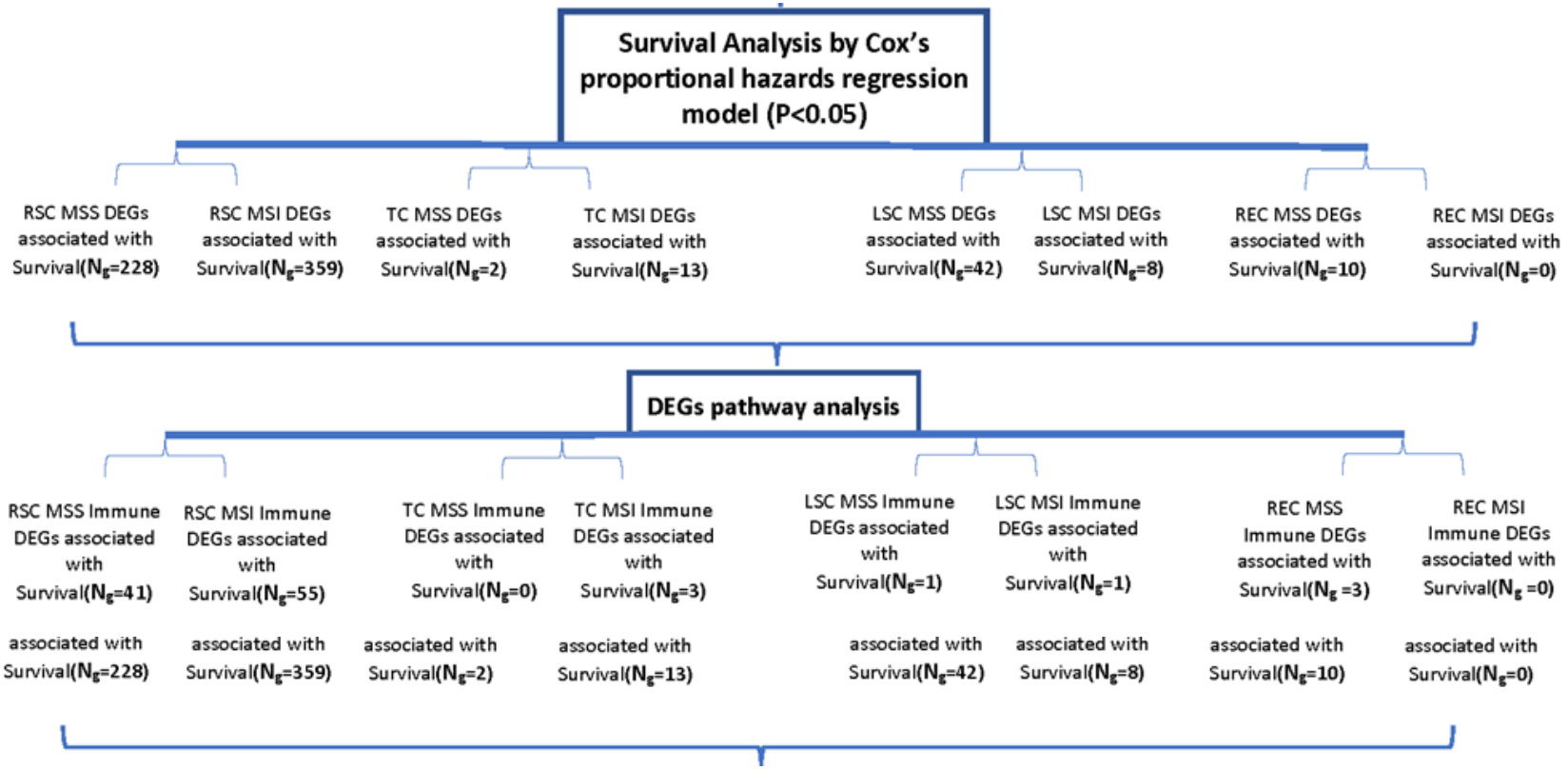


Shen YY, et al, in review

Why do MSI patients have more T cells?



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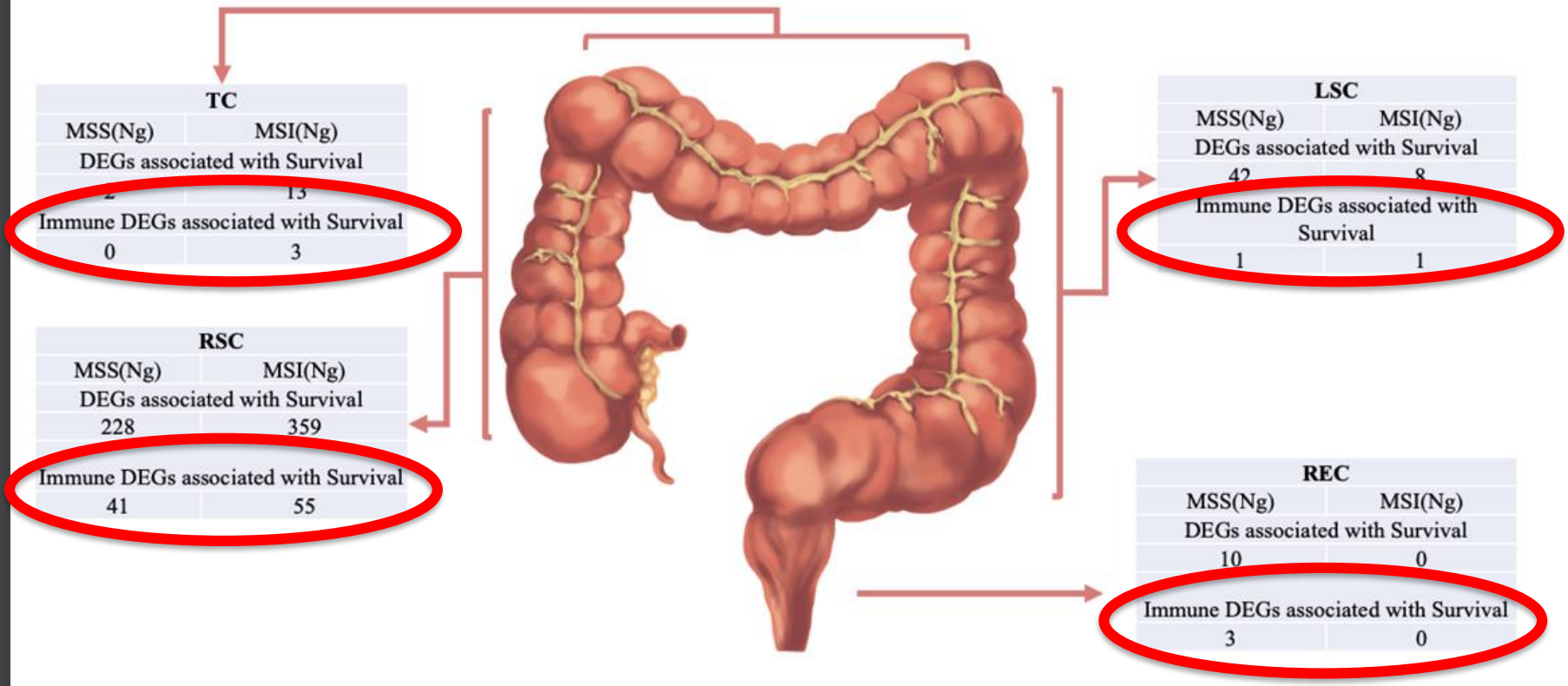
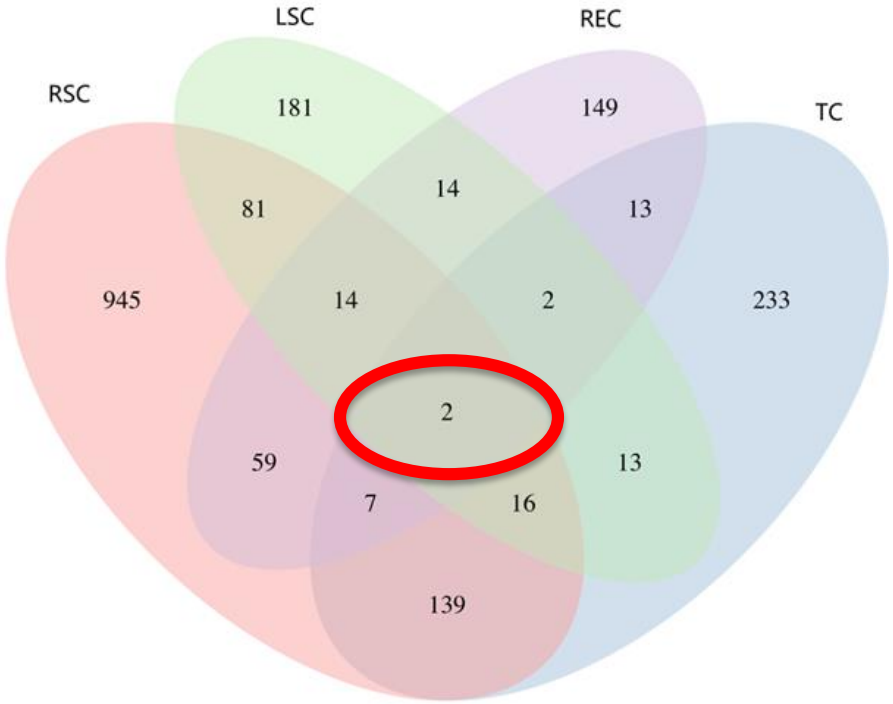


Shen YY, et al, in review

Why do MSI patients have more T cells?

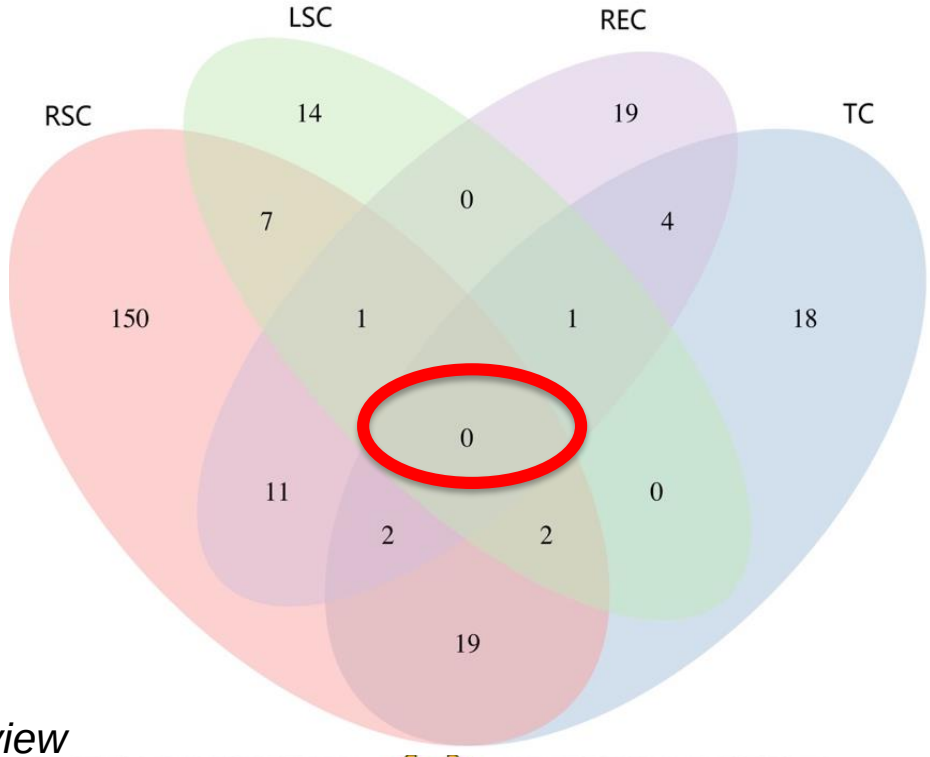
Anatomical location	DEGs
RSC, n	1263
TC, n	425
LSC, n	324
REC, n	260



Shen YY, et al, in review

Why do MSI patients have more T cells?

Anatomical location	DEGs	Immune DEGs
RSC, n (%)	1263	192 (15)
TC, n (%)	425	56 (13)
LSC, n (%)	324	24 (7)
REC, n (%)	260	37 (14)



Shen YY, et al, in review

What did we learn?

Overcoming resistance to immune based therapy in Colorectal Cancer.

- **Future Directions**
  - **Immune based therapy represents an opportunity to improve the care of patients with colorectal cancer.**
  - **We must combine patient data with basic research to maximize our ability to improve patient care.**

THANKS!

TRIAL Lab:

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- Emma Teixeiro, Ph.D.

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Improving Decision Making in Elderly Patients with Valvular Heart Disease

Suzanne V. Arnold, MD, MHA

Saint Luke's Mid America Heart Institute
University of Missouri-Kansas City
Kansas City, Missouri, USA

Valvular Heart Disease in the Elderly

Aortic stenosis:

- 2% >65yo; 4% >85yo

Mitral regurgitation:

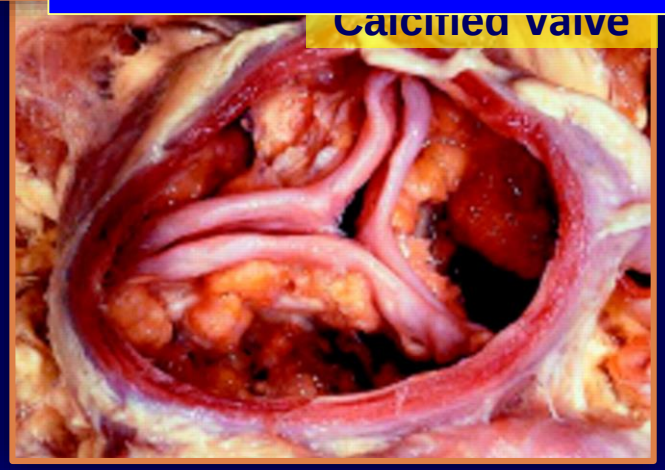
- ~10% >75 years

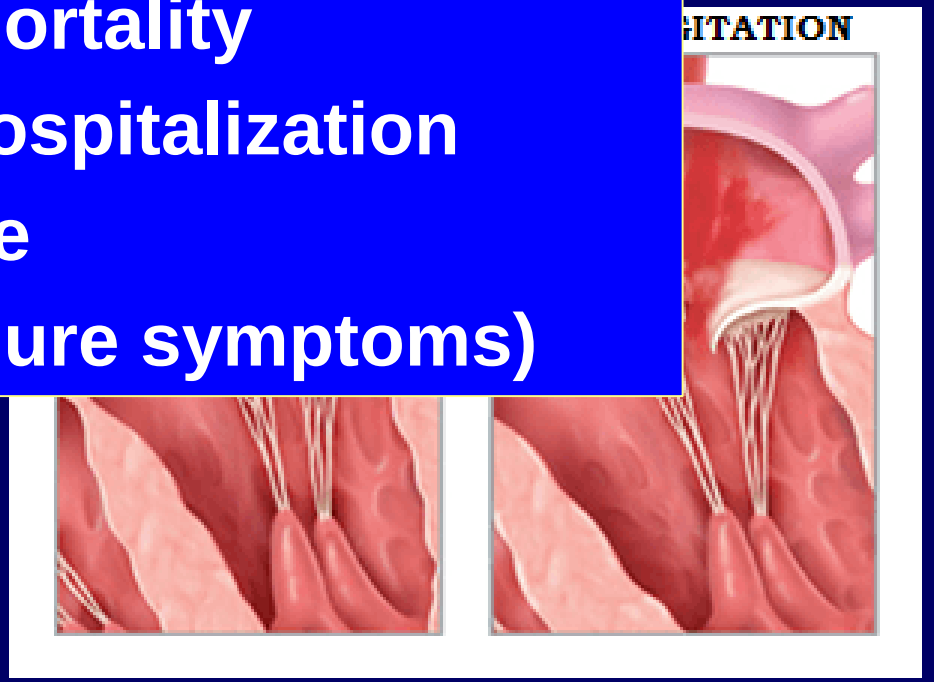
Increased risk of mortality

Increased risk of hospitalization

Worse quality of life

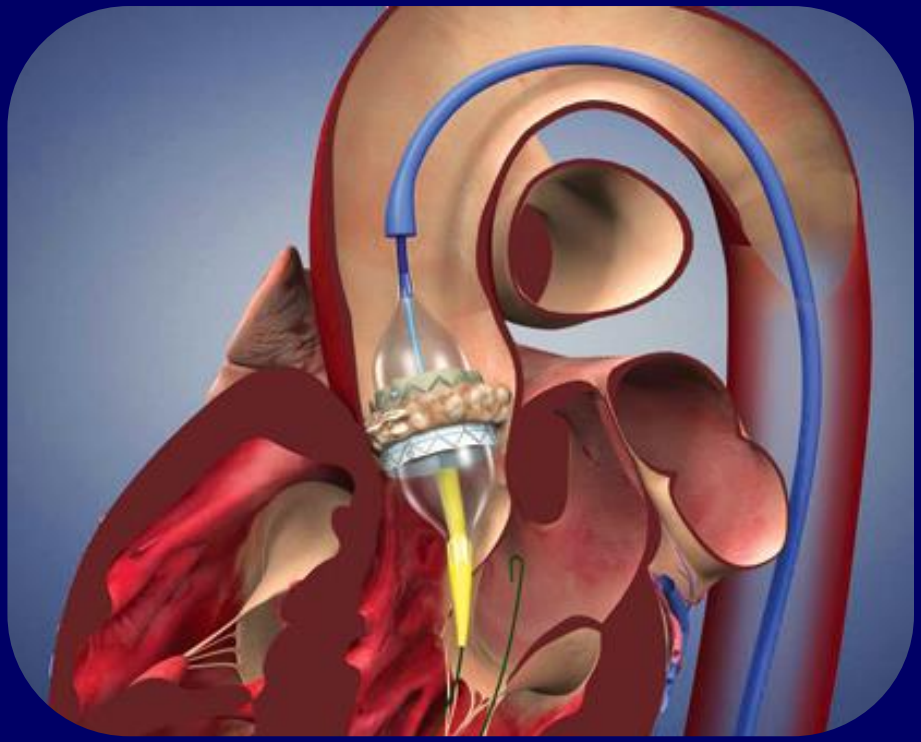
(mostly heart failure symptoms)



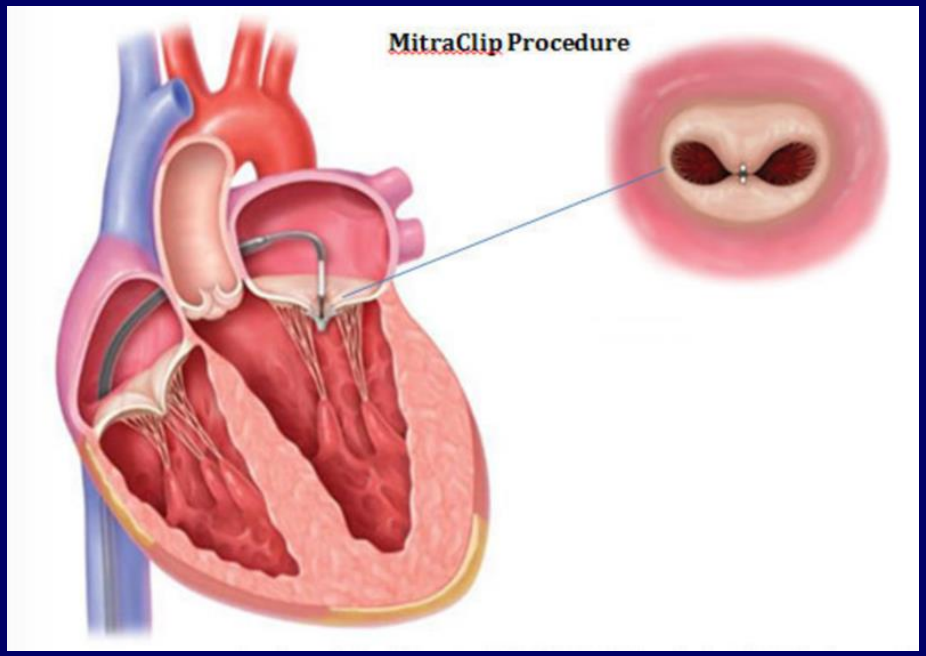


Transcatheter Procedures

Transcatheter Aortic Valve Replacement (TAVR)



Transcatheter Mitral Valve Repair/MitraClip (TMVr)



Who Are The Patients?

	TAVR	TMVr
Age	83	81
Female	48%	47%
Prior myocardial infarction	24%	26%
Prior coronary bypass surgery	29%	28%
Peripheral artery disease	31%	18%
Atrial fibrillation	41%	62%
Diabetes	37%	26%
Home oxygen	12%	14%

Arnold SV et al. JAMA Card. 2017
Arnold SV et al. JAMA Card. 2018

Transcatheter Procedures

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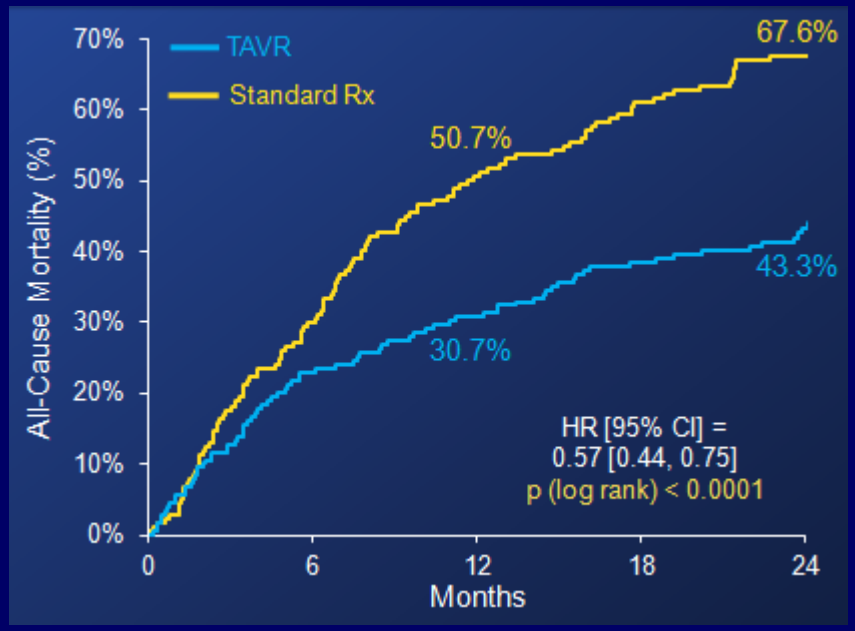

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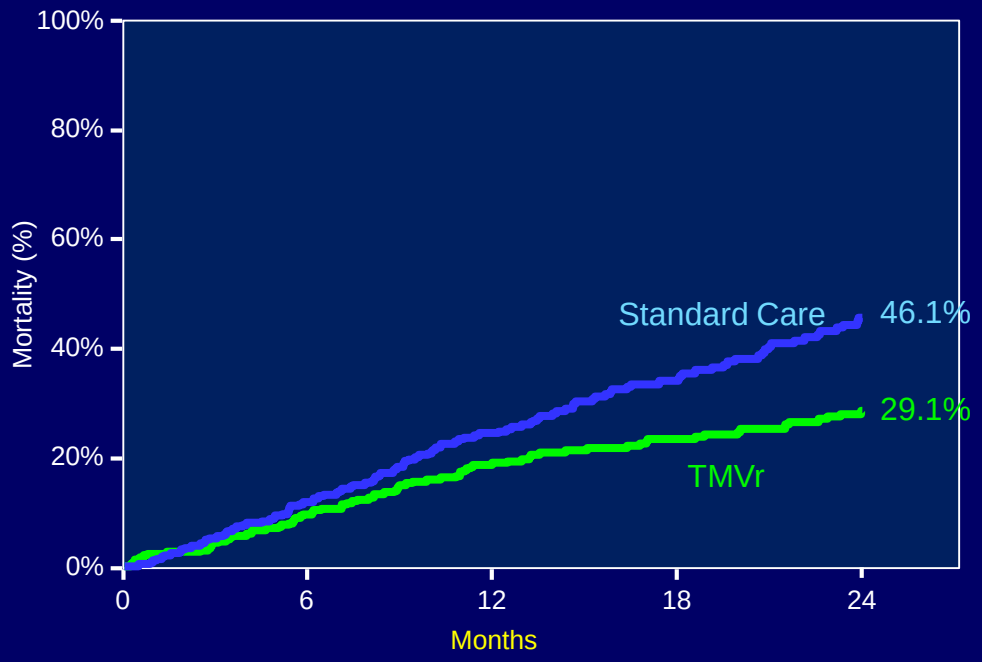


Makkar RR et al. N Engl J Med. 2012

Stone GW et al. N Engl J Med. 2018

Survival Isn't All That Matters to Patients

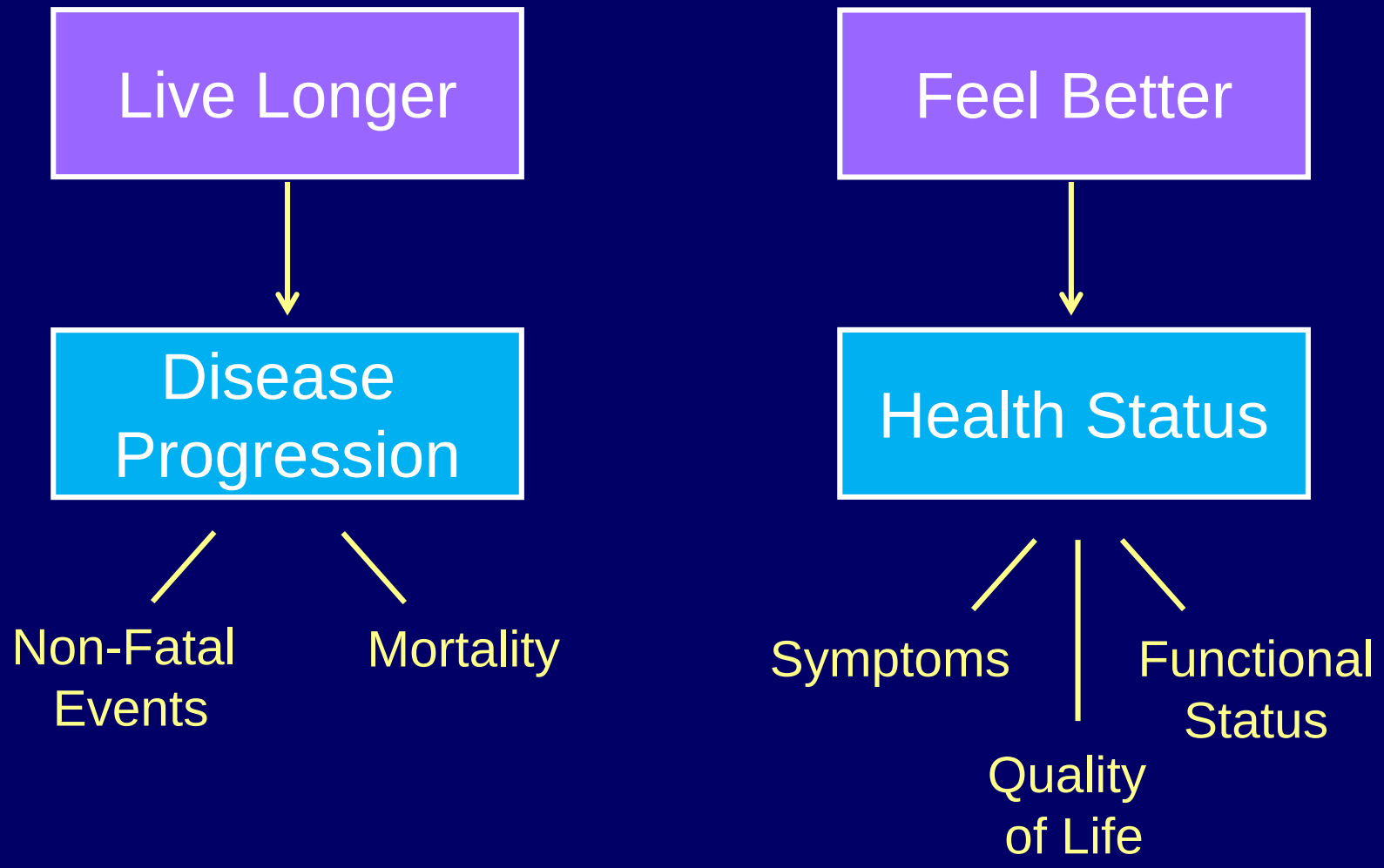
- Two studies of patients with systolic heart failure
  - Mean age ~60
  - 67%-74% with NYHA III or IV symptoms

- 65% of patients placed a greater importance on symptom relief vs. survival

- 25% of patients were willing to give up over half of their remaining survival for perfect health

Lewis J et al. Heart Lung Transplant. 2001.
Stanek EJ et al. J Cardiac Fail. 2000.

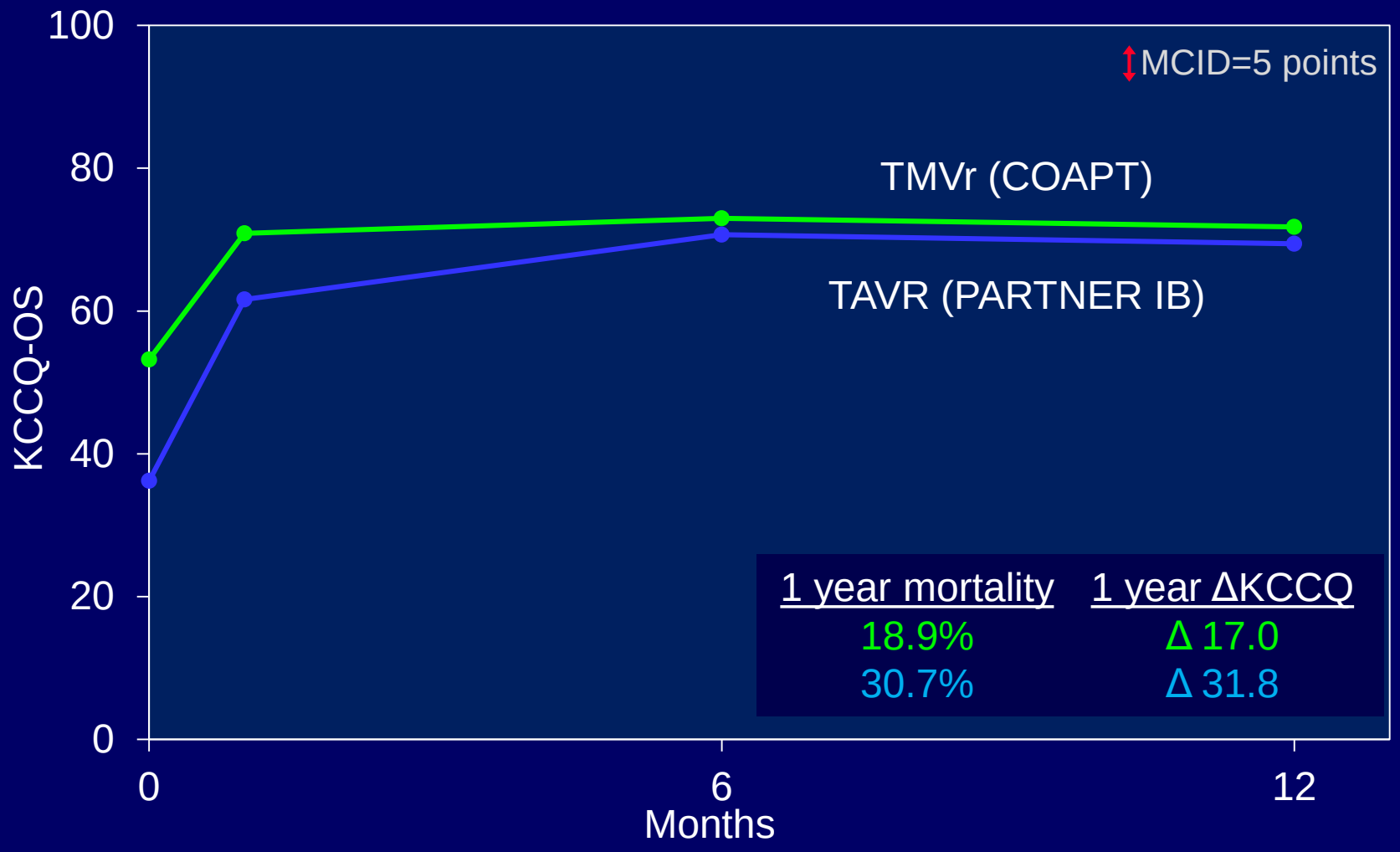
Treatment Goals



Health Status in Valve Disease

- Kansas City Cardiomyopathy Questionnaire
  - Assesses symptoms, functional limitations, social limitations, quality of life
  - Scores 0-100; higher=better
    - 5 points=small clinical change
    - 10 points=moderate clinical change
    - 20 points=large clinical change
  - Challenge: Health status can only be assessed in survivors, but those with worse health status are more likely to die

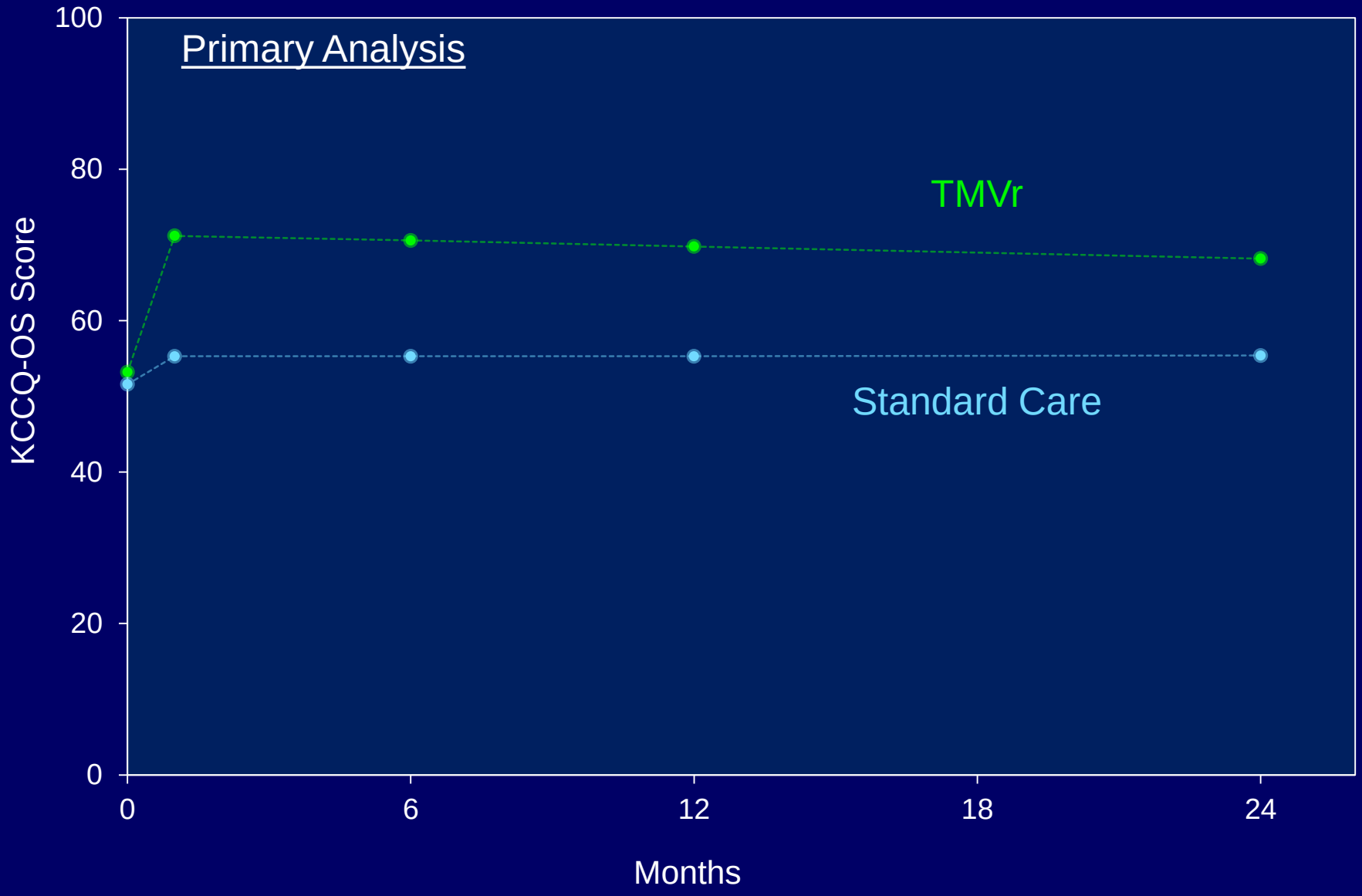
Quality of Life Outcomes



Reynolds MR et al. Circ. 2011
Arnold SV et al. JACC. 2019

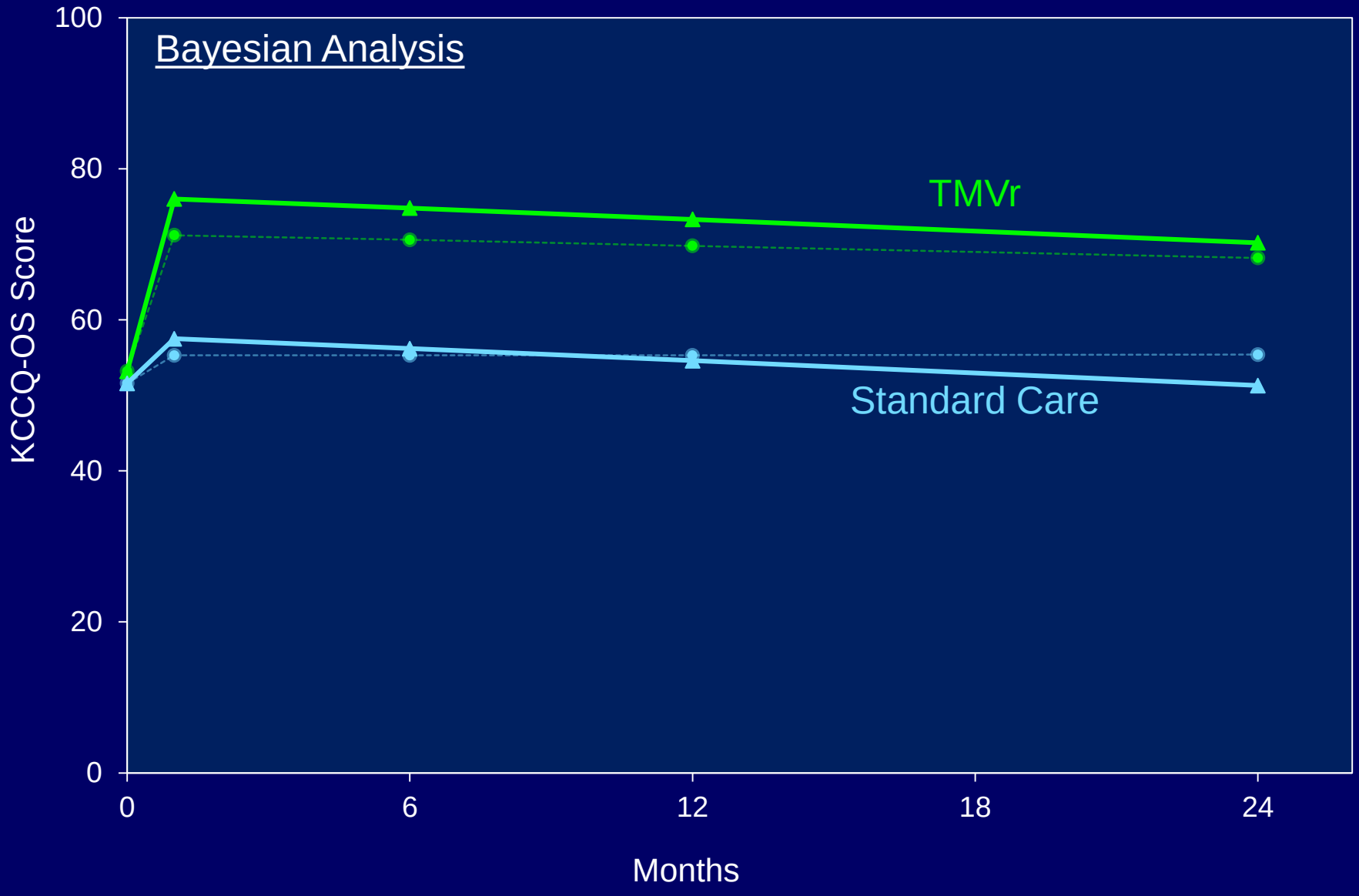
COAPT TRIAL

Joint Model Results: KCCQ-OS

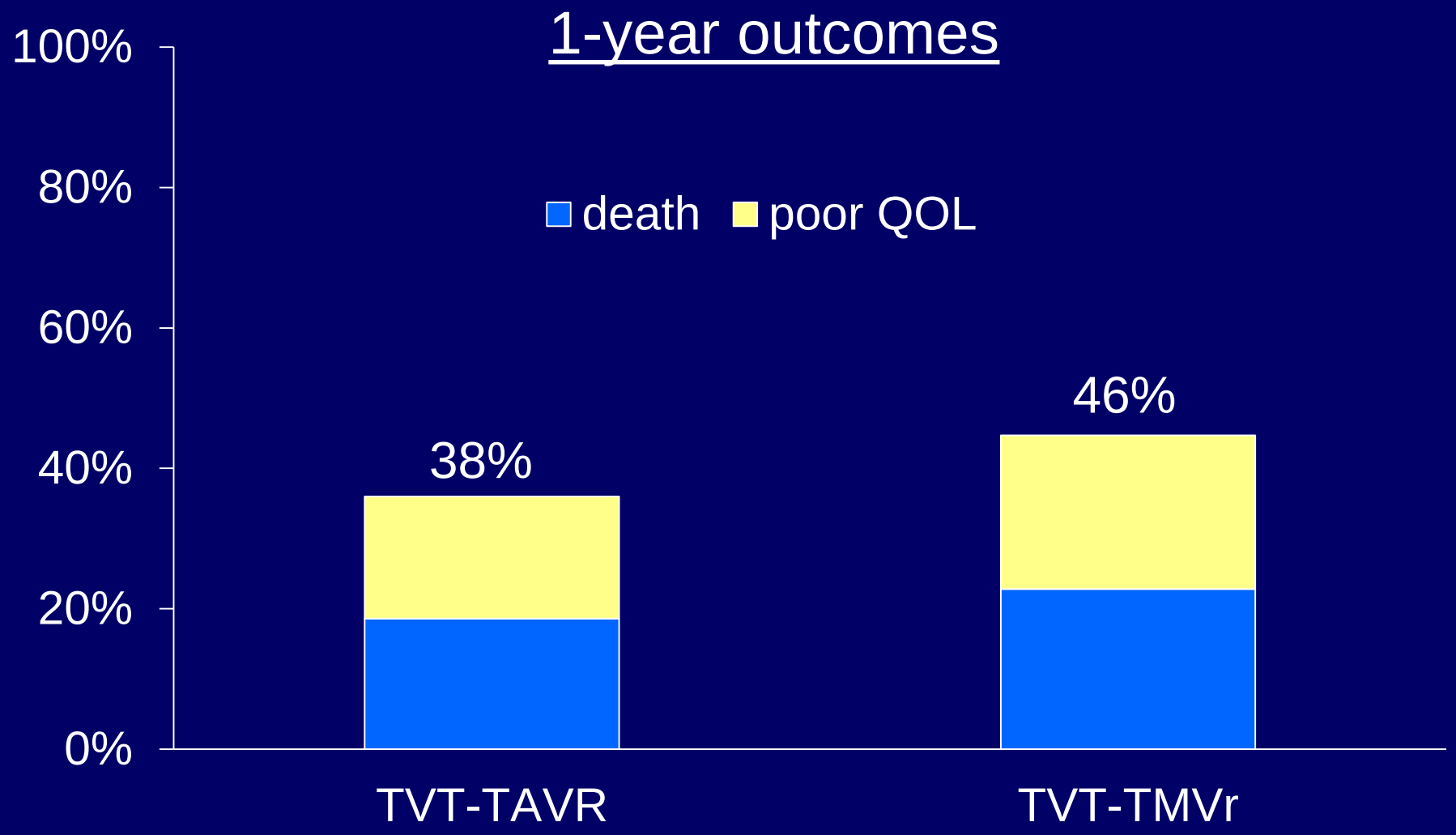


COAPT TRIAL

Joint Model Results: KCCQ-OS



Categorical Outcomes



Arnold SV et al. JAMA Card. 2017
Arnold SV et al. JAMA Card. 2018

Improving Valve Decision-Making

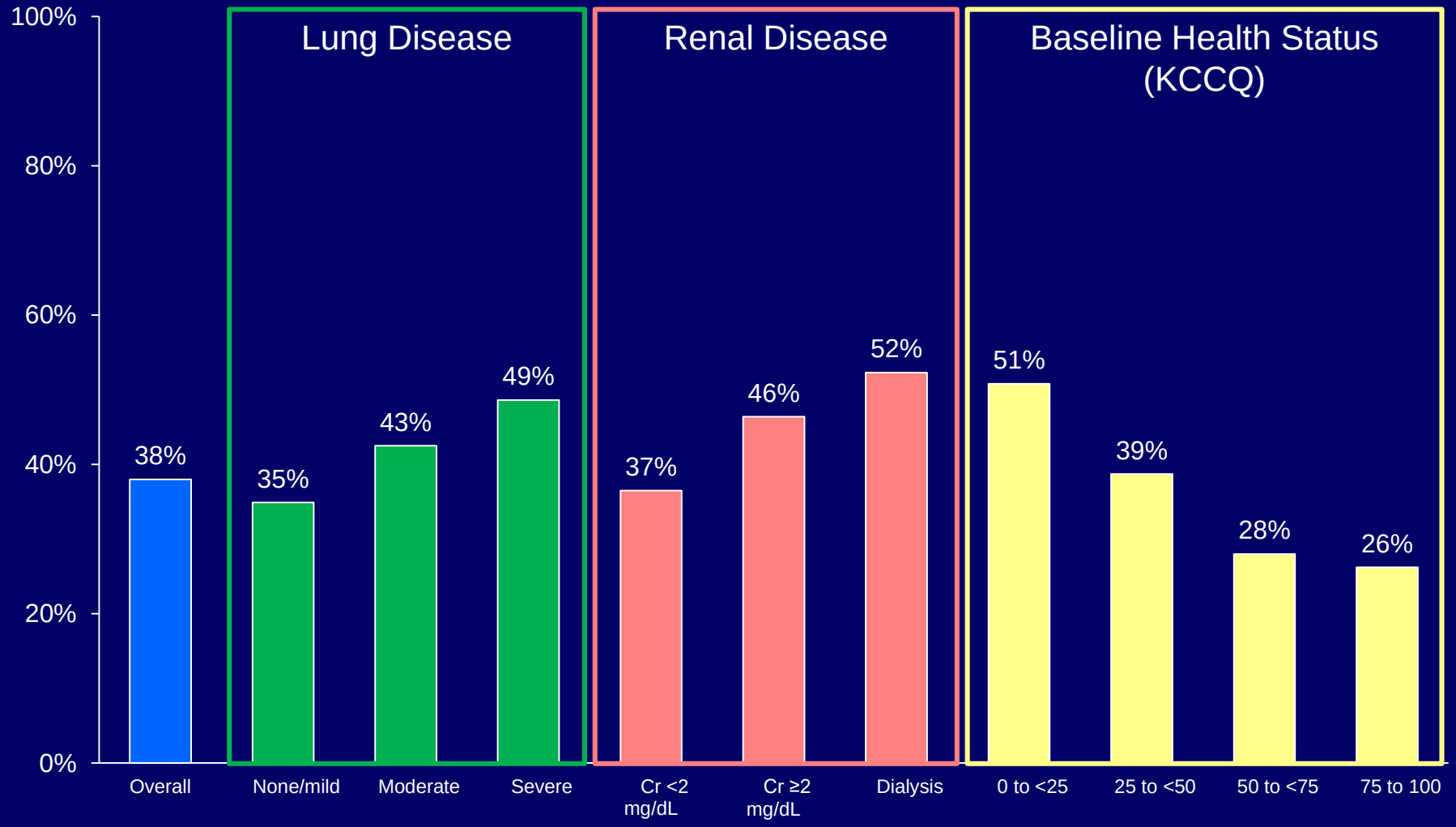
Valve Clinic

Eligibility
- Risk for surgery
- Severity of disease
- Symptomatic status

Feasibility
- Access site (AV)
- Ability to clip (MV)

Appropriateness
- Ability to recover

Poor Outcome After TAVR



Arnold SV et al. JAMA Cardiol 2017.

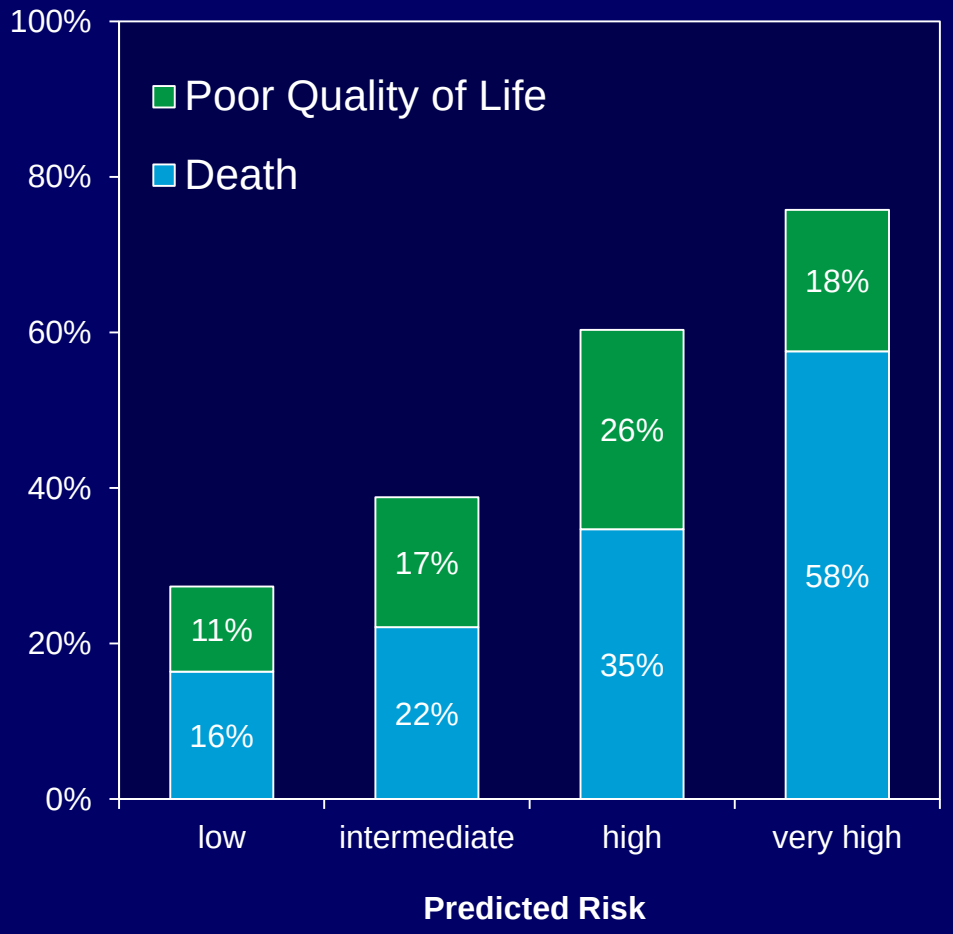
Poor Outcome Risk Model

Patients:

- 2,137 TAVR (PARTNER I)
- 2,830 TAVR (CoreValve ER/HR)
- 13,351 TAVR (TVT: 2012-2016)

Factors with increased risk:

- Clinical: home oxygen, renal dysfunction, afib, diabetes, low mean aortic gradient
- Frailty: poor functional status (or low KCCQ), ADL dependencies, unintentional weight loss, dementia



Arnold SV et al. Circulation 2014

Arnold SV et al. J Am Coll Cardiol 2016

Arnold SV et al. Circ Cardiovasc Qual Outcomes. 2018

Poor Outcome Risk Model: Examples

	Model Coefficients	Patient 1 (high risk)	Patient 2 (low risk)
Intercept	0.0022		
KCCQ-12 score	-0.0151	25 points (NYHA IV)	65 points (NYHA II)
Mean aortic valve gradient	-0.0039	30 mmHg	50 mmHg
Home oxygen	0.6007	1 (yes)	0 (no)
Creatinine	0.1733	2.5 mg/dL	1 mg/dL
Atrial fibrillation/flutter	0.3529	1 (yes)	0 (no)
Diabetes mellitus	0.0704	0 (no)	0 (no)
Estimated Risk of Poor Outcome*		**71%**	**27%**

Arnold SV et al. Circ Cardiovasc Qual Outcomes. 2018

Summary

- To understand the full value of novel valve therapies, it is critical to measure health status
- Interpreting the effects of these therapies on health status can be challenging due to the high mortality
- Defining outcomes that matter to patients and feeding these data back to those deciding can improve these decisions and set appropriate expectations

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TigerPlace
Aging in Place Initiative: Key Outcomes

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laneka@Missouri.edu

Sinclair School of Nursing
University of Missouri Health

http://agingmo.com
https://eldertech.missouri.edu/

Our Aging in Place Vision (1996)

- Develop and implement a new approach to serving long-term care needs of Missouri Seniors
- Become a national model of excellence for other health science centers and those committed to investing in state-of-the-art care
- Dramatically change the way long-term care is provided in this country

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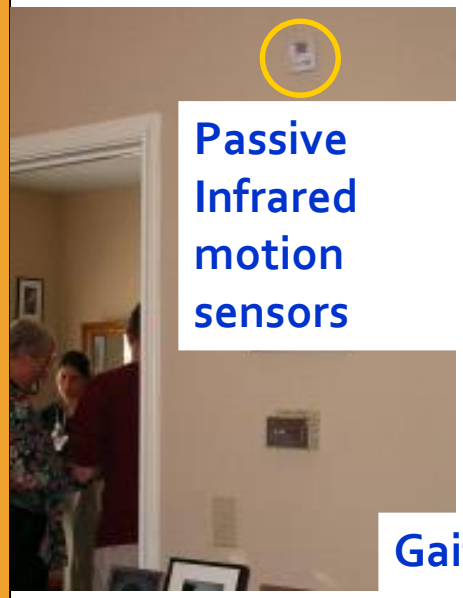
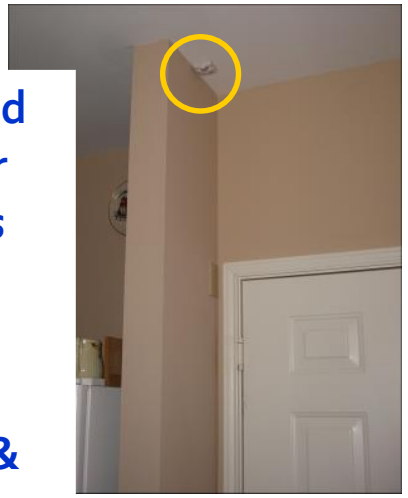
TigerPlace™

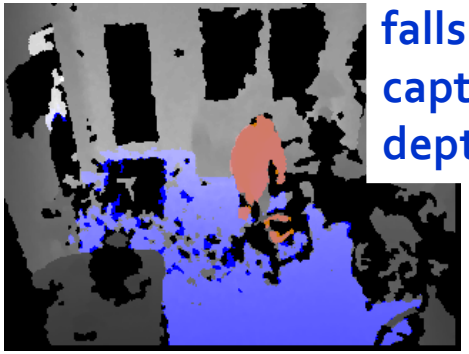
- Enabled by legislation 1999 and 2001
- 31 apartments opened 2004, 23 more in 2009
- Designed to promote independence and aging in place with **RN care coordination** as key
- Built to nursing home standards but operated as independent living with services, can live in apartment through end of life
- 2011 opening 85 (mostly private rooms)skilled rehabilitation



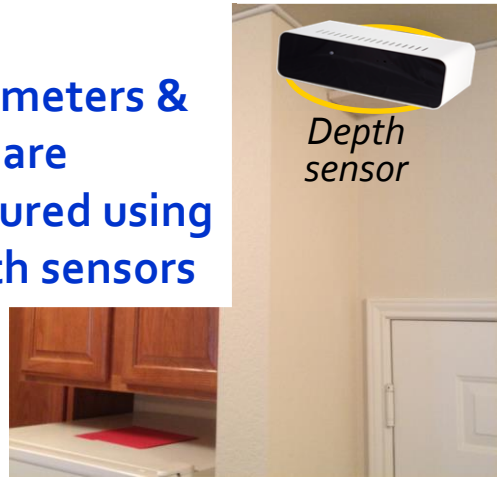
Passive Infrared motion sensors

Hydraulic bed sensor under the mattress captures quantitative pulse, respiration & restlessness





Gait parameters & falls are captured using depth sensors

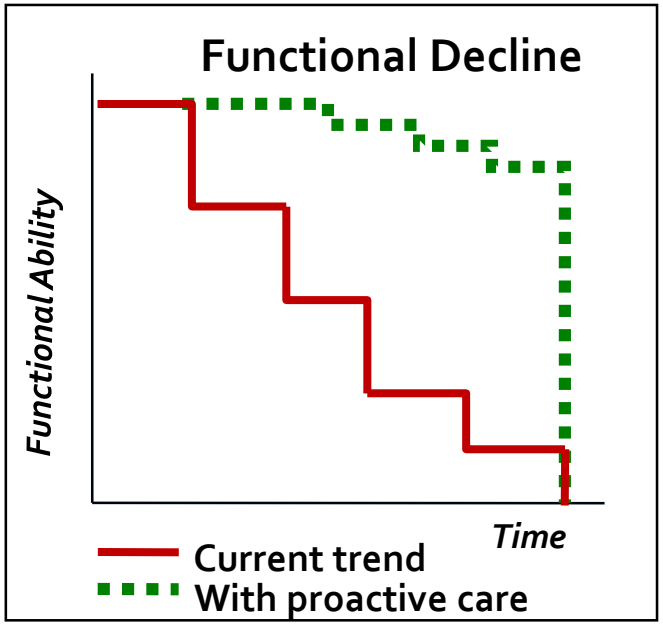


Squaring the Life Curve

Proactive health management through integration of sensor data and health data

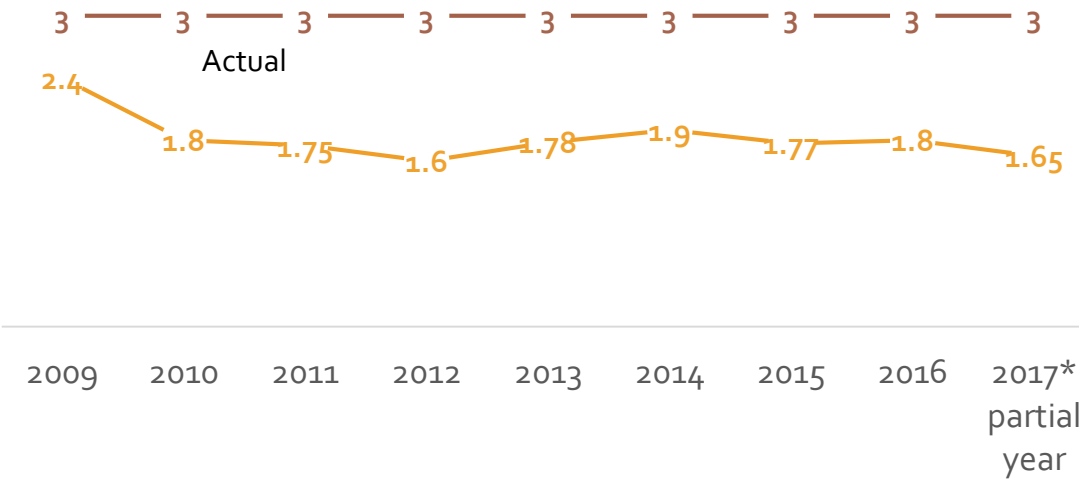
Reduce functional decline by

- Assessing behavior patterns
- Assessing gait & activity level
- Recognizing pattern changes
- Detecting early signs of health decline (so can intervene before things become major events)
- Detecting falls
- Informing RN Care Coordination

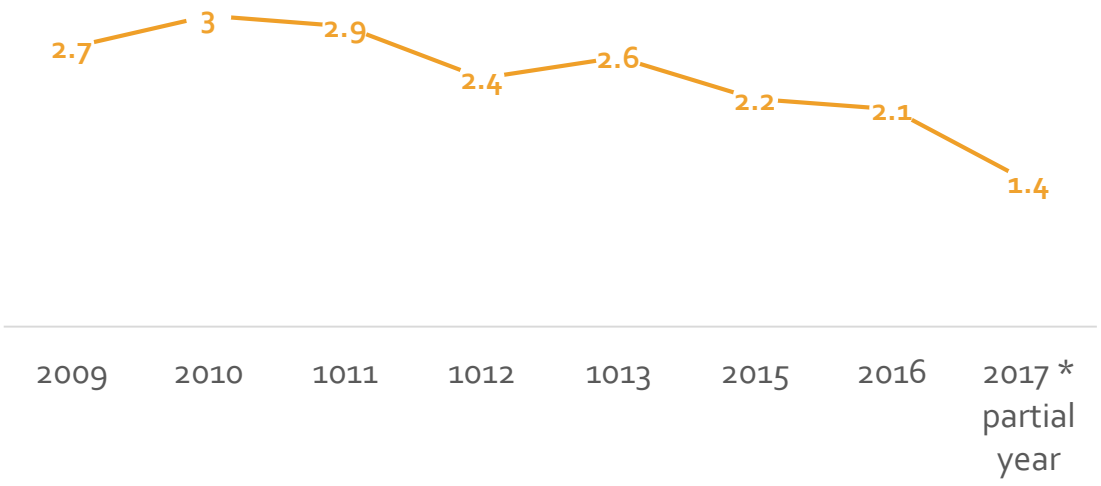


Rantz, Marek, Aud, Tyrer, Skubic, Demiris, & Hussam, *Nursing Outlook*, 2005.

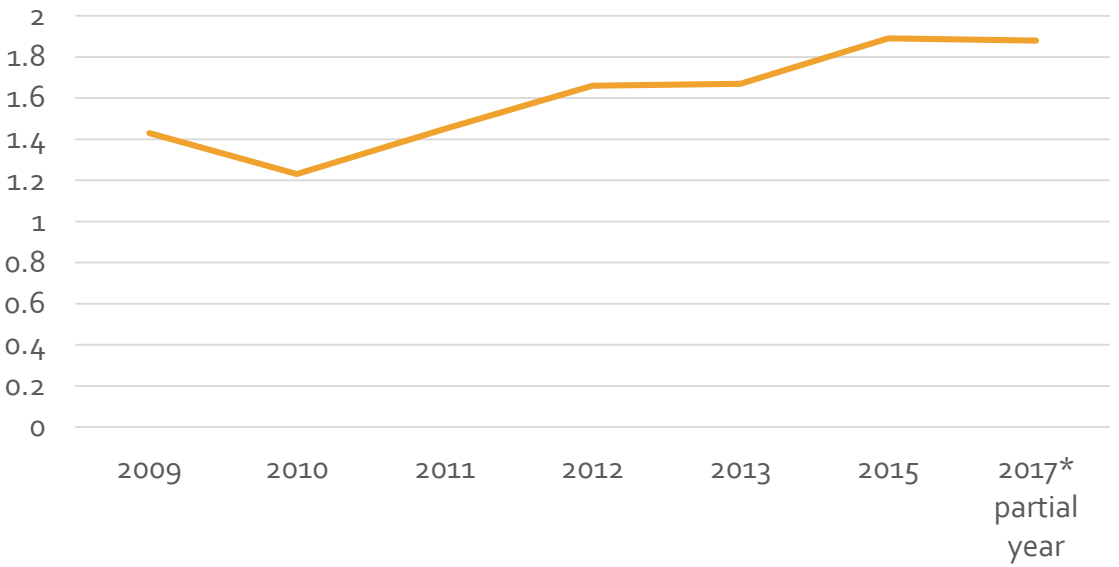
FALL RATE PER 1,000 OCCUPIED BED DAYS



EMERGENCY ROOM VISITS PER 1,000 OCCUPIED BED DAYS



Transfers/Hospital Admissions Rate per 1,000 Bed Days



- Physical, Occupational and Cognitive Therapy
- Activities and social engagement
- Social Work
  - Strengths based
  - Individual therapies
    - Solution Focused
    - Motivational Interviewing
    - Reminiscence Therapy
    - Problem Solving Treatment
    - Grief and Bereavement Counseling

- Social Work
  - Group Approaches
    - Empowerment Group – Vision Group
    - Relationship Building – Welcome Home Project
    - Mindfulness Based Stress Reduction
    - Creative Aging – "My Life" Photography Project
    - New Resident Transition and Support – Neighbor to Neighbor Group

TigerPlace/AIP Evaluation Results 2004-2008

- RN nurse care coordination reduces adverse health events, improves care outcomes, reduces nursing home utilization, and is cost-effective
- Costs for any participant (even through end of life) has not approached nursing home care (average annual care cost for 2008 was $7,331 for those nursing home eligible and $2591 for those not eligible, plus housing cost)

AIP Cost Estimates

* Cost estimates comparing cost of

living at TigerPlace with the sensor technology vs. nursing home reveal potential saving of about $30,000 per person.

*Potential cost savings to Medicaid funded

nursing home (assuming the technology and care coordination were reimbursed)

are estimated to be about $87,000 per person.

Enhanced registered nurse care coordination with sensor technology: Impact on length of stay and cost in aging in place housing, Nursing Outlook, 63, 2015, 650-655.

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Children's Mercy

12:30pm

Lunch

1:00pm

Mock Interviews

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