This Morning

Assembling a Deep EHR → Deep Learning Mechanisms → Applying Deep Insights

Tighe | Rashidi | Price

UF

When Things Get Tens(or)

Preemptively Addressing **Affect** in Artificial Intelligence?

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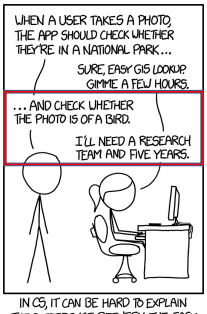
PeCAN Perioperative Cognitive & Anesthesia Collaborative Network

UF



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

https://xkcd.com/1425/

Disclosures

- I have *no* financial conflicts of interest to report
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  - R01 GM114290
  - R01 AG055337

Objectives

1. Problems with our Data.

2. What Do Data Look Like…and How Did We Get Here?

3. Deep EHR: Vector-Embedded and Related Approaches to Understanding our Patients

The Problem with Data

Part 1: Of tools and perspectives.

Medicine is **Not** Applied Data Science.

…and it may not even be a science at all.

- Medicine is about healing.
- Medicine restores patients to function.
- What is the parameter estimate for "chief complaint"?

It is at least worth considering that data is an accessory, rather than the engine

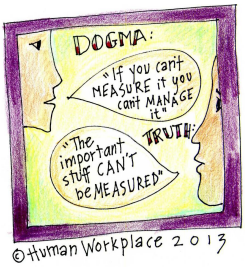
- Would you hold up an entire OR theatre for **one** patient?

What gets measured gets improved.

-Peter Drucker

Why so many data proxies?

- Age
- Sex (Gender)
- BMI (Height, Weight, circumferences)
- Race, Ethnicity
- Occupation
- Education Level
- Pain Intensity
- Frequency of leaving the house



Precision Carries Problems!

Rolling up codes for TKA

CPT	Description
27445	Arthroplasty, knee, hinge prosthesis
27446	Arthroplasty, knee, condyle and plateau; medial OR lateral compartment
27447	Arthroplasty, knee, condyle, and plateau; medial and lateral compartments with or without patella resurfacing (total knee arthroplasty)
27486	Revision of total knee arthroplasty, with or without allograft; 1 component
27487	Revision of total knee arthroplasty, with or without allograft; femoral and entire tibial component

Which of these are similar?

Is a *Revision* a *Revision* a *Revision*?

Under which circumstances can we group with THA? TSA? Other knee surgeries?

What about different component manufacturers?

Precision Carries Problems!

List your comorbidities.

Rank	Description
1	Knee osteoarthritis
2	Heart Failure
3	Aortic Stenosis
4	COPD
5	Factor IX Deficiency

Knee OA	CHF	...	CHF	...	AS	...	...	F IX Def	.....
Yes	Yes	No	Yes	No	Yes	No	No	Yes	No

Does Rank Matter?

Is sparsity ok?

Charlson Comorbidity Index:
Assumptions probably don't apply!

Is Severity a Problem?

Is Severity a Problem?

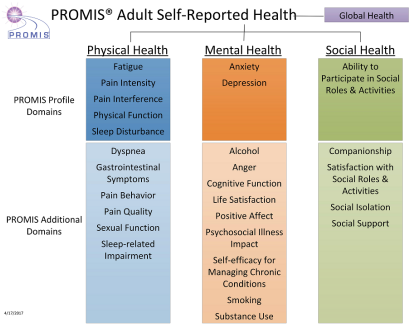
Neither ICD9 *nor* ICD10 Designed to Gauge *Acute* Severity

Emphysema ICD-9-CM	Description
492	**Emphysema**
	492.0 Emphysematous bleb • Giant bullous emphysema • Ruptured emphysematous bleb • Tension pneumatocele • Vanishing lung
	492.8 Other emphysema (lung or pulmonary) • Bullous • Interstitial • Centriacinar • Vesicular • Centrilobular • Macleod's syndrome • Obstructive • Swyer-James syndrome • Panacinar • Unilateral hyperlucent lung • Panlobular
506.4	**Chronic respiratory conditions due to fumes and vapors** • Emphysema (diffuse) (chronic)
	Other Chronic Respiratory Diseases
ICD-9-CM	**Description**
494	**Bronchiectasis** • Bronchiectasis (factitious) (postinfectious) (recurrent) • Bronchiectectasis
	494.0 Bronchiectasis without acute exacerbation
	494.1 Bronchiectasis with acute exacerbation
496	**Chronic airway obstruction, not elsewhere classified** • Chronic: – Nonspecific lung disease – Obstructive lung disease – Chronic obstructive pulmonary disease [COPD] NOS **NOTE:** This code should not be used with any code from categories 491-492.
506	**Respiratory conditions due to fumes and vapors**
	506.4 Chronic respiratory conditions due to fumes and vapors • Emphysema (diffuse) (chronic) • Obliterative bronchiolitis (chronic) (subacute) • Pulmonary fibrosis (chronic)

Emphysema ICD-10-CM	Description
J43	**Emphysema**
	J43.0 Unilateral pulmonary emphysema [MacLeod's syndrome] • Swyer-James syndrome • Unilateral emphysema • Unilateral hyperlucent lung • Unilateral pulmonary artery functional hypoplasia • Unilateral transparency of lung
	J43.1 Panlobular emphysema • Panacinar emphysema
	J43.2 Centrilobular emphysema
	J43.8 Other emphysema
	J43.9 Emphysema, unspecified • Emphysema (lung) (pulmonary) – NOS – Bullous – Vesicular • Emphysematous bleb
	Other Chronic Respiratory Diseases
ICD-10-CM	**Description**
J44	**Other chronic obstructive pulmonary disease** • Asthma with chronic obstructive pulmonary disease • Chronic bronchitis: – Chronic (simple/mucous)/emphysematous with (airway(s)) obstruction, emphysema • Chronic obstructive: – Asthma/bronchitis/tracheobronchitis
	J44.0 Chronic obstructive pulmonary disease with acute lower respiratory infection
	J44.1 Chronic obstructive pulmonary disease with acute exacerbation, unspecified
	J44.9 Chronic obstructive pulmonary disease, unspecified • Chronic obstructive – Airway disease NOS – lung disease NOS
J47	**Bronchiectasis** • Bronchiectasis

https://www.copdfoundation.org/pdfs/ICD%20Reference%20Codes.pdf

Can We Go Beyond *Administrative* Outcomes?



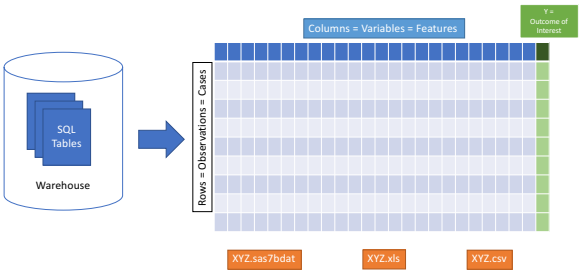
http://www.healthmeasures.net/explore-measurement-systems/promis/intro-to-promis

What Do Data Look Like?

Part 2:

A Deep Look at Organization

The Comforting Flat File.



Why So Comforting?

Y = Outcome of Interest = Columns = Variables = Features ✖ Importance of Features

$$Y = X\beta$$

$$Y = X\beta$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} X_{1,1} & X_{1,2} & X_{1,3} & X_{1,n} \\ X_{2,1} & X_{2,2} & X_{2,3} & X_{2,n} \\ X_{3,1} & X_{3,2} & X_{3,3} & X_{3,n} \\ \vdots & \vdots & \vdots & \vdots \\ X_{m,1} & X_{m,2} & X_{m,3} & X_{m,n} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_m \end{bmatrix}$$

Y = Outcome of Interest = Columns =Variables =Features ✖ Importance of Features

$$Y = X\beta$$

$$\text{Residuals} = e = y - X\hat{\beta}$$

$$\text{Sum of Squared Residuals} = e'e$$

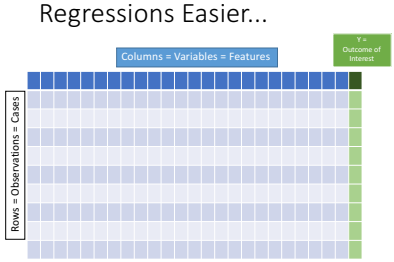
$$\begin{aligned} e'e &= (y - X\hat{\beta})'(y - X\hat{\beta}) \\ &= y'y - 2\hat{\beta}'X'y + \hat{\beta}'X'X\hat{\beta} \end{aligned}$$

$$\frac{\partial e'e}{\partial \hat{\beta}} = -2X'y + 2X'X\hat{\beta} = 0$$

$$(X'X)\hat{\beta} = X'y$$

$$\hat{\beta} = (X'X)^{-1}X'y$$

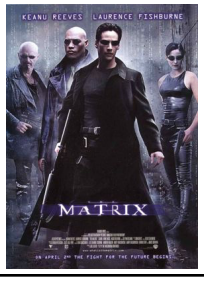
The Comforting Flat File Helps Make Regressions Easier...



$$Y = X\beta$$

$$\hat{\beta} = (X'X)^{-1}X'y$$

How do you fit a video into a flat file?



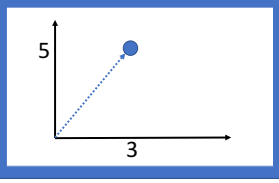
A short taxonomy of data structures

atomic
(scalars)

32

vectors

[3,5]



A short taxonomy of data structures

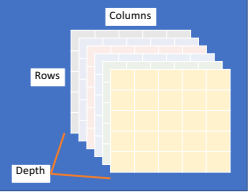
Matrix
(2-dimensional tensor)

Columns

Rows

1	3	9	3	9
2	3	8	4	8
7	4	6	8	2
5	6	3	7	3
3	7	2	6	1

Tensor
(n-dimensional)



Dimensionality refers to the number of indices necessary to definitively label an individual component of a tensor.

More on Tensors.

Wikipedia: "Tensors are geometric objects that describe linear relations between geometric vectors, scalars, and other tensors."

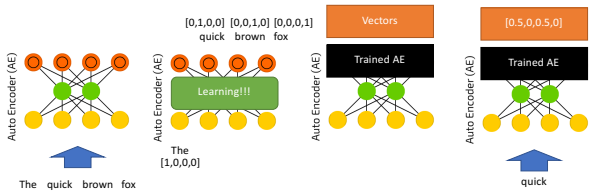
"A tensor is a generalization of vectors and matrices to potentially higher dimensions. Internally, TensorFlow represents tensors as n-dimensional arrays of base datatypes." Google (TensorFlow)

Tensor

DataType	Shape	Data

Let's Import a Movie!

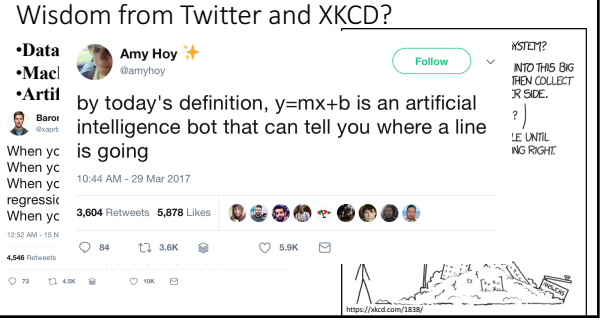
What Is Vector Embedding?



Deep EHR

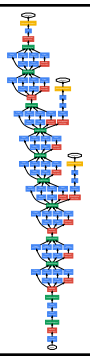
Part 3: Vector-Embedded and Related Approaches to Understanding our Patients

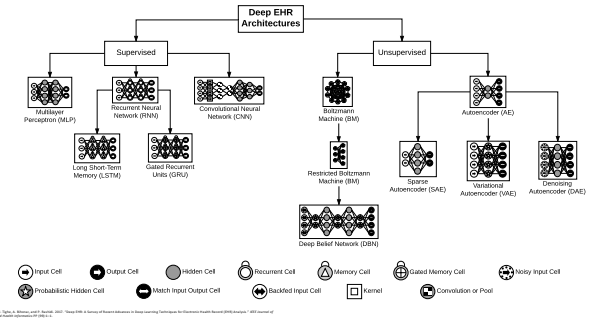
Wisdom from Twitter and XKCD?



What's Special about a Deep EHR?

- Focus on **Representations**
  - Differentiates DL from ML
- Minimal **Feature Engineering**
  - Explicit masks, filters, and pre-processing not required
- **Flexibility** in Data Structure
  - Incorporate multiple data types without adhering to strict matrices
- Implicit **Regularization**
  - Non-functional without!
- **Depth** + Breadth
  - http://www.asimovinstitute.org/neural-network-zoo/





DeepEHR Applications: An Overview

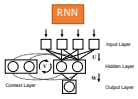
Task	Subtasks	Input Data	Models
EHR Information Extraction	(1) Single Concept Extraction (2) Temporal Event Extraction (3) Relation Extraction (4) Abbreviation Expansion	Clinical Notes	LSTM, bi-LSTM, GRU, CNN RNN + Word Embedding AE Custom Word Embedding
EHR Representation Learning	(1) Concept Representation (2) Patient Representation	Medical Codes	RBM, Skip-gram, AE, LSTM RBM, Skip-gram, GRU, CNN, AE
Outcome Prediction	(1) Static Prediction (2) Temporal Prediction	Mixed	AE, LSTM, RBM, DBN LSTM
EHR Phenotyping	(1) New Phenotype Discovery (2) Improving Existing Definitions	Mixed	AE, LSTM, RBM, DBN LSTM
EHR De-identification	Clinical text de-identification	Clinical Notes	Bi-LSTM, RNN + Word Embedding

DeepEHR Applications: Information Extraction

Objective: **Temporal Information Extraction**
Constructing a timeline of events in a clinical document.

Word2Vec
(300 dimensions)

RNN



TimeEx3

Event

Corpus	Note Type	Tokens	Vocab
MIMIC-III	Mixed (15 types)	758M	260K
UIHC-ALL	Mixed (41 types)	6.5B	899K
UIHC-CN	Clinic Notes	2.3B	378K
UIHC-PN	Progress Notes	1.8B	378K

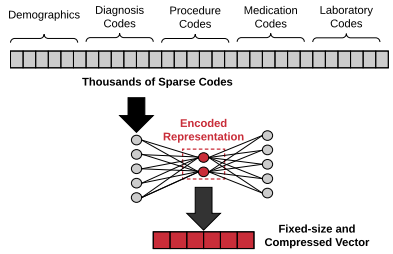
Table 1: Summary statistics for embedding corpora.

Method	Span		
	P	R	F_1
Baseline: memorize	0.878	0.834	0.855
BluLab (2015)	0.887	0.864	0.875
Median System (2016)	*0.887*	*0.846*	*0.874*
Best (2016):	***0.915***	***0.891***	***0.903***
DeepDive: run 1	0.864	0.836	0.850
DeepDive: run 2	**0.900**	0.864	0.882
DeepDive: run 3	**0.900**	0.866	0.883
RNN+emdim-100	0.864	0.889	0.866
RNN+MIMIC-III-100	0.861	0.877	0.869
RNN+UIHC-CN-100	0.873	0.887	0.880
RNN+UIHC-PN-100	0.878	0.882	0.880
RNN+UIHC-ALL-100	0.878	0.880	0.879
RNN+emdim-300	0.862	0.859	0.861
RNN+UIHC-CN-300	0.880	0.879	0.879
RNN+UIHC-PN-300	0.864	**0.892**	0.878
RNN Best Ensemble	0.882	0.889	**0.885**
Phase 1 RNN Submission	0.883	0.660	0.735

Table 3: EVENT span extraction performance.

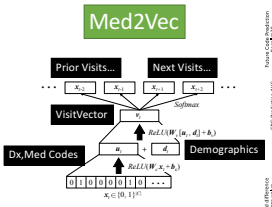
J. A. Frias, "Brandfellehy at SemEval-2016 Task 12: Recurrent Neural Networks vs. Joint Inference for Clinical Temporal Information Extraction," in *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, 2016, pp. 1274–1279. [Online]. Available: http://www.aclweb.org/anthology/S16-1198

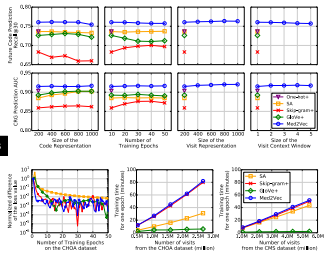
DeepEHR: Representation Learning



Ahmad, R., P. Tighe, A. Bihorac, and F. Sarolidi. 2017. "Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis." *IEEE Journal of Biomedical and Health Informatics* PP (99): 1–1.

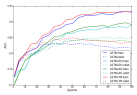
DeepEHR: Representation Learning





E. Choi, M. T. Bahadori, E. Searles, C. Coffey, and J. Sun, "Multi-layer Representation Learning for Medical Concepts," arXiv. pp. 1–20, 2016. [Online]. Available: http://arxiv.org/abs/1602.05568.

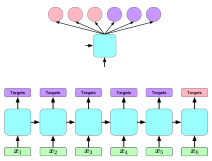
DeepEHR: Outcome Prediction



SBP
DBP
CR
ETCO2
FIO2
RR
SpO2
GCS
Gluc
HR
pH
Temp
UOP

128 Diagnostic Labels (429 avail.)

RNN
Target Replication ~ Local Error
Auxiliary Outputs ~ Informative

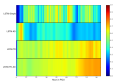


LSTM Models with Dropout (probability 0.5) and two 128-cell hidden layers

LSTM-DO	0.8377	0.7741	0.2748	0.1371	0.1130
LSTM-DO-AO (Diagnoses)	0.8365	0.7785	0.2581	0.1366	0.1104
LSTM-DO-AO (Categories)	0.8399	0.7781	0.2604	0.1361	0.1123
LSTM-DO-TR	**0.8507**	0.7970	**0.2936**	0.1485	**0.1172**
LSTM-DO-TR-AO (Diagnoses)	0.8470	0.7929	0.2875	0.1465	0.1149
LSTM-DO-TR-AO (Categories)	0.8543	0.8015	0.2887	0.1446	0.1161
LSTM-DO-TR (Linear Gain)	0.8480	0.7986	0.2896	**0.1530**	0.1160

Top 6 diagnoses measured by F1 score

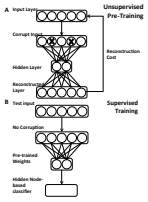
Label	***F1***	**AUC**	**Precision**	**Recall**
Diabetes mellitus with ketoacidosis	0.8571	0.9966	1.0000	0.7500
Scoliosis, idiopathic	0.6809	0.8543	0.6957	0.6667
Asthma, unspecified with status asthmaticus	0.5641	0.9232	0.7857	0.4400
Neoplasm, brain, unspecified	0.5430	0.8522	0.4317	0.7315
Delayed milestones	0.4751	0.8178	0.4057	0.5733
Acute Respiratory Distress Syndrome (ARDS)	0.4468	0.9595	0.3409	0.7500

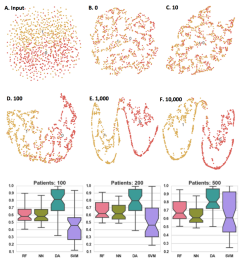


(a) Septic Shock

E. A. Choi, N. A. Kale, C. Xiao, and B. Westover, "Learning to Diagnose with LSTM Recurrent Neural Networks," arXiv, 2016. [Online]. Available: http://arxiv.org/abs/1511.03677.

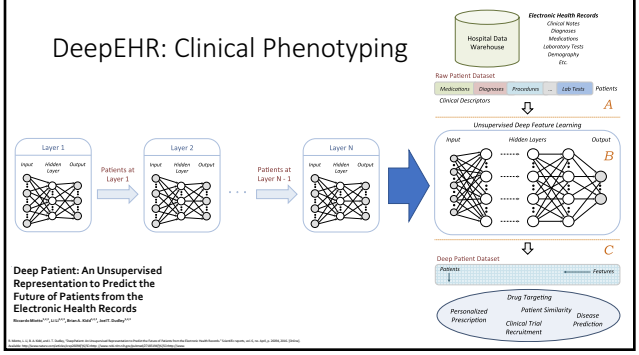
DeepEHR: Clinical Phenotyping





R. A. Rasmussen and T. S. Evanoff, "Tensor-Supervised Learning of the Electronic Health Record to Assessing Innovations for Phenotype Stratification," bioRxiv, p. 059808, 2016. [Online]. Available: http://biorxiv.org/content/early/2016/02/16/059808.abstract.

DeepEHR: Clinical Phenotyping



Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records

Ricardo Miotto[1,*], Li Li[2,3,*], Brian A. Kidd[1,*], Joel T. Dudley[1,*]

R Miotto, L Li, B A Kidd, and J T Dudley, "DeepPatient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records," Scientific reports, vol. 6, no. April, p. 26094, 2016. [Online]. Available: http://www.nature.com/articles/srep26094%5Cnhttp://www.ncbi.nlm.nih.gov/pubmed/27077195%5Cnhttp://www.

DeepEHR: Clinical Phenotyping

Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records

Incidence of New Disease Prediction

Time Interval = 1 year (76,214 patients)			
		Classification Threshold = 0.6	
Patient Representation	AUC-ROC	Accuracy	F-Score
RawFeat	0.659	0.805	0.084
PCA	0.696	0.879	0.104
GMM	0.632	0.891	0.072
K-Means	0.672	0.887	0.093
ICA	0.695	0.882	0.101
DeepPatient	**0.773***	**0.929***	**0.181***

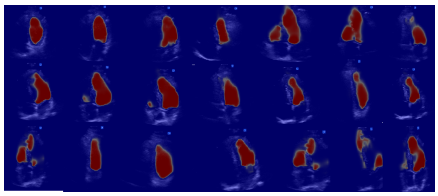
Time Interval = 1 year (76,214 patients)			
	Area under the ROC curve		
Disease	RawFeat	PCA	DeepPatient
Diabetes mellitus with complications	0.794	0.861	**0.907**
Cancer of rectum and anus	0.863	0.821	**0.887**
Cancer of liver and intrahepatic bile duct	0.830	0.867	**0.886**
Regional enteritis and ulcerative colitis	0.814	0.843	**0.870**
Congestive heart failure (non-hypertensive)	0.808	0.808	**0.865**
Attention-deficit and disruptive behavior disorders	0.730	0.797	**0.863**
Cancer of prostate	0.692	0.820	**0.859**
Schizophrenia	0.791	0.788	**0.853**
Multiple myeloma	0.783	0.739	**0.849**
Acute myocardial infarction	0.771	0.775	**0.847**

R Miotto, L Li, B A Kidd, and J T Dudley, "DeepPatient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records," Scientific reports, vol. 6, no. April, p. 26094, 2016. [Online]. Available: http://www.nature.com/articles/srep26094%5Cnhttp://www.ncbi.nlm.nih.gov/pubmed/27077195%5Cnhttp://www.

DeepEHR in Perioperative Medicine

Sarah Stern MD Candidate
Sean Kiley MD
Patrick Tighe MD MS

Deep Learning Approaches to Perioperative Ultrasound Image Interpretation

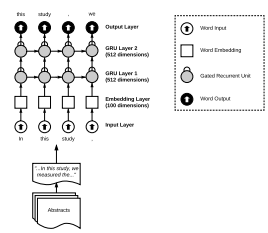


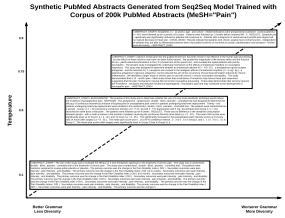
Convolutional Neural Network Classifying LV Volumes

What Would PubMed Write about Pain?

Ben Shickel PhD Candidate
Patrick Tighe MD MS
Parisa Rashidi PhD

What Would PubMed Write about Pain? Automated PubMed Abstract Text Generation using Seq2Seq Deep Learning Techniques Trained on 200k PubMed Pain Research Abstracts





What Would PubMed Write about *Pain*?

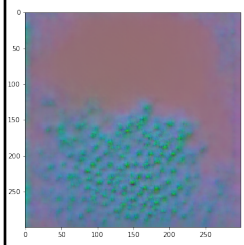
Epoch 0:

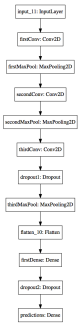
[0.50] BACKGROUND DATA method for the patient with a 5 - 3 and its role in the right ventricular ejection fraction and the basis of the incidence of the left ventricular failure . The study with no significant risk factors . The study and for 2 . A - based on the incidence of the proportion , and for treatment . The study with a "

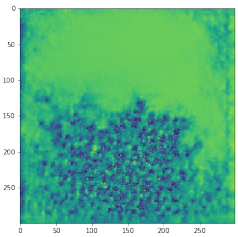
What Would PubMed Write about *Pain*?

<ABSTRACT_START> The development of new and new mechanisms of pain are not known . In this study , we evaluated the relationship between different aspects of pain sensitivity in the rat formalin test . The effects of serotonin (5 - HT) , which occurred in the tail flick test , were examined using a hot - plate test . The formalin test was performed on , the pain field , and the number of thresholds oedema . The present study was conducted on the lumbar dorsal horn of the left induced a 5 % formalin and formalin induced pain . In rats , the amount of pain threshold was measured with the postoperative paw withdrawal latency of the hind paw . At the same time , the aversive muscle soreness was induced by the administration of either 0 . 1 - or 0 . 1 - 0 . 0 microg / kg , or a 5 . 5 - micrograms / kg Pain models to applied to the hind paw . In the second phase , the dose was < or = 5 . 0 mg / kg and increased . Moreover , the performance of the nociceptive stimulus was reduced by 44 % and 91 % after 1 year , respectively . In this study , the explored dose of study drugs (7 , 10 , and 20 mg / kg) reversed the persistent pain . A dose of 10 mg / kg of paracetamol was administered . In contrast , the activity of the prostaglandin E2 were significantly increased after the initial dose of the dose of the NMDA antagonist highlights the co - occurrence of nociceptive behavior induced by carrageenan . On the other hand , the in - treated animals exhibited increased

DeepEHR in Periope Medicine

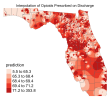


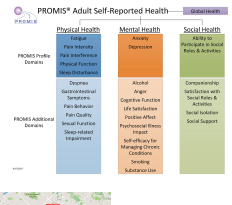




What Else Can We Embed?

WATCH





STRAVA

Review

1. Problems with our Data.
2. What Do Data Look Like…and How Did We Get Here?
3. Deep EHR: Vector-Embedded and Related Approaches to Understanding our Patients

Thank You!

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Next Up!

Assembling a Deep EHR → Deep Learning Mechanisms → Applying Deep Insights

Tighe | Rashidi | Price