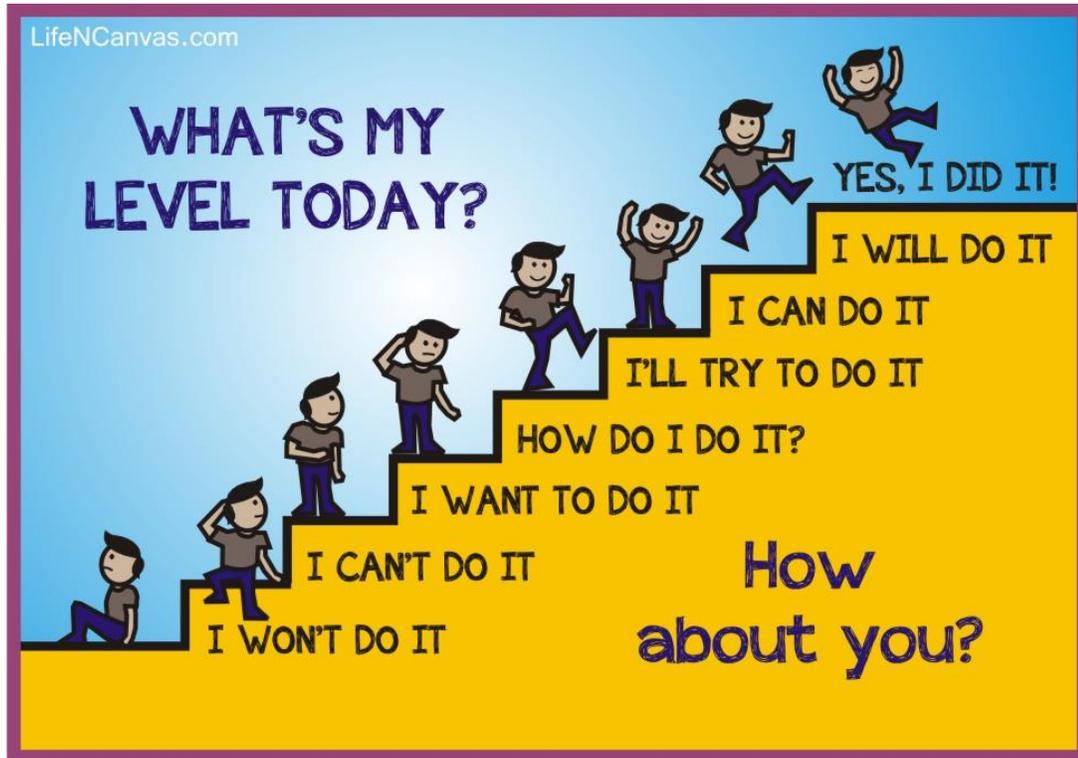


# Der digitale Arzt: Die Zukunft hat bereits begonnen

Michael Forsting

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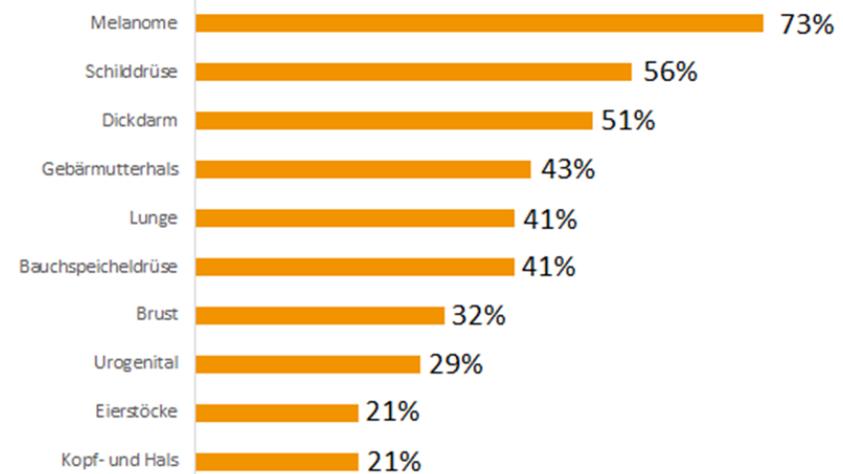
# Best practice



# Megatrends in der Medizin



Anteil Krebspatienten, deren Tumore mittels personalisierter Medizin behandelt werden könnten



Modifiziert nach Statistika

# Megatrend in der Welt



# Wir müssen die Trends zusammen bringen!



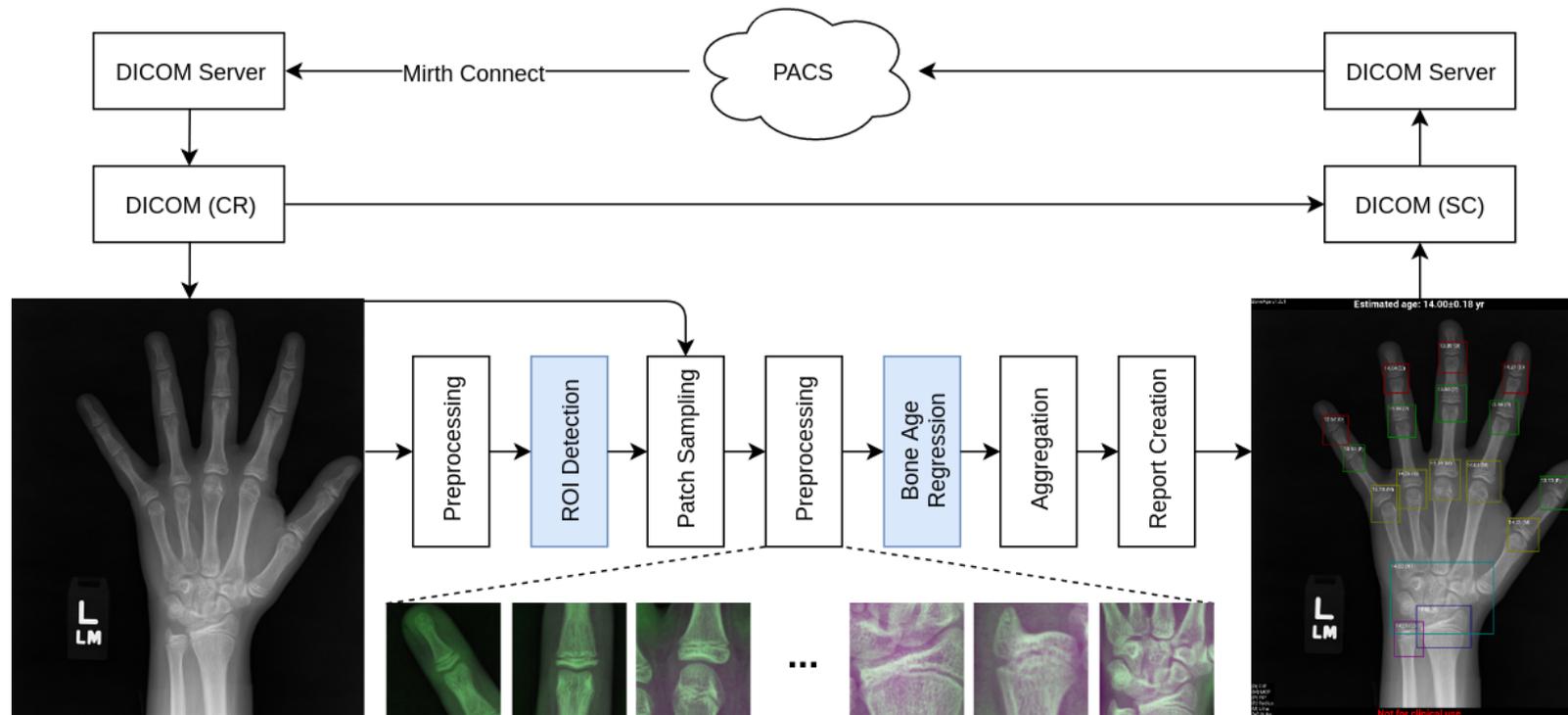
1. Digitalisierung ist die Voraussetzung für die Anwendung von Künstlicher Intelligenz
2. Nur mit Künstlicher Intelligenz wird personalisierte Medizin möglich sein

# Applications in radiology

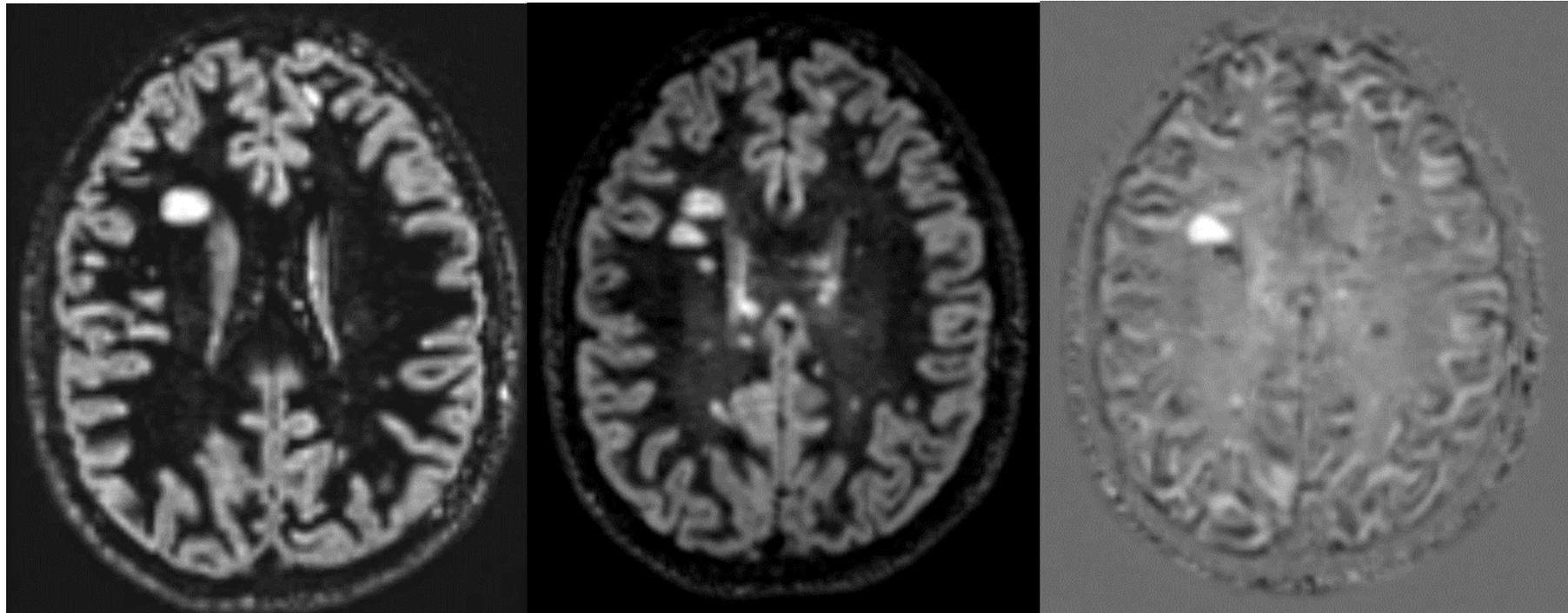


- Where do we have excellent groundtruth data?
- Define „unmet needs“:
  - What is boring?
  - Is boredom a source of error?
  - What is time-consuming?
  - In which areas is radiology not good?
- Define the data lake
- Low hanging fruits first
- More difficult tasks later on

# Bone age prediction



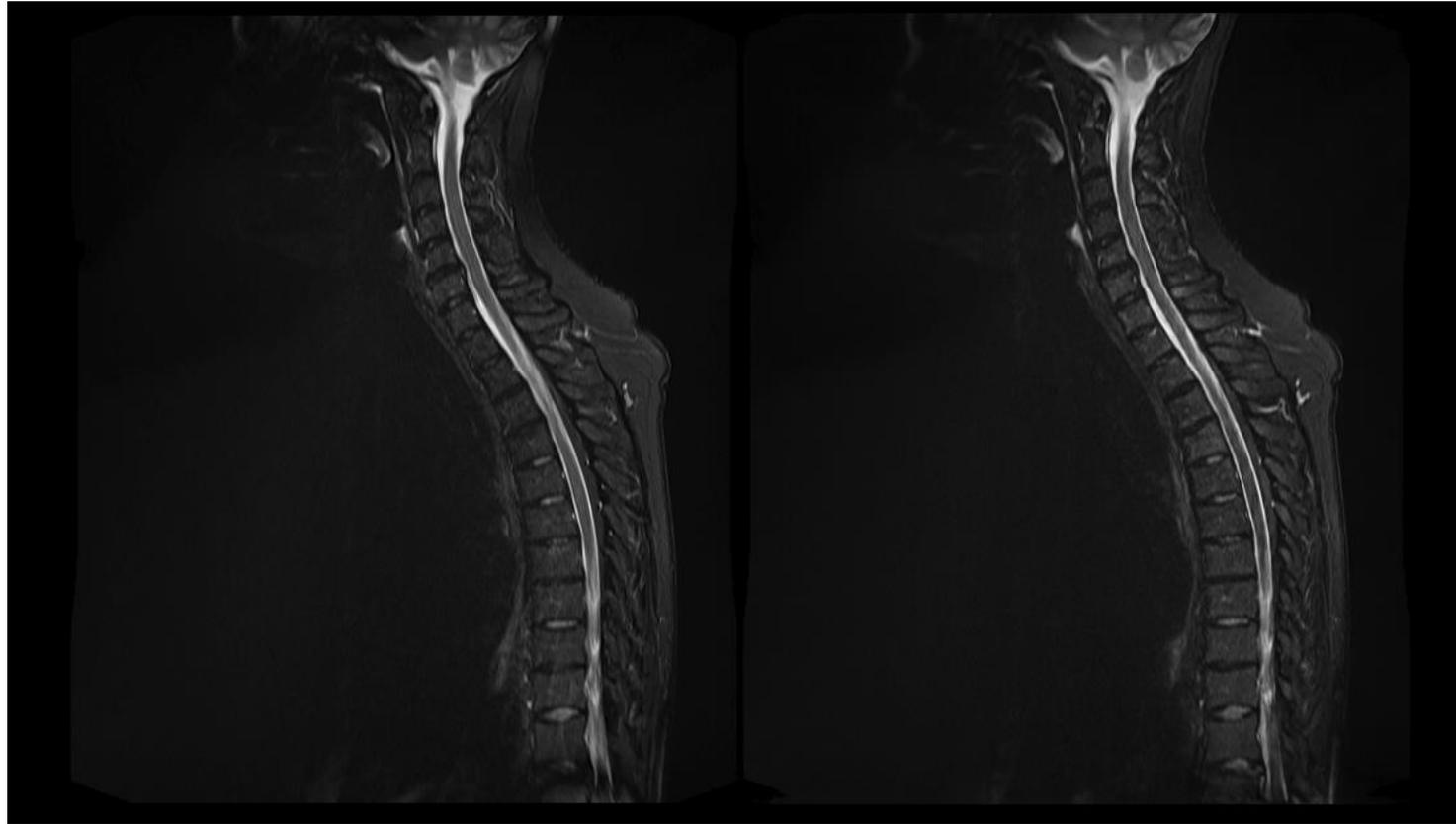
## Subtraction of MS plaques in F-U examinations



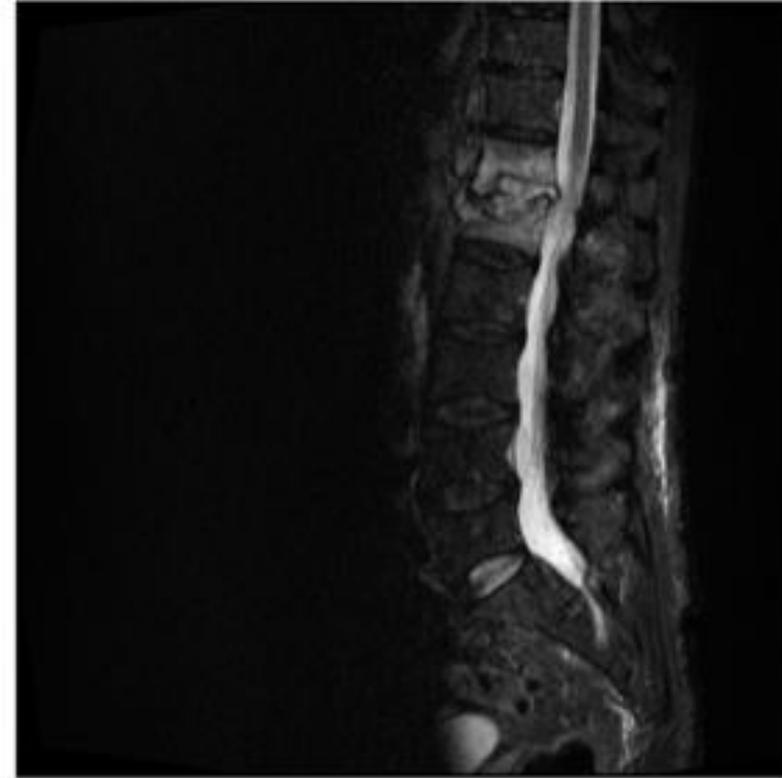
What does the neurologist want to know?



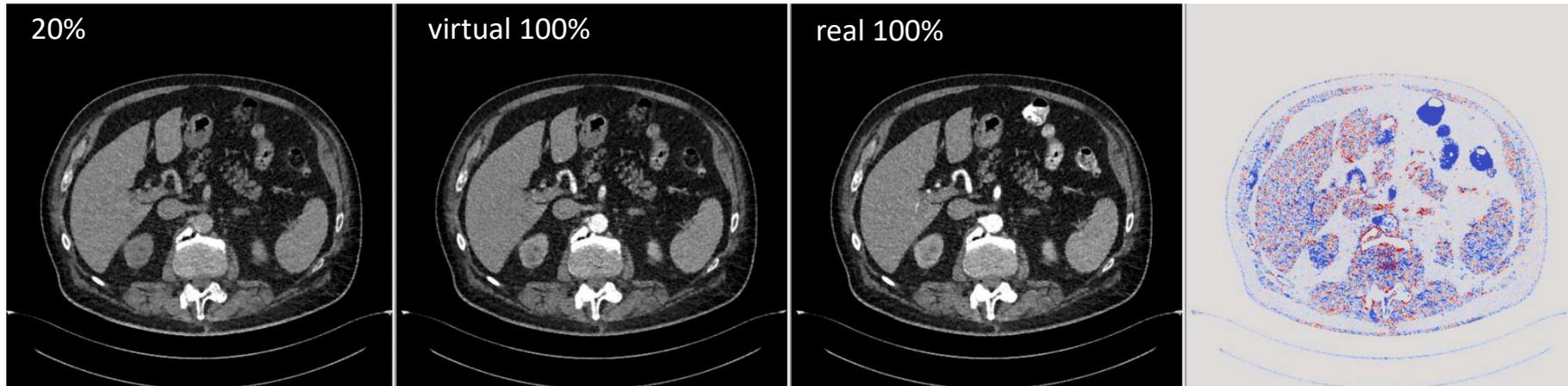
# Virtual sequences (STIR): Reduction of time; reduction of problems in standardisation



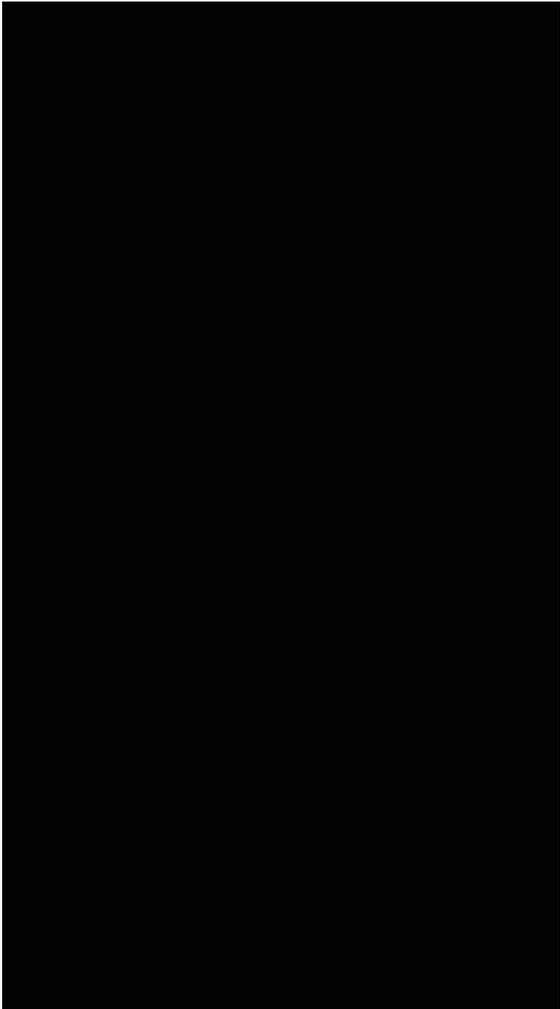
# Virtual sequences (STIR): Reduction of time; reduction of problems in standardisation



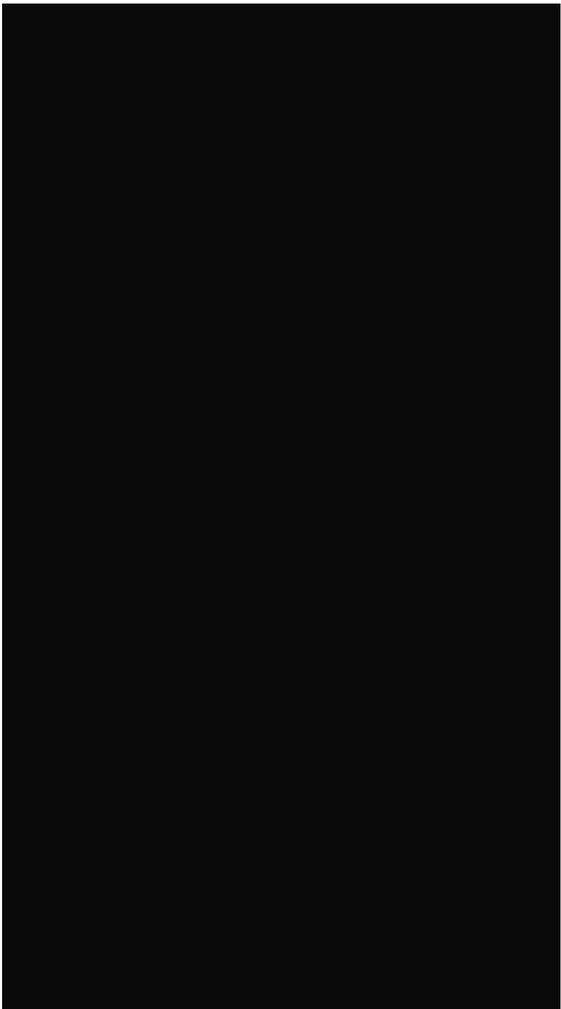
# Contrast media dose reduction



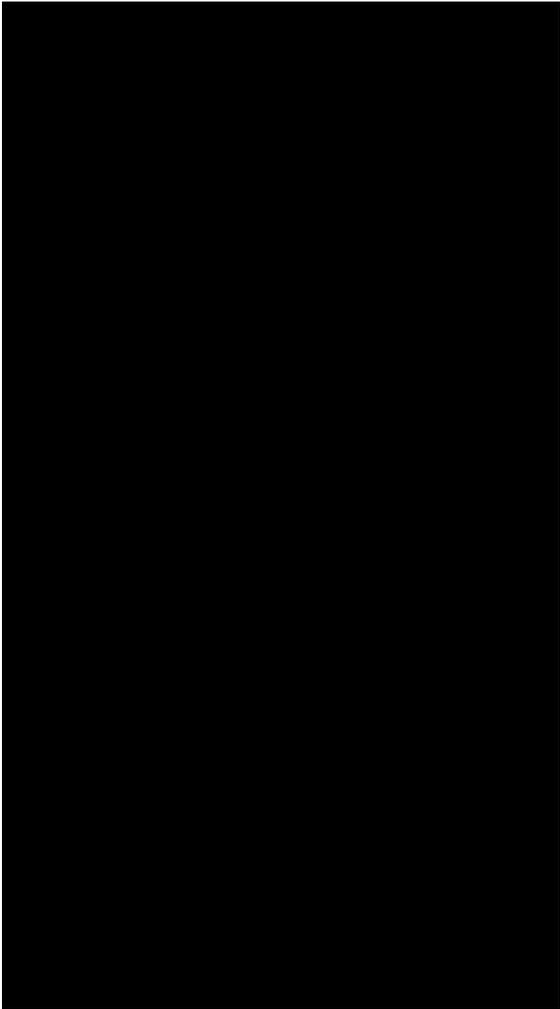
# Virtual Contrast Agent Prediction Normal



T1w  
native

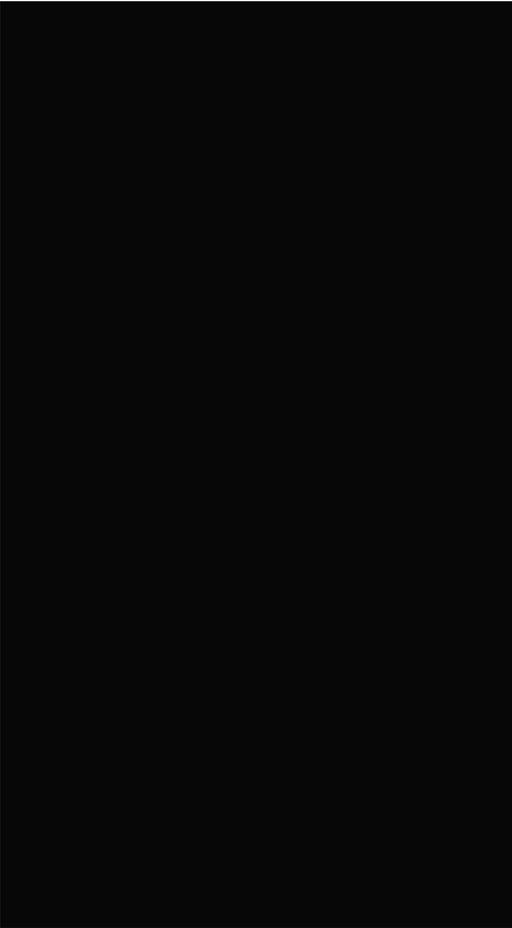


ceT1w  
groundtruth

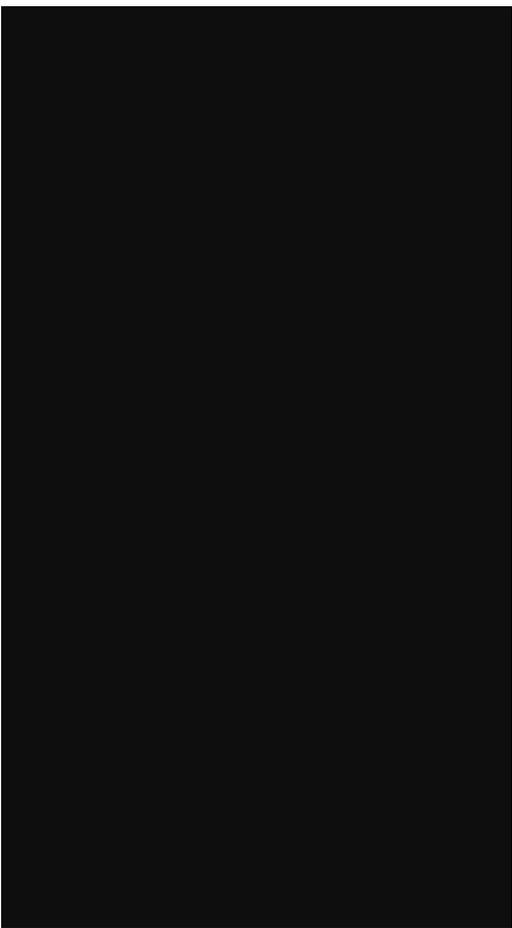


vT1w  
predicted

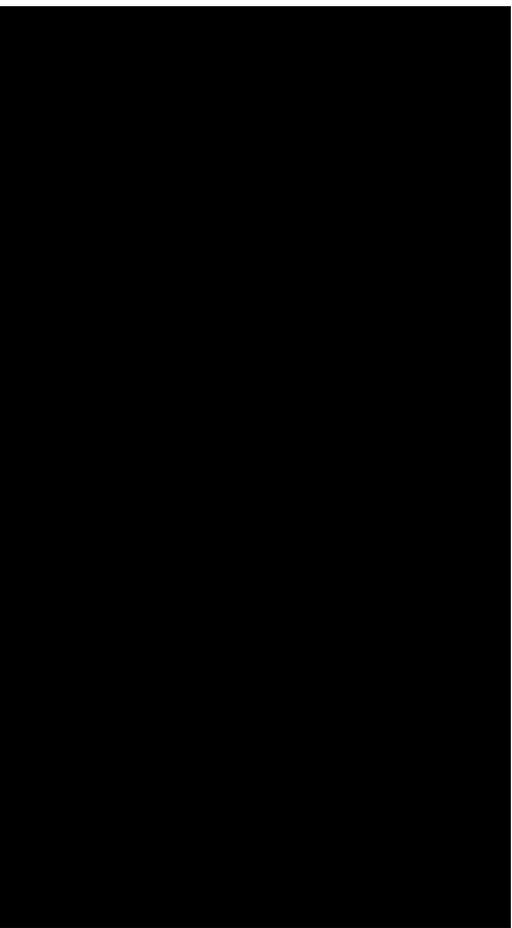
# Virtual Contrast Agent Prediction Tumor



T1w  
native



ceT1w  
groundtruth



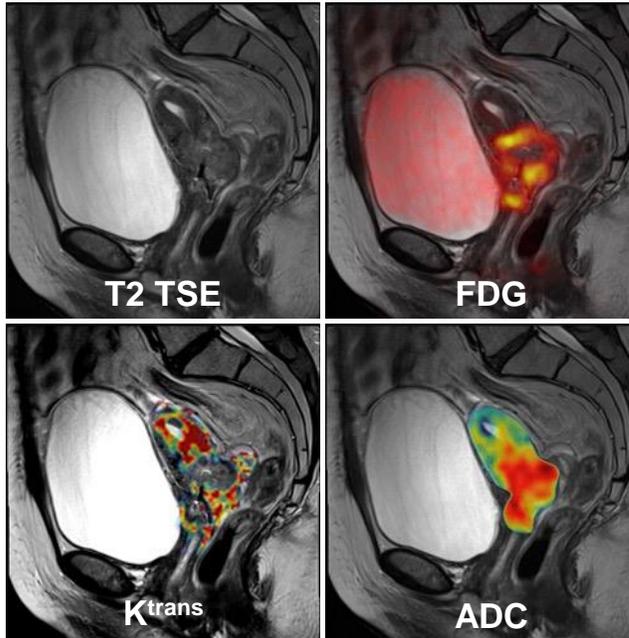
vT1w  
predicted

# How can we improve radiology?

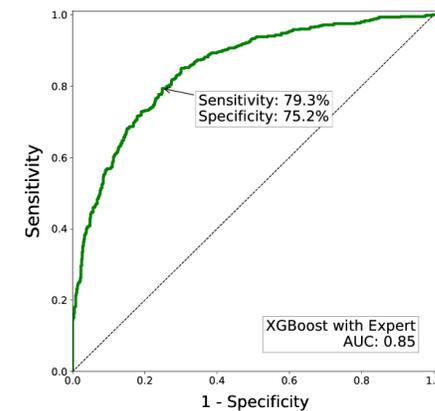
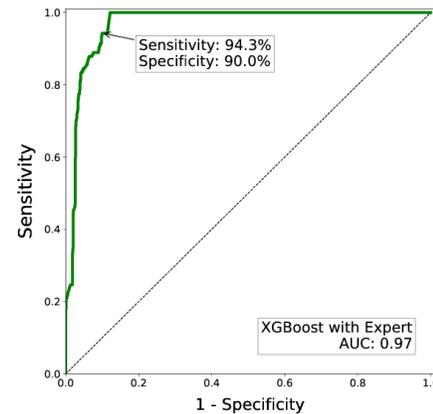
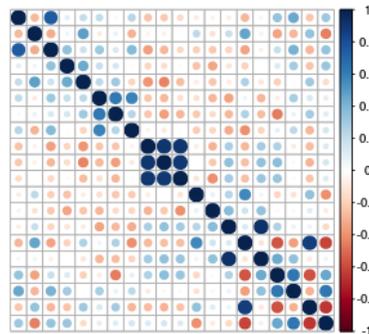
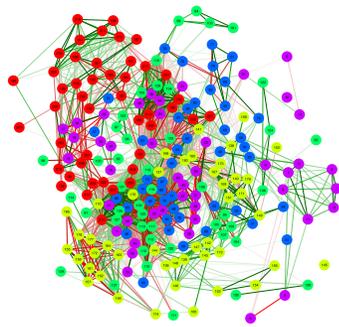
- Gain more information from pixels



# PET/MRT Radiomics



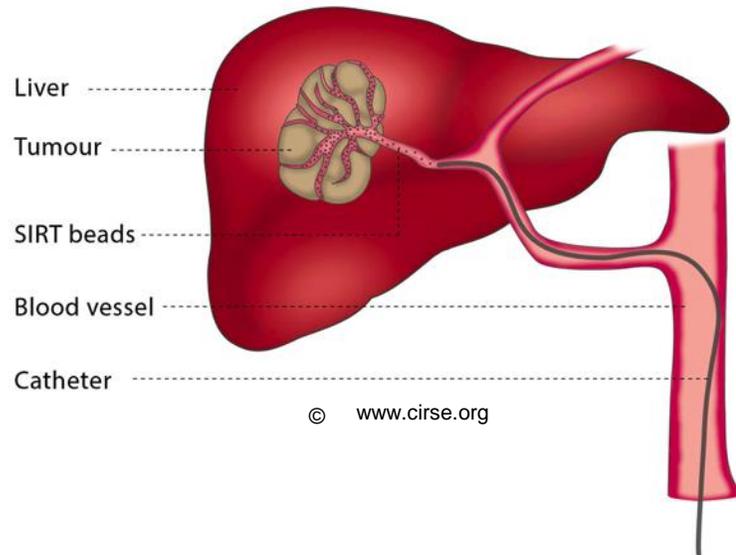
M-stage				N-stage			
Name	P	P <sub>adj</sub>		Name	P	P <sub>adj</sub>	
T2_TSE_glcM_differenceEntropy	0.0000	0.00		PET_calc_median	0.0001	0.01	
T1_Nativ_glcM_differenceEntropy	0.0002	0.02		T2_TSE_glcM_correlation	0.0005	0.05	
T2_TSE_glcM_correlation	0.0005	0.05		PET_calc_energy	0.0008	0.08	
Ktrans_1616_calc_min	0.0009	0.09		PET_glrM_LRHGLE	0.0008	0.08	
T2_TSE_glcM_energy	0.0019	0.19		ADC_glcM_autoCorrelation	0.0013	0.13	
T2_TSE_glrM_LRE	0.0019	0.19		Ktrans_1616_glcM_cShade	0.0013	0.13	
ADC_glcM_contrast	0.0083	0.82		ADC_calc_skewness	0.0016	0.16	
PET_glcM_correlation	0.0083	0.82		T2_TSE_glcM_differenceEntropy	0.0023	0.22	
PET_glcM_IDMN	0.0098	0.97		ADC_glcM_cProminence	0.0023	0.22	
ADC_glcM_IDMN	0.0115	1.00		ADC_glcM_mean	0.0027	0.26	
ADC_glcM_inverseVariance	0.0156	1.00		ADC_glcM_cShade	0.0032	0.31	
T1_Nativ_glcM_correlation	0.0210	1.00		Ktrans_1616_glcM_maxProb	0.0037	0.37	
Ktrans_1616_glcM_cShade	0.0210	1.00		Ktrans_1616_glrM_GLN	0.0043	0.43	
T1_Nativ_glrM_LRLGLE	0.0241	1.00		ADC_glrM_LRLGLE	0.0059	0.58	
PET_glcM_contrast	0.0241	1.00		PET_calc_uniformity	0.0068	0.68	
ADC_calc_uniformity	0.0277	1.00	PET_calc_max	0.0068	0.68		
PET_glrM_LRE	0.0277	1.00	T1_Nativ_glrM_LRLGLE	0.0079	0.78		
Ktrans_1616_calc_median	0.0299	1.00	T2_TSE_glrM_LRE	0.0079	0.78		
T2_TSE_calc_skewness	0.0317	1.00	PET_glcM_IDMN	0.0079	0.78		
ADC_calc_entropy	0.0317	1.00	Ktrans_1616_glrM_LRLGLE	0.0079	0.78		



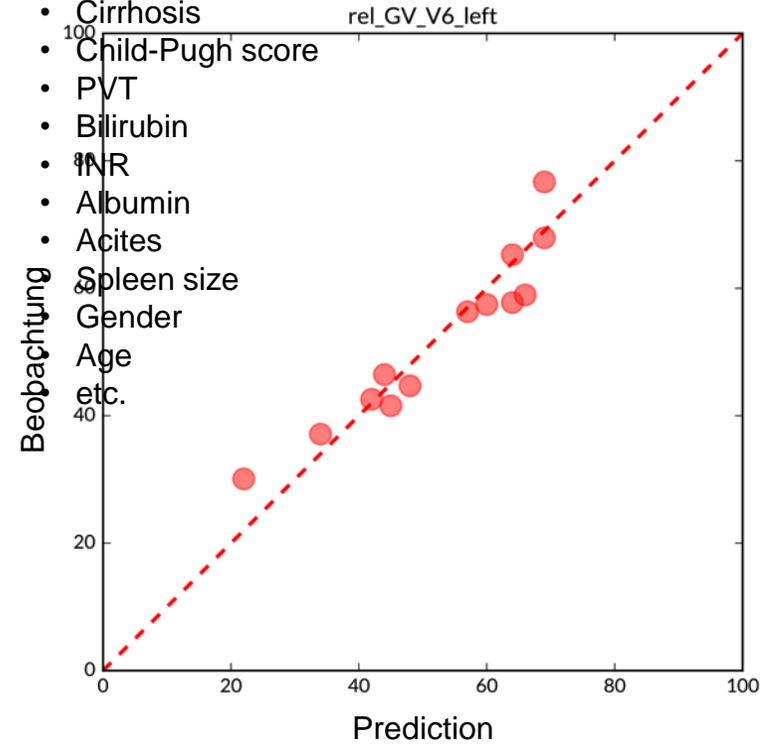
Umutlu L, Grüneisen J, Nensa F, et al. 2017. Unpublished

# Selective internal radiation therapy

## Selective internal radiation therapy (SIRT)



- Liver size
- Growth of untreated liver part
- Cirrhosis
- Child-Pugh score
- PVT
- Bilirubin
- INR
- Albumin
- Ascites
- Spleen size
- Gender
- Age
- etc.



# Summary for radiology

- artificial intelligence will relieve radiologists of boring tasks
  - It'll be quick.
- AI will improve quality of radiology
  - Radiomics: get more information from pixels
  - It'll take some time.
- AI will affect other disciplines much more than radiology

# Wo wird KI die grössten Veränderungen bringen?



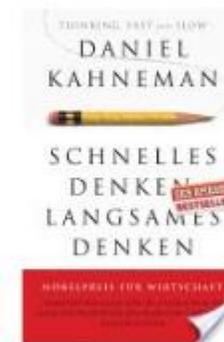
- Technische Disziplinen sind fehlerfrei
- „Sprechende Medizin“ ist hypothesengetrieben und macht viele Fehler

# Kahneman-Zitat

(Nobelpreisträger für Behavioural Economics)

Der Mensch ist nicht in der Lage, statistisch-quantitative Entscheidungen permanent gut genug zu treffen und lässt sich häufig täuschen (meist durch Optimismus).

Lange Liste von typischen Denkfehlern:  
[http://en.wikipedia.org/wiki/List\\_of\\_cognitive\\_biases](http://en.wikipedia.org/wiki/List_of_cognitive_biases)



# Die optimistische Annahme: „Wird schon in mein Fachgebiet gehören“

- Kardiologie
- Neurochirurgie
- Orthopädie
- Angiologie
- ....



# Instagram photos reveal predictive markers of depression

Andrew G Reece  and Christopher M Danforth 

*EPJ Data Science* 2017 6:15 | <https://doi.org/10.1140/epjds/s13688-017-0110-z> | © The Author(s) 2017

Received: 28 March 2017 | Accepted: 22 June 2017 | Published: 8 August 2017

 The Erratum to this article has been published in *EPJ Data Science* 2017 6:21

## Abstract

Using Instagram data from 166 individuals, we applied machine learning tools to successfully identify markers of depression. Statistical features were computationally extracted from 43,950 participant Instagram photos, using color analysis, metadata components, and algorithmic face detection. Resulting models outperformed general practitioners' average unassisted diagnostic success rate for depression. These results held even when the analysis was restricted to posts made before depressed individuals were first diagnosed. Human ratings of photo attributes (happy, sad, etc.) were weaker predictors of depression, and were uncorrelated with computationally-generated features. These results suggest new avenues for early screening and detection of mental illness.

# Predicting Depression via Social Media

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## Abstract

Major depression constitutes a serious challenge in personal and public health. Tens of millions of people each year suffer from depression and only a fraction receives adequate treatment. We explore the potential to use social media to detect and diagnose major depressive disorder in individuals. We first employ crowdsourcing to compile a set of Twitter users who report being diagnosed with clinical depression, based on a standard psychometric instrument. Through their social media postings over a year preceding the onset of depression, we measure behavioral attributes relating to social engagement, emotion, language and linguistic styles, ego network, and mentions of antidepressant medications. We leverage these behavioral cues, to build a statistical classifier that provides estimates of the risk of depression, *before* the reported onset. We find that social media contains useful signals for characterizing the onset of depression in individuals, as measured through decrease in social activity, raised negative affect, highly clustered

laboratory test for diagnosing most forms of mental illness; typically, the diagnosis is based on the patient's self-reported experiences, behaviors reported by relatives or friends, and a mental status examination.

In the context of all of these challenges, we examine the potential of social media as a tool in detecting and predicting affective disorders in individuals. We focus on a common mental illness: Major Depressive Disorder or MDD<sup>1</sup>. MDD is characterized by episodes of all-encompassing low mood accompanied by low self-esteem, and loss of interest or pleasure in normally enjoyable activities. It is also well-established that people suffering from MDD tend to focus their attention on unhappy and unflattering information, to interpret ambiguous information negatively, and to harbor pervasively pessimistic beliefs (Kessler et al., 2003; Rude et al., 2004).

People are increasingly using social media platforms,

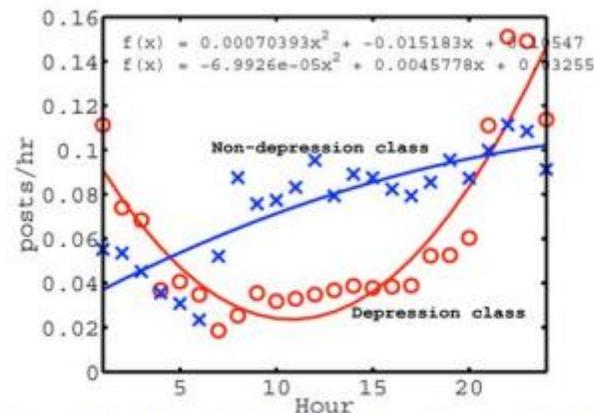


Figure 2: Diurnal trends (i.e. mean number of posts made hourly throughout a day) for the two classes. The line plots correspond to least squares fit of the trends.

# Depression detector

Analyzing speech patterns can predict if a subject is depressed.

by Rob Matheson October 23, 2018

**T**

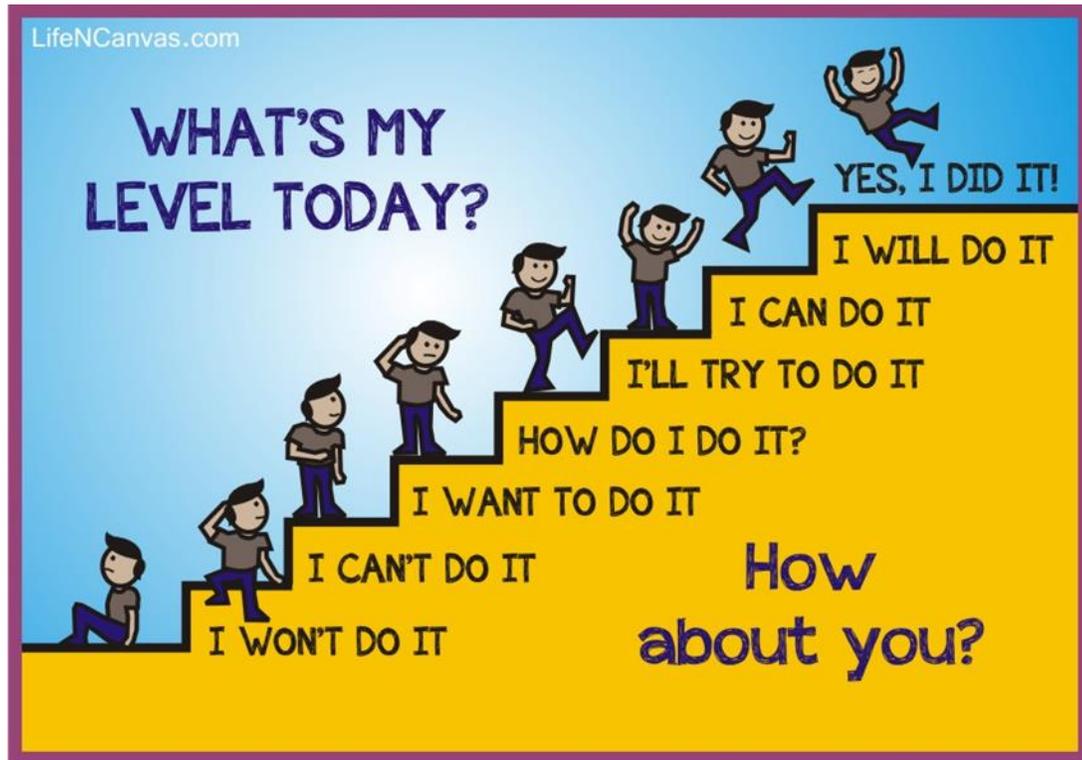
**o diagnose depression, clinicians interview patients, asking** specific questions—about, say, past mental illnesses, lifestyle, and mood.

Machine learning that can detect words and intonations associated with depression could help with diagnostics. But such models tend to predict depression from the person's specific answers to very specific questions.

A new neural-network model developed at MIT can be unleashed on raw text and audio data from interviews to discover speech patterns indicative of depression. Given a new subject, it can accurately predict whether the individual is depressed without needing any other information about the questions and answers.

“The model sees sequences of words or speaking style, and determines that these patterns are more likely to be seen in people who are depressed or not depressed,” says EECS graduate student and CSAIL

# Fazit



*The International No.1 Bestseller*

## The TIPPING POINT



*HOW LITTLE THINGS CAN MAKE  
A BIG DIFFERENCE*

MALCOLM  
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