# Machine Learning for Clinical Predictive Analytics

Workshop

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BIG DATA FOR HEALTH WORKSHOPS AND CONFERENCE Jul 10, 2018





the American cognitive scientist Marvin Minsky as the science of making machines do things

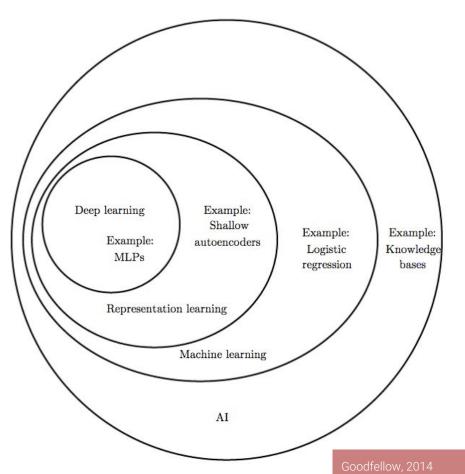
Artificial intelligence (AI) is defined by

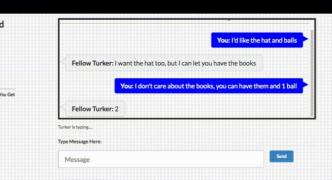
that would require intelligence if done by man

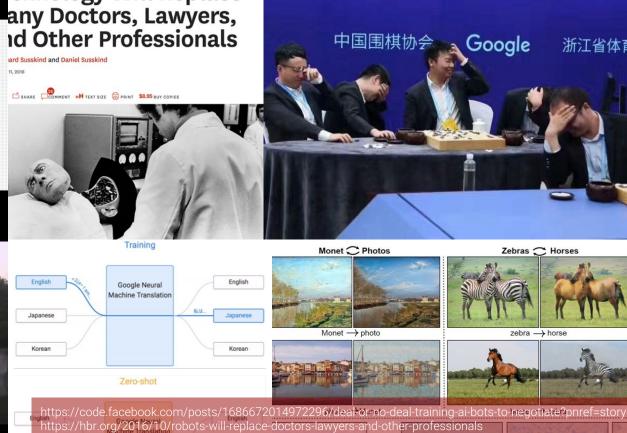
# AI?

Human intelligence as a goal

Algorithms / Data science as an **approach** 







https://twitter.com/DeepMindAl/status/867996695778410497/photo/1

https://research.googleblog.com/2016/11/zero-shot-translation-with-googles.html

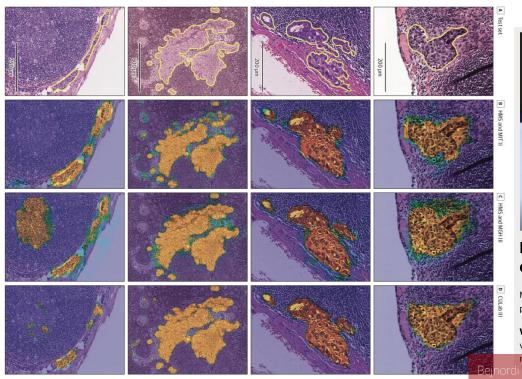
chnology Will Replace

http://selfdrivingcars.mit.edu/

https://github.com/junyanz/CycleGAN\_



# **Biomedical Imaging Informatics**





# FDA approves first Al-powered diagnostic that doesn't need a doctor's help

Marking a new era of "diagnosis by software," the US Food and Drug Administration on Wednesday gave permission to a company called IDx to market the first Al-powered diagnostic device.

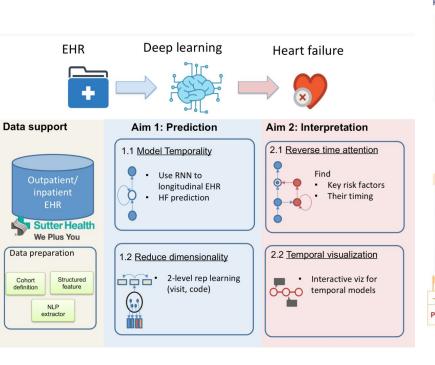
What it does: The software is designed to detect greater than a mild level of diabetic retinopathy, which causes vision loss and affects 30 million people in the US. It occurs when high blood sugar damages blood vessels in the

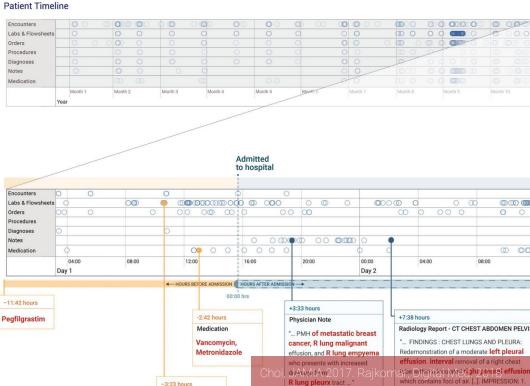
retina.

rdi et al. JAMA 2017

https://www.technologyreview.com/the-download/610853/fda-approves-first-ai-poweredagnostic-that-doesnt-need-a-doctors-help/

# Clinical / Public Health Informatics





Nursing Claushaut

Interval progression of disease in the chest and

## Sciences Behind

Data organization / structuring

- Database
- Knowledge representation / Ontology
- Visualization

Learning from data (Algorithms)

- Statistics, probability, information theory, ...
- Machine learning
  - Computer vision, natural language processing, signal processing, ...

# Machine Learning

Optimize a performance criterion using example data or past experience

- Given data X, we want to learn a function mapping f(X) for certain purpose
  - Patient age, gender, vitals, labs, ... → mortality Y/N
- ML Given objective and evaluation metrics, and get high quality f(X)

#### Three steps

- Modeling
  - Choose functions, features, (hyper)parameters
- 2. Evaluating the function
  - Define loss function, optimizer
- 3. Choosing the best one
  - Decide bias/variance trade-off

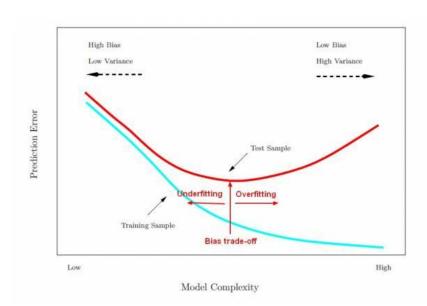
## Bias vs. Variance

#### Bias (underfitting)

- High training/validation error
- Train more, increase model complexity, decrease regularization, add features

### Variance (overfitting)

- Low training error but high validation/testing error
- More data, reduce model complexity, add regularization, reduce features

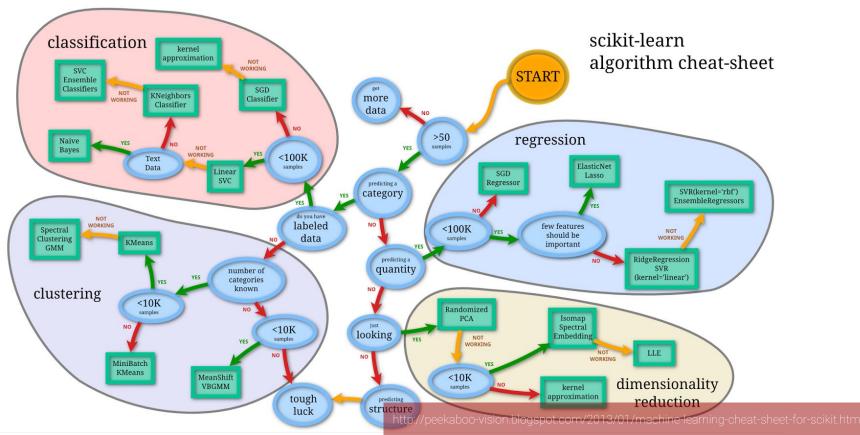


https://gerardnico.com/\_media/data\_mining/model\_complexity\_error\_training\_te st.jpg?w=600&tok=9ed6da

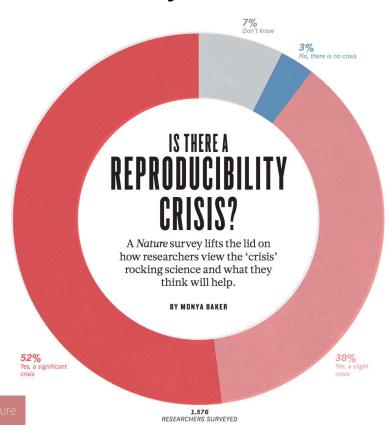
## Scenario

- Supervised learning
  - Regression
  - Classification
    - Linear
    - Non-linear (e.g. **deep learning**, SVM, decision tree, ...)
  - Structured learning
- Unsupervised learning
  - Clustering
  - Dimensionality reduction
- Transfer learning
- Reinforcement learning

# Algorithms



# Reproducibility



#### HAVE YOU FAILED TO REPRODUCE AN FXPFRIMENT? Most scientists have experienced failure to reproduce results. Someone else's My own Chemistry Biology Physics and engineering Medicine Earth and environment Other 60 80 100% HAVE YOU ESTABLISHED PROCEDURES FOR REPRODUCIBILITY? Among the most popular strategies was having different lab members redo experiments. 34% No 33% 1,576 Within the past 5 years researchers surveyed 26% Procedures have 7% been in place More than since I started 5 years ago working in my lab

# ICLR 2018 Reproducibility Challenge

#### Background:

One of the challenges in machine learning research is to ensure that published results are reliable and reproducible. In support of this, the goal of this challenge is to investigate reproducibility of empirical results submitted to the <a href="2018 International Conference on Learning Representations">2018 International Conference on Learning Representations</a>.

We are choosing ICLR for this challenge because the timing is right for course-based participants (see below), and because papers submitted to the conference are automatically made available publicly on <a href="Open Review">Open Review</a>.

The Challenge is inspired by discussions at the ICML 2017 Workshop on Reproducibility in Machine Learning.

#### Task Description

You should select a paper from the 2018 ICLR submissions, and aim to replicate the experiments described in the paper. The goal is to assess if the experiments are reproducible, and to determine if the conclusions of the paper are supported by your findings. Your results can be either positive (i.e. confirm reproducibility), or negative (i.e. explain what you were unable to reproduce, and potentially explain why).

Essentially, think of your role as an inspector verifying the validity of the experimental results and conclusions of the paper. In some instances, your role will also extend to helping the authors improve the quality of their work and paper.

# Reproducibility

What may be useful...

- Executable notebooks .ipynb
- Code publishing platform GitHub
- Version control Git

Google colab

## "FINAL".doc







FINAL.doc!

FINAL\_rev. 2. doc







FINAL\_rev.6.COMMENTS.doc

FINAL\_rev.8.comments5. CORRECTIONS.doc







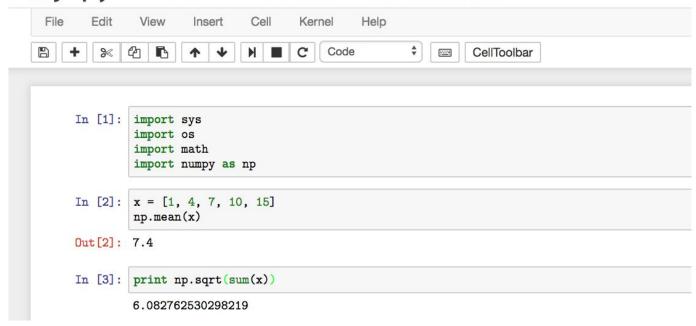
FINAL\_rev.18.comments7. corrections9.MORE.30.doc

FINAL\_rev.22.comments49. corrections.10.#@\$%WHYDID ICOMETOGRADSCHOOL????.doc

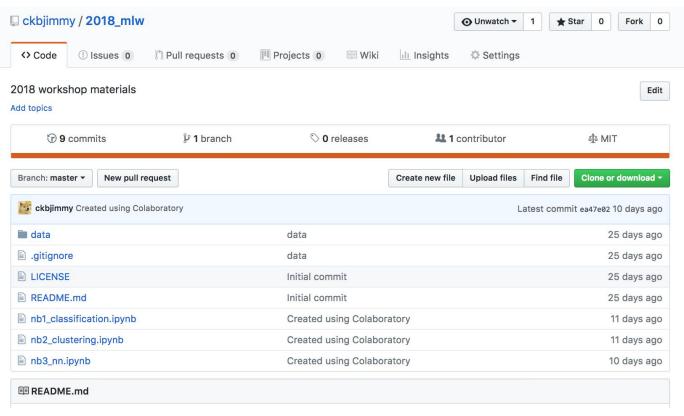
# Jupyter Notebook

Execute (Shift + Enter) code cells and get your output underneath the cells

Jupyter Untitled Last Checkpoint: a minute ago (unsaved changes)



# Code Publishing Platform



## **Version Control**

- git add .
- git status
- git commit -m 'first commit'
- git push
- git reset '.DS\_Store'

# CoLab (CoLaboratory)

#### http://g.co/colab

Write code just as you would on a Jupyter Notebook

Use one of google's virtual machines to carry out your tasks

Free

Can write shell commands preceded with a '!'

- !pip install gensim
- !1s

## **Tutorial**

- https://github.com/ckbjimmy/2018 mlw
  - Open → "File" -> "Save a copy in Drive..."
- Use python scikit-learn / keras
- Two datasets
- Part 1 Supervised learning (classification)
  - When you have some labeled data
  - Given features, predict malignancy
  - ML general approaches, missing data imputation, normalization, important feature identification, ...
- Part 2 Unsupervised learning (clustering / dimensionality reduction)
  - When you don't have labeled data
  - Grouping the similar cases
  - K-means / PCA

## **Tutorial**

- Part 3 Neural network
  - Deep feedforward neural network
    - ICU structured data
    - Breast cancer prediction data
  - Convolutional neural network (CNN) for image (MNIST)
  - Recurrent neural network (RNN) for text (IMDB reviews)

## More ICU Problems

#### Classification

- Fit paCO2 to pH / fit paCO2 and HCO3 to pH
- Classify ICU mortality using HCO3 min/median & paCO2 max/median
- Decision tree / random forest to determine mortality based on Hct, PLT min or WBC max (or based on vital signs, etc.)

#### Clustering

- Identify clusters of patients with HCO3/paCO2 or vital signs who did die or did not die during ICU stay
- Clustering vital signs and risk of being initiated on mechanical ventilation

# Further Readings

#### Theory and mathematics

- Coursera Machine Learning (Andrew Ng)
- Deep learning book
- Stanford CS224n: Natural Language Processing with Deep Learning
- Stanford CS231n: Convolutional Neural Networks for Visual Recognition

#### Practical

- TensorFlow, PyTorch, Keras, Scikit-learn documents, guide, tutorials
- Google Machine Learning Crash Course
- Coursera Deep Learning Specialization
- Coursera Machine Learning with TensorFlow on Google Cloud Platform