Machine Learning & Gynecological Oncology

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4/18/18

Intro to Machine Learning

AKA Artificial Intelligence

AKA Predictive Analytics

VS.

Do the math…

19038 + 9054 * 98 = ?

 **vs.** 

Find the cats...















 **VS.** 

Find the cheapest fare…

From	To	Fare
Atlanta, GA (ATL)	Brussels, Belgium (BRU)	$1,459
Atlanta, GA (ATL)	Venice, Italy (VCE)	$1,519
Atlanta, GA (ATL)	Seoul-Incheon, South Korea (ICN)	$1,782
Boston, MA (BOS)	Dublin, Ireland (DUB)	$1,759
Boston, MA (BOS)	London-Heathrow, United Kingdom (LHR)	$1,849
Detroit, MI (DTW)	Beijing, China (PEK)	$1,536
Detroit, MI (DTW)	Seoul-Incheon, South Korea (ICN)	$1,672
Detroit, MI (DTW)	Shanghai, China (PVG)	$1,622
Houston-Intercontinental, TX (IAH)	Paris-Charles de Gaulle, France (CDG)	$1,679
Los Angeles, CA (LAX)	Amsterdam, Netherlands (AMS)	$1,159
Los Angeles, CA (LAX)	Shanghai, China (PVG)	$1,962
Minneapolis, MN (MSP)	Tokyo-Haneda, JP (HND)	$2,009
New York-Kennedy, NY (JFK)	Zurich, Switzerland (ZRH)	$1,609
Pittsburgh, PA (PIT)	Paris-Charles de Gaulle, France (CDG)	$1,049
Seattle, WA (SEA)	Hong Kong, Hong Kong (HKG)	$1,182
Seattle, WA (SEA)	Seoul-Incheon, South Korea (ICN)	$1,153
Seattle, WA (SEA)	Shanghai, China (PVG)	$1,906
Seattle, WA (SEA)	Tokyo-Narita, Japan (NRT)	$1,561

VS.

Cross a duck and an otter…

🙋🏾 **VS.** 🖥

Objective

Calculations

Pattern Recognition

High volume

Creativity

Calculations

+

High volume

Pattern Recognition

Training process

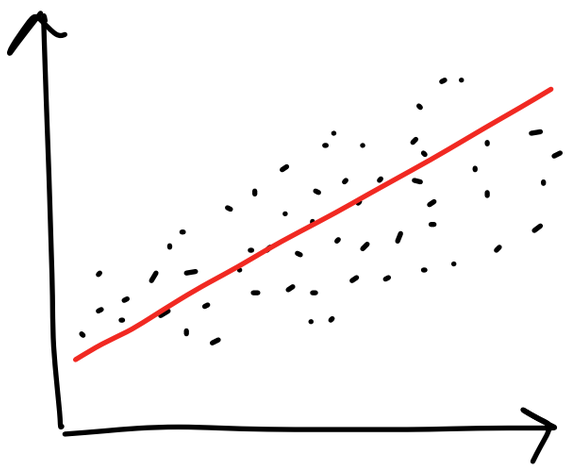
Data

Labels **Not Cat** **Cat** **Not Cat** **Not Cat** **Not Cat** **Cat**

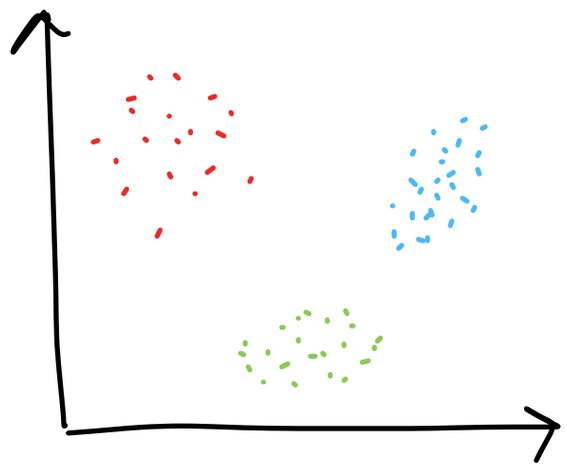
Cycles through data till it finds the least wrong mathematical relationship (model) between Data & Labels

There are procedures to ensure the model is not overly specific

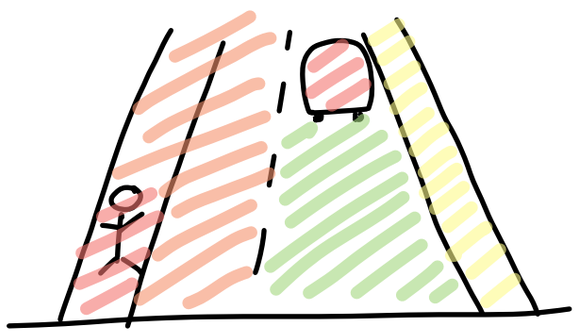
Not limited to finding cats…



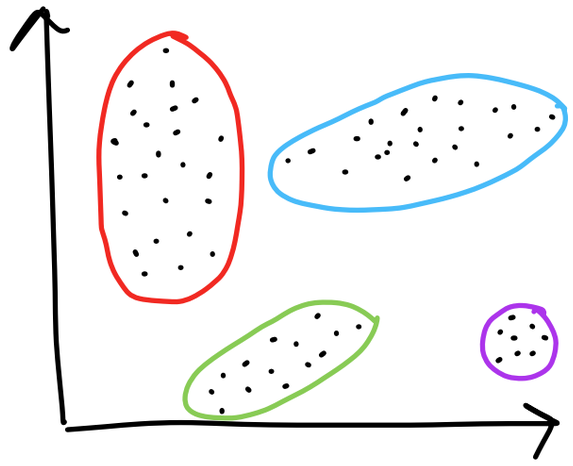
Regression



Classification



Reinforcement

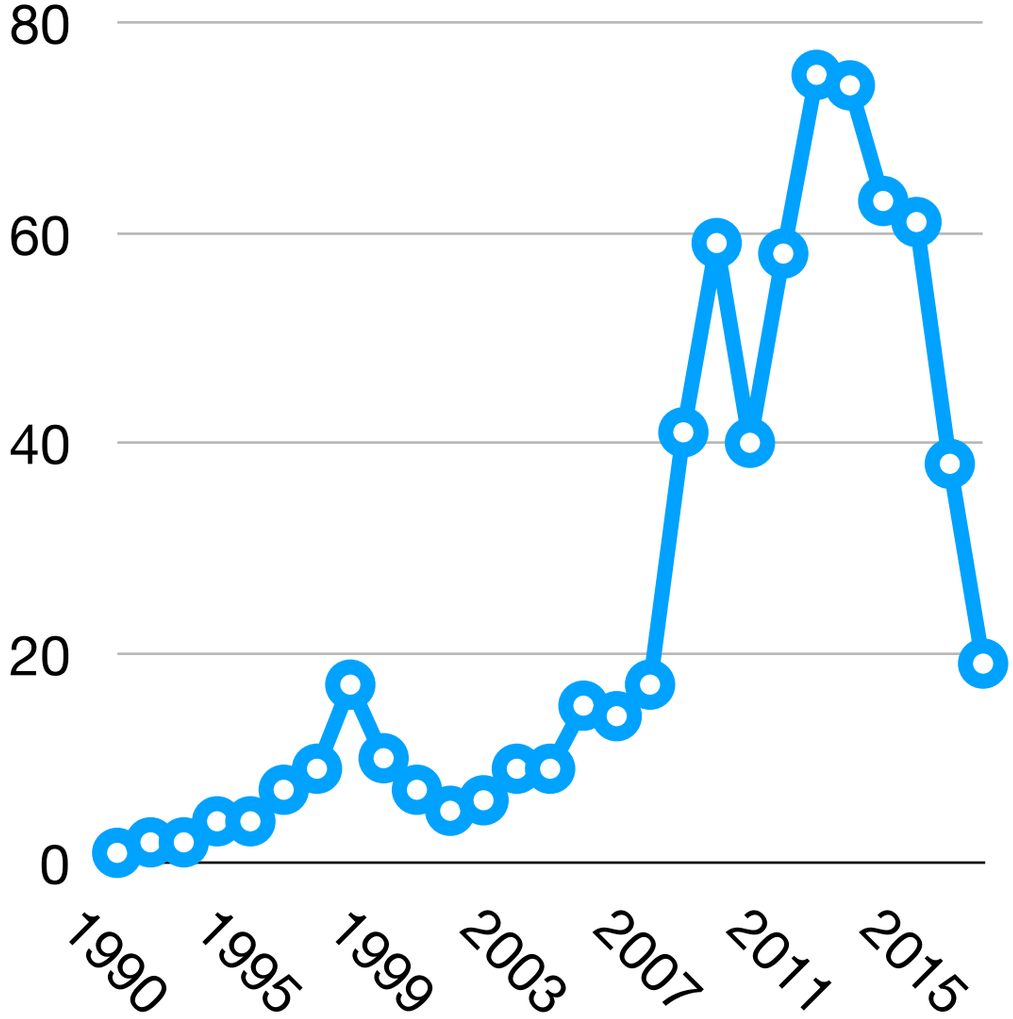


Unsupervised

How does this relate to Gyn Onc?

Where’s the literature at?

((Machine Learning OR Artificial Intelligence)
AND ("genital neoplasms, female”)
N=669



When we drop the AI → N=45

Prediction of 5-year overall survival in cervical cancer patients treated with radical hysterectomy using computational intelligence methods.

A pilot study in using deep learning to predict limited life expectancy in women with recurrent cervical cancer.

Integration of data mining classification techniques and ensemble learning to identify risk factors and diagnose ovarian cancer recurrence.

Autodelineation of cervical cancers using multiparametric magnetic resonance imaging and machine learning.

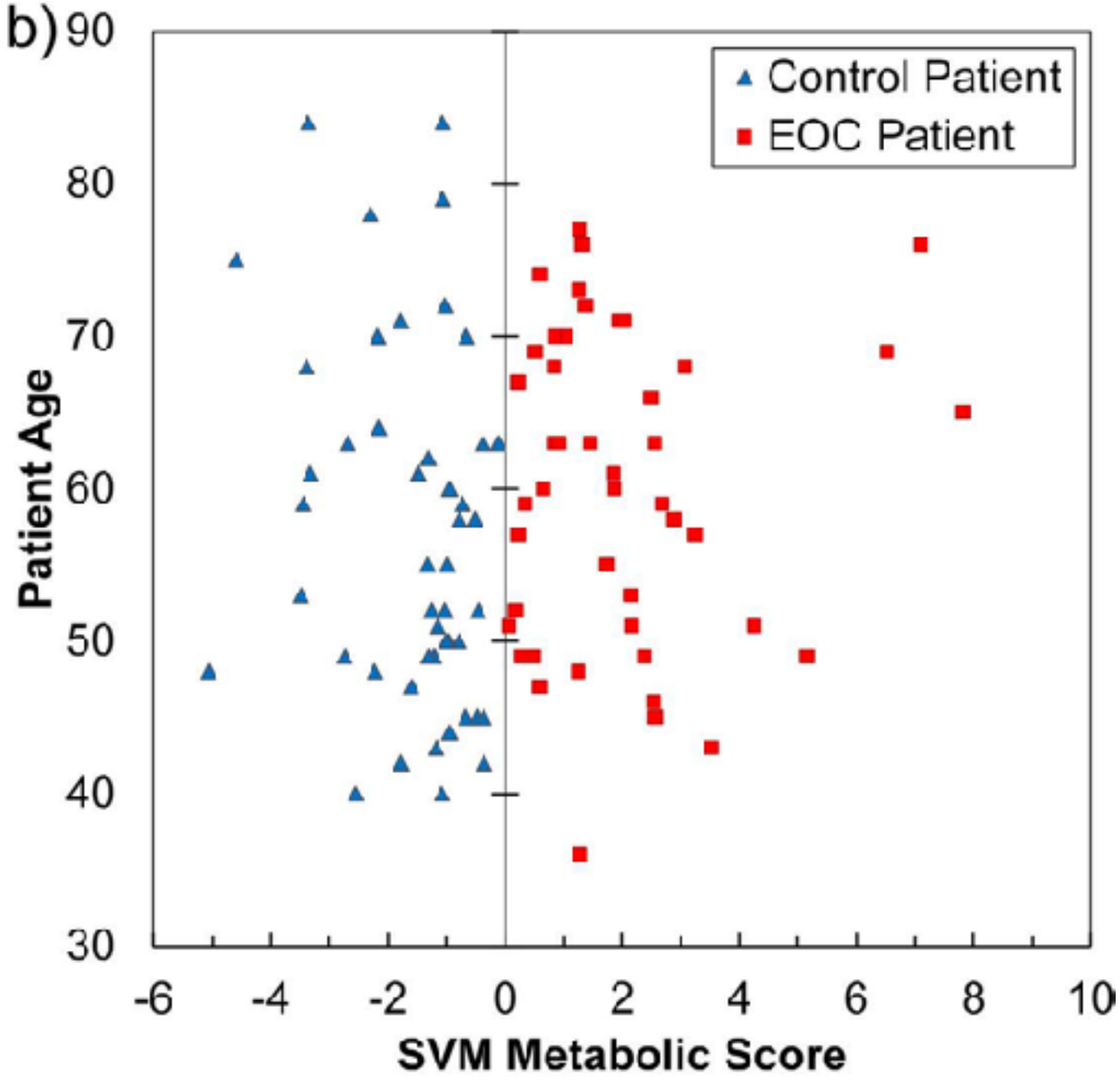
Gene set-based analysis of mucinous ovarian carcinoma.

Highly-accurate metabolic detection of early-stage ovarian cancer

Serum metabolome mass spectrometry on early-stage ovarian cancer (EOC) patients and controls.

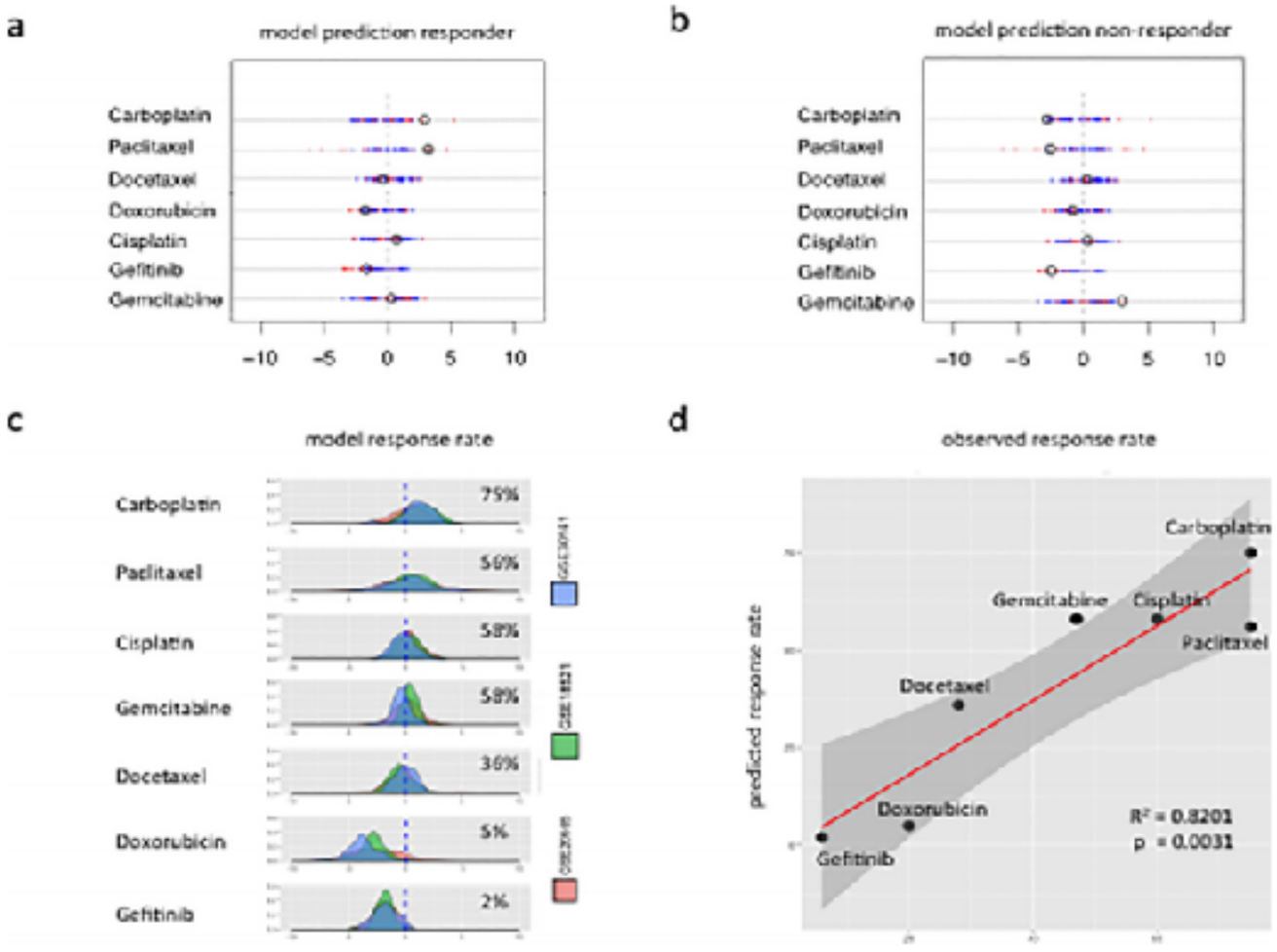
Thousands of metabolites
→ 16 diagnostic (FA metabolism)

Potential for eventual diagnostic or screening tests



Gaul, D. A. et al. Highly-accurate metabolomic detection of early-stage ovarian cancer. Sci. Rep. 5, 16351; doi: 10.1038/srep16351 (2015).
http://www.nature.com/articles/srep16351.pdf

Prediction of optimal cancer drug therapies



Learn personalized drug responses from gene expression profiles (NCI-60)

Accurately predicts responsiveness (NCI-DREAM)

Ovarian cancer: predictions consistent with current lit.

Huang C, Mezencev R, McDonald JF, Vannberg F (2017) Open source machine-learning algorithms for the prediction of optimal cancer drug therapies. PLoS ONE 12(10): e0186906. http://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0186906&type=printable

Puff piece: IBM Watson for cervical cancer

Natural language processing to provide oncologists with ranked, evidence-based treatment options for cancer.

WFO recommendations compared to practice at Gachon University.

80.8% were concordant (299/370)

Lim S, Lee KB. Use of a cognitive computing system for treatment of cervical cancer. J Gynecol Oncol. 2017 Sep;28(5):e67. https://doi.org/10.3802/jgo.2017.28.e67f

Final thoughts

Always ask “how generalizable is this model?”

The devil is in the data: garbage in → garbage out

How will these models be useful in clinical practice?

Potentially promising toolset - with a ton of hype. We need approach it critically.

Appendix

VS.

Do the math...

19038 + 9054 * 98 = ?

Find the cats...

Find the cheapest fare...

From	To	Fare
[illegible]	[illegible]	[illegible]
Atlanta, GA (ATL)	Venice, Italy (VCE)	$1,269
[illegible]	[illegible]	[illegible]
Boston, MA (BOS)	Dublin, Ireland (DUB)	$1,753
[illegible]	[illegible]	[illegible]
Detroit, MI (DTT)	Beijing, China (PEK)	$1,336
[illegible]	[illegible]	[illegible]
Detroit, MI (DTT)	Shanghai, China (PVG)	$1,320
Brookfield, [illegible]	Paris/Charles de Gaulle, France (CDG)	$1,379
Los Angeles, CA (LAX)	Amsterdam, Netherlands (AMS)	$1,163
San Francisco, CA (SFO)	Shanghai, China (PVG)	$1,300
[illegible]	[illegible]	$1,209
New York/Syracuse, NY (JFK)	Zurich, Switzerland (ZRH)	$1,303
[illegible]	[illegible]	$1,389
Seattle, WA (SEA)	Hong Kong, Hong Kong (HKG)	$1,332
Seattle, WA (SEA)	[illegible]	$1,379
Seattle, WA (SEA)	Shanghai, China (PVG)	$1,203
[illegible]	[illegible]	[illegible]

Cross a duck and an otter...

VS.

Do the math...

19038 + 9054 * 98 = ?

906330

Find the cats...

Find the cheapest fare...

From	To	Fare
Atlanta, GA (ATL)	Venice, Italy (VCE)	$1,269
Boston, MA (BOS)	Dublin, Ireland (DUB)	$1,253
Detroit, MI (DTT)	Beijing, China (PEK)	$1,838
Detroit, MI (DTT)	Shanghai, China (PVG)	$1,820
Los Angeles, CA (LAX)	Amsterdam, Netherlands (AMS)	$1,263
Los Angeles, CA (LAX)	Shanghai, China (PVG)	$1,368
New York (Kennedy), NY (JFK)	Zürich, Switzerland (ZRH)	$1,283
Seattle, WA (SEA)	Hong Kong, Hong Kong (HKG)	$1,332
Seattle, WA (SEA)	Shanghai, China (PVG)	$1,268

Cross a duck and an otter...