# A Critical Introduction to Machine Learning

#### Momin M. Malik

Data Science Postdoctoral Fellow, Berkman Klein Center for Internet & Society at Harvard Slides: https://www.mominmalik.com/tapia2019.pdf

#### **2019 ACM RICHARD TAPIA**

CELEBRATION OF DIVERSITY IN COMPUTING CONFERENCE THURSDAY, SEPTEMBER 19 | MARRIOTT 12





- Machine learning is correlations
- When to use machine learning
- Background needed to do machine learning
- Key concepts
- Example for demo: Titanic

Demo

Q & A



A Critical Introduction to Machine Learning

- **Basis: Meredith Broussard's book** 
  - Artificial Unintelligence: How Computers Misunderstand the World (MIT Press, 2018)
  - Chapter 7 is the single best introduction to machine learning!
  - Based on a datacamp tutorial, with commentary: I expand on this
  - (One subtle but important mistake: see https://www.mominmalik.com/ broussard)



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### "So, it's not real AI?"

Meredith Broussard

#### Artificial **Un**intelligence

HOW COMPUTERS MISUNDERSTAND THE WORLD



- "So, it's not real AI?" he asked.
- "Oh, it's real," I said. "And it's spectacular. But you know, don't you, that there's no simulated person inside the machine? Nothing like that exists. It's computationally impossible."
- His face fell. "I thought that's what AI meant," he said. "I heard about IBM Watson, and the computer that beat the champion at Go, and self-driving cars. I thought they invented real AI."



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#### **Preliminaries**

Install R + Rstudio Introductions Learning goals Machine learning? Critical? Outline

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- If you don't have it already, download and install R (search: "install R")
- Also install RStudio (search: "install RStudio")
- Installation should, at most, take about as long as the introduction



#### About me



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Berkman The Berkman Center for Internet & Society at Harvard University









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## What about you?

- Undergrad student?
- Grad student?
- Academia?
- Industry?
- Public sector?



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# Learning goals by background

- No background in programming or statistics:
  - See what doing machine learning looks like in practice
  - Identify appropriateness of machine learning
- Linear regression (Excel, SPSS, Stata, Java):
  Use cross-validation
- Logistic regression, and/or Python or R:
  - Build, evaluate, and critique a basic machine learning model



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#### ML = Finding correlations for prediction

- Textbook definitions are aspirational.
- In practice, machine learning is about finding correlations that we can use for prediction
- Spurious correlations are fine, so long as they are robust
- Machine learning is not well suited for understanding (although people assume it is)



## Critical = "See your glasses"

Preliminaries

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- Critical: To be able to see the glasses with which you see the world (Agre, 2000)
- A critical *theory*: identifies a *false consciousness,* and seeks to expose it to spur transformative action (Fay, 1987)
  - I think "Data positivism" (Jones, 2019) is the false consciousness of machine learning



#### Outline

- Preliminaries
- Machine learning is correlations
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- 1. Machine learning is correlations
- 2. When to use machine learning
- 3. Background needed
- 4. Key concepts
- 5. Live, interactive demo
- 6. Q & A



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# Reminder: prepare for later!

- If you don't have it already, download and install R (search: "install R")
- Also install RStudio (search: "install RStudio")
- Installation should, at most, take as long as the talk portion



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## Machine learning is correlations

Machine learning is used to build systems Takes *labels*, correlates with other data "Predictions" are correlations

Correlations can go wrong



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## **ML examples: Building systems**

- Recommend/narrow people's choices to "relevant" ones (friend connections, search results, products)
- Detection (facial, fraud)
- Anticipation (customer demand, equipment failure)

It "works"....



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#### How? Correlates *labels* and other data

"Source subject": Marquese Scott

# **Everybody Dance Now**

Motion Retargeting Video Subjects

Caroline Chan, Shiry Ginosar, Tinghui Zhou, Alexei A. Efros

UC Berkeley

Caroline Chan, "Everybody Dance Now: Motion Retargeting Video Subjects." https://youtu.be/PCBTZh41Ris



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#### ML is all statistical



Baron Schwartz 📀

When you're fundraising, it's Al When you're hiring, it's ML When you're implementing, it's linear regression When you're debugging, it's printf()

12:52 AM - 15 Nov 2017

5,545 Retweets 12,654 Likes ♀ 90 1, 5.5K ♡ 13K ▷

statistics Artificial intelligence, **Machine Learning** 

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Follow



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## (Critiques of statistics apply!)



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# (Critiques of statistics apply!)

CYBORGOLOGY

Fact Check: Your Demand for Statistical Proof is Racist

Candice Lanius on January 12, 2015

Society Pages

Today we're reposting our most popular guest post of the year. This essay has garnered a lot of attention and for good reason: it speaks directly to a kind of liberal racism that is endemic to the institutions and professions that see themselves as the good guys in this problem. -db

• "A white woman can say that a neighborhood is 'sketchy' and most people will smile and nod. She felt unsafe, and we automatically trust her opinion. A black man can tell the world that every day he lives in fear of the police, and suddenly everyone demands statistical evidence to prove that his life experience is real."



## "Predictions" are just correlations

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- Spurious (non-causal) correlations/trends can be used for prediction!
- But this can break down...
- Google Flu Trends: half flu detector, half winter detector (Lazer et al., 2014)
- "X predicts Y" is really "X is correlated with Y"



"According to our current predictive analytics solution, the mouse should be exiting from this hole in 3... 2... 1..." #betterdata



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## **Correlations can go wrong**

- Do we know if a specific output is right or wrong?
- Treating people based on correlations denies agency and individuality
- Correlations are *proxies*, which can be <u>gamed</u>
- Correlations <u>optimize to the average</u>, leaving out those who are not "average" (as measured!) (Rose, 2014; Keyes, 2018)
- Mistakes can be unequally distributed across groups



## **Ex: Chocolate and Nobel prizes**



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Consume

chocolate

- (Nobel prizes supposedly awarded on "merit," does that fit in? Where/How?)
- (What about prejudice?)



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- Probably won't win more Nobel prizes by feeding population more chocolate
- Very different sets of correlations can "predict" equally well (Mullainathan & Spiess, 2017)

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Can't intervene based on correlations



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## The surprising part

- The best-fitting (most accurate\*) model does not necessarily reflect how the world works
- This has been shocking in statistics for decades (Stein's paradox, Leo Breiman's "two cultures"), but little known outside
- We can "predict" without "explaining"!
- \* Or other relevant metric of success A Critical Introduction to Machine Learning



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#### When to use machine learning

Key components of a good use case Example of a "responsible" use case



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## Key components of a good use case

- 1. We have "ground truth" (e.g., human labels, previous failures/fraud), and
- 2. Ground truth is hard to collect, and
- 3. We have some readily available proxy measure, and
- 4. We don't care how or what in the proxy recovers the ground truth, only that it does



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## "Responsible" use case

- Baseline: Clinical diagnosis of breast cancer
- Researchers built a machine learning model that correlated gene expressions with developing breast cancer
- Which is better? Experimentally test! (Cardoso et al., 2016)

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## **Real-world testing**



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## **Real-world testing**



Q & A



## **Real-world testing**



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Don't treat with chemo

(Still: whose data went into the model? Who were the subjects in the experiment?)

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## **Real-world testing: Details**

Preliminaries

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Cardoso et al., 2016, NEJM

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100-90-100 -Chemotherapy 80-95-70-No chemotherapy 60-90-50-85-40-30-80-20-10-0-Ó Low model risk, high clinical risk: chemo makes no difference

Clinicial says high risk, Model says low risk



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#### Background needed to do ML

How much programming/CS? How much math? Which language/environment?

Resources



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# How much programming/CS?

- For personal use: at least be able to write loops and functions, and know up to sorting algorithms. Nothing more!
- For production: some software development principles.
- Alternatives: Weka and Rapid Miner have graphical interfaces, no programming or required



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# How much math?

THIS IS YOUR MACHINE LEARNING SYSTEM? YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.



- To be a practitioner, same as what you need to do social statistics: algebra and a bit of calculus
- To understand and advance underlying *mechanics*: linear algebra, multivariate calculus
- To understand underling *principles*: learn probability and mathematical statistics

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- Background needed to do machine learning

# Which language/environment?

- Weka, Rapid Miner
  - Basic use
- Python (numpy, scipy, scikitlearn, pandas)
  - Scale, integrating into production, best visualizations (sometimes), all deep learning
- R

- More flexibility in how to use techniques, a selfcontained environment, and better integration with (social) statistics



#### Resources



Background needed to do machine learning



Theory

Unfortunately, I haven't spent time looking through online courses to have one I recommend.

programming

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MI in action

needing to know any

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#### Key concepts



## Model "fit"

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- All machine learning and statistics models take in data, process them via some assumptions, and then give out something: relationships, and/or likely future values.
- The processing is called "fitting", and the output is called a "fit." Machine learning uses "learning" or "training," but it's the same.



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# **Overfitting: fit to noise**



 If we are no longer guided by theory, and use automatic methods, we risk overfitting: fitting to the the noise, not the signal ("memorize the data")



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# Data splitting: Catch overfitting



- Idea: if we split data into two parts, the signal should be the same but the noise would be different
- Cross validation: Fitting the model on one part of the data, and "testing" on the other

https://medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6803a989c76



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### (Discrete version of overfitting)





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# "Accuracy paradox"

- Say, 5 out of 1000 observations are positive ("extreme class imbalance")
- A classifier that always predicts negative is 99.5% accurate, but useless
- Other metrics are more meaningful
- Use the confusion matrix



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## **Confusion matrix**

True label

	N	Positive	Negative
Predicted	Predicted positive	True positive	False positive
label	Predicted negative	False negative	True negative



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### **Confusion matrix**

	N	Positive	Negative
Predicted	Predicted positive	True positive	False positive
label	Predicted negative	False negative	True negative



↑ Overall correct

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True label

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### **Confusion matrix**

	N	Positive	Negative
Predicted	Predicted positive	True positive	False positive
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↑ Overall correct

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True label

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### **Confusion matrix**

	N	Positive	Negative
Predicted label	Predicted positive	True positive	False positive
	Predicted negative	False negative	True negative
		Recall/ sensitivity = TP/(TP+FN)	← How many you detect

True label



↑ Overall correct



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#### **Confusion matrix**

True label

	N	Positive	Negative		Accuracy = (TP+TN)/ <i>N</i>
Predicted	Predicted positive	True positive	False positive	Precision = TP/(TP+FP)	↑ Overall correct
label	Predicted negative	False negative	True negative	1 How much is relevant	
		Recall/ sensitivity = TP/(TP+FN)	← How many you detect	-	



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### **Confusion matrix**

True label

	N	Positive	Negative		Accuracy = (TP+TN)/ <i>N</i>
Predicted	Predicted positive	True positive	False positive	Precision = TP/(TP+FP)	↑ Overall correct
label	Predicted negative	False negative	True negative	1 How much is relevant	
-		Recall/ sensitivity = TP/(TP+FN)	← How many you detect		
		How many→ you correctly reject	Specificity = TN/(TF+TN)		



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### **Confusion matrix**

True	label

	N = 165	Positive: 105	Negative: 60		Accuracy = 0.91
Predicted	Predicted positive: 110	TP = 100	FP = 10	Precision = 0.91	↑ Overall correct
label	Predicted negative: 55	FN = 5	TN = 50	1 How much is relevant	
		Recall/ sensitivity = 0.95	← How many you detect		
		How many→ you correctly reject	Specificity = 0.83		



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## Feature engineering

- In social science, we have the variables (e.g., the survey responses)
- In machine learning, you might have lots of text data, or lots of sensor data, for a single outcome
- "Feature engineering": heuristics to extract variables to summarize the data. Huge part of ML, no systematic solution for every data type
- Deep learning exciting because it does "automatically", but only for very specific data types



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#### **Example for demo:** *Titanic*



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### Datacamp "Titanic" example



John Jacob Astor was among the passengers who went down with the ship, according to a wireless dispatch received by Bradstreets last night from the liner Olympic. Mrs. Astor was saved and is being brought to shore by the Carpathia.

The Wireless Operator at Cape Race, Newfoundland, Flashes: "Eighteen Hundred Lives Have Been Lost in the Wreck of the Titanic."





## **Broussard's Commentary**

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#### Artificial **Un**intelligence

HOW COMPUTERS MISUNDERSTAND THE WORLD



- Captain: "Put the women and children in and lower away."
- First Officer: women and children first
- Second Officer: women and children only
- "the lifeboat number isn't in the data. This is a profound and insurmountable problem. Unless a factor is loaded into the model and represented in a manner a computer can calculate, it won't count... The computer can't reach out and find out the extra information that might matter. A human can."

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## Fit a "decision tree" for survival





Exal

#### Social science baseline for comparison

Behavior under Extreme Conditions: The *Titanic* Disaster

Bruno S. Frey, David A. Savage, and Benno Torgler

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 5 econometrics papers from Frey, Savage, and Torgler (2009-2011) give a comparative "social statistics" approach

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# **Compare: narrative and "prediction"**

Preliminaries

Machine learning is correlations

When to use machine learning

Background needed to do machine learning

Key concepts

Example for demo: Titanic

Demo

Q & A



a three act opera based upon the life of Josoph Philippo Le Morcior La Rocho

> the only black passenger on the ill-fated Titanic

Music and Libretto by Sharan J. Willis

Saturday, April 14 &15, 2012 3:00 and 7:00 p.m. shows

Atlanta Metropolitan College 1630 Metropolitan Parkway Atlanta, Georgia 30310

- Joseph Philippe Lemercier Laroche
- Haitian engineer
- Married French woman, Juliette Lafargue
- Denied jobs in France
- Was returning to Haiti where his uncle was president (!) with Juliette, pregnant, and their two children, Simonne and Louise
  2003 opera by Sharon J. Willis

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Machine learning is correlations

When to use machine learning

Background needed to do machine learning

Key concepts

Example for demo: Titanic

Demo

Q & A

#### **Demo time!**

Data:

https://www.mominmalik.com/titanic.csv

https://github.com/momin-malik/guides/raw/master/titanic.csv



#### End note: Decide how distracted to be

Preliminaries

Machine learning is correlations

When to use machine learning

Background needed to do machine learning

Key concepts

Example for demo: Titan

Demo

Q & A



"The function, the very serious function of racism is distraction. It keeps you from doing your work. It keeps you explaining, over and over again, your reason for being. Somebody says you have no language and you spend twenty years proving that you do. Somebody says your head isn't shaped properly so you have scientists working on the fact that it is. Somebody says you have no art, so you dredge that up. Somebody says you have no kingdoms, so you dredge that up. None of this is necessary. There will always be one more thing."

-Toni Morrison, 1931-2019

(Thanks to my partner, Maya Randolph)

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Slides: https://MominMalik.com/tapia2019.pdf



- Machine learning is correlations
- When to use machine learning
- Background needed to do machine learning

Key concepts

Example for demo: Titanic

Demo

Q & A

# Thank you! Questions?

- Please send feedback! <u>https://forms.gle/TrY7z6qivuVf2C8p7</u>
- Contact me: <u>momin\_malik@cyber.harvard.edu</u>
- Summary:
  - Machine learning is correlations
  - Can be powerful, but also can fail and (both in successes and failures) be oppressive
  - It leaves out a lot



- Machine learning is correlations
- When to use machine learning
- Background needed to do machine learning

Key concepts

Example for demo: Titanio

Demo

Q & A

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# Extra: problems with "explainability"

Or "interpretability"



# Explanations of models seem to be about the world

if male and adult then *survival probability* 21% (19%–23%) else if 3rd class then *survival probability* 44% (38%–51%) else if 1st class then *survival probability* 96% (92%–99%) else *survival probability* 88% (82%–94%)

- Decision list: interpretable and explainable
- Lethan, Rudin et al.: "For example, we predict that a passenger is less likely to survive than not because he or she was in the 3rd class."
- "Because" the model, or "because" the world?

# But ML is correlations, not causes

- Finale Doshi-Velez & Been Kim: "one can provide a feasible explanation that fails to correspond to a causal structure, exposing a potential concern."
- Rich Caruana et al.: "Because the models in this paper are intelligible, it is tempting to interpret them causally. Although the models accurately explain the predictions they make, they are still based on correlation."
- Zachary Lipton: "Another problem is that such an interpretation might explain the behavior of the model but not give deep insight into the causal associations in the underlying data... The real goal may be to discover potentially causal associations that can guide interventions."

# Wish list for interpretability

- Face validity as a way to check the model
- Anticipate where the model might break down (e.g., when it fails face validity)
- Use domain knowledge to 'fine-tune' the model

# Female, 3rd class less likely to survive because of higher fare?



## Lacks face validity, but holds on test data



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# Converse: has face validity, but fails to generalize?





# Yes. Interpretability doesn't help anticipate breakdowns



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# Interpretations to 'fine-tune' model?



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# Model is already optimally tuned



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#### Extra: Discrete "correlations"

# ML model = "Ground truth" + proxy



- Correlate known values/ labels with available proxy for unknown values/labels
- Find decision boundary/ criterion/threshold. Use this to treat new observations
- Shift that boundary to prioritize certain metrics
- Most ML is basically this!


## **Regression: Continuous relationship**



Chocolate Consumption (kg/yr/capita)

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## **Classification: Discrete relationship**



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## Fit the decision boundary



## The prediction: the majority class



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