# Computational Communication Science 2 Week 8 - Lecture »A Deep Dive into Supervised Machine Learning«

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May, 2022

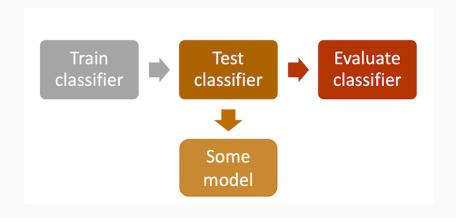
Some classical ML models

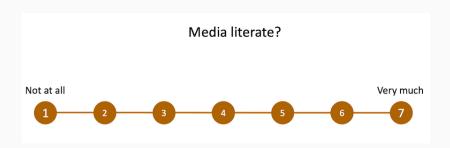
Validating models

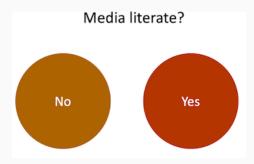
SML: Strenghts and Challenges

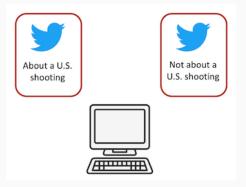
Short recap of last week.

# Some classical ML models



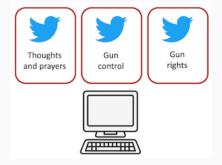






Zhang, Y., Shah, D., Foley, J., Abhishek, A., Lukito, J., Suk, J., Kim, S. J., Sun, Z., Pevehouse, J., & Garlough, C. (2019). Whose lives matter? mass shootings and social media discourses of sympathy and policy, 2012–2014.

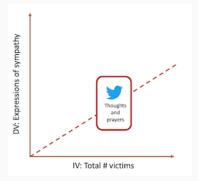
Journal of Computer-Mediated Communication, 24(4), 182–202. https://doi.org/10.1093/jcmc/zmz009



 $Zhang,\,Y.,\,Shah,\,D.,\,Foley,\,J.,\,Abhishek,\,A.,\,Lukito,\,J.,\,Suk,\,J.,\,Kim,\,S.\,\,J.,\,Sun,\,Z.,\,Pevehouse,\,J.,\,\&\,\,Garlough,\,C.\,\,Authors,\,A.,\,Lukito,\,J.,\,Suk,\,J.,\,Kim,\,S.\,\,J.,\,Sun,\,Z.,\,Pevehouse,\,J.,\,\&\,\,Garlough,\,C.\,\,Authors,\,A.,\,Lukito,\,J.,\,Suk,\,J.,\,Kim,\,S.\,\,J.,\,Sun,\,Z.,\,Pevehouse,\,J.,\,\&\,\,Garlough,\,C.\,\,Authors,\,A.,\,Lukito,\,J.,\,Suk$ 

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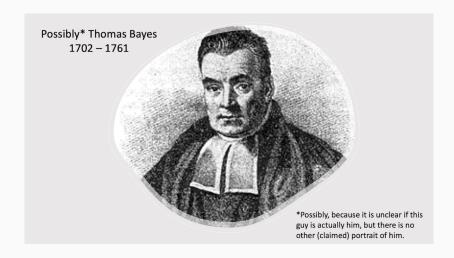
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#### Naïve Bayes



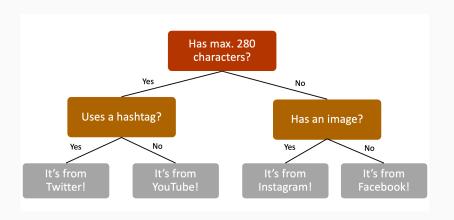
#### Naïve Bayes

$$P(A \mid B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Mathematicians' language for: the probability of A is B is the case/present/true.

$$P(\text{label} \mid \text{features}) = \frac{P(\text{features} \mid \text{label}) \cdot P(\text{label})}{P(\text{features})}$$

#### **Decision Trees and Random Forests**



#### **Decision Trees and Random Forests**

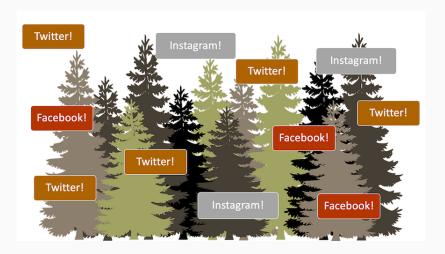
#### Advantages of decision trees:

- Transparency
- Suitable for non-linear relationships

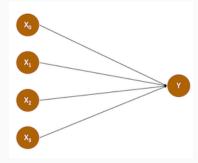
#### Disadvatanges of decision trees:

- Loss of nuance due to yes/no-design
- Cannot correct early mistakes
- Prone to overfitting

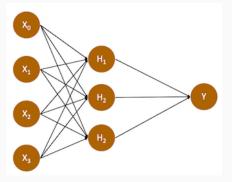
#### **Decision Trees and Random Forests**



#### **Neural Networks**



#### **Neural Networks**



Ha, Y., Park, K., Kim, S. J., Joo, J., & Cha, M. (2021). Automatically detecting image–text mismatch on instagram with deep learning.  $Journal\ of\ Advertising,\ 50(1),\ 52-62.$ 

Many different models available for machine learning.

How do you know what is the best for your case? Try it out and validate!

# **Zooming out**

#### We talked about:

- The principles behind SML
- The steps of SML
- Some commonly used ML models

#### Next, we will talk about:

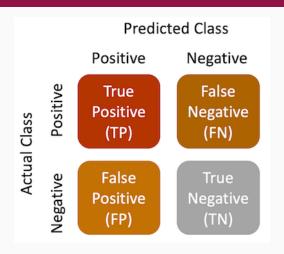
Validating models

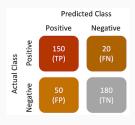
Precision quantifies the number of positive class predictions that actually belong to the positive cases.

OR: How much of what we found is actually correct?

Recall quantifies the number of positive class prediction made out of all positive examples in the dataset.

OR: How many of the cases that we wanted to find did we actually find?





Precision is calculated as:  $\frac{TP}{TP+FP}$  In our case  $\frac{150}{150+50}$  which is 0.75 Recall is calculated as  $\frac{TP}{TP+FN}$  In our case  $\frac{150}{150+20}$  which is 0.88

Table 2

		100	200	500	1000	2000	3000	4000
Linear support vector machine classifier	AC	0.63	0.65	0.70	0.73	0.80	0.84	0.91
	PC	0.45	0.48	0.59	0.62	0.76	0.80	0.90
	RC	0.38	0.43	0.51	0.59	0.71	0.79	0.86
	AUC	0.41	0.45	0.59	0.61	0.69	0.76	0.85
	KA	0.09	0.10	0.39	0.41	0.54	0.65	0.79
Naïve Bayes classifier	AC	0.63	0.65	0.71	0.75	0.82	0.86	0.91
	PC	0.42	0.46	0.62	0.68	0.81	0.86	0.92
	RC	0.27	0.33	0.47	0.49	0.61	0.69	0.79
	AUC	0.33	0.38	0.60	0.62	0.69	0.77	0.84
	KA	0.08	0.13	0.39	0.40	0.56	0.67	0.78
Logistic regression classifier	AC	0.66	0.67	0.71	0.74	0.79	0.85	0.89
	PC	0.48	0.51	0.63	0.70	0.78	0.89	0.93
	RC	0.04	0.22	0.35	0.39	0.53	0.64	0.73
	AUC	0.08	0.31	0.51	0.55	0.62	0.74	0.82
	KA	0.01	0.09	0.21	0.32	0.48	0.64	0.74

Van Zoonen, W., & Van der Meer, T. G. (2016). Social media research: The application of supervised machine

learning in organizational communication research.. Computers in Human Behavior, 63, 132-141.

https://doi.org/10.1016/j.chb.2016.05.028

Slide about accuracy. Discuss class imbalance (https://machinelearningmastery.com/what-is-imbalanced-classification/)

Slide about F1-score.

Slide about Area Under the Curve.

Slide about Cross-validation and grid search.

## **Zooming out**

#### We talked about:

- The principles behind SML
- The steps of SML
- Some commonly used ML models
- Validating models

#### Next, we will talk about:

Strengths and challenges associated to SML

**SML: Strenghts and Challenges** 

#### **Strengths and Challenges**

#### Strengths:

- Easier to code large datasets
- Enhances replicable research
- Easier to study "natural" human behavior

#### Disadvantages:

- Resource constraints
- Ethical considerations
- Criticism required (see next slide)

#### Strengths and Challenges



Het systeem van de Belastingdienst koos ervoor om de

kinderopvangtoeslag vooral bij mensen met een laag inkomen extra te controleren. Dat heeft de fiscus toegegeven in antwoord op vragen van

Trouw en RTL Nieuws.

Fraudejacht bij Toeslagen

#### Trouw

Toeslagen

# Belastingdienst ging vooral achter lage inkomens aan

Om toeslagen te controleren op fouten en fraude gebruikte de Belastingdienst een zelflerend algoritme. Dat selecteerde vooral lage inkomens voor controle.

Jan Kleinnijenhuis 22 november 2021

e Belastingdienst heeft jarenlang specifiek burgers met een laag inkomen geselecteerd voor extra controle op

# Belastingdienst controleerde extra bij lage inkomens in jacht op fraude

22 november 2021 22:59

# Zooming out I

#### We talked about:

- The principles behind SML
- The steps of SML
- Some commonly used ML models
- Validating models
- Strengths and challenges associated to SML

#### **Zooming out II**

#### This week's tutorial:

- Hands-on approach to take a further look into validating models
- Tutorial goals:
  - To get you some experience with the SML process and selecting a model
  - To provide a stepping stone so that you can (independently) advance your machine learning skills