

Getting Started

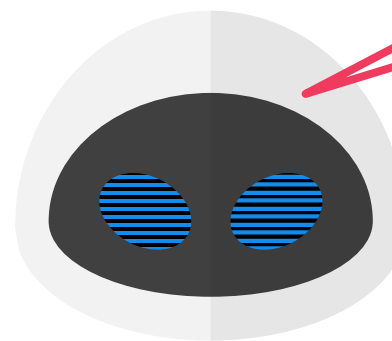
CS771: Introduction to Machine Learning

Purushottam Kar

An overview of ML

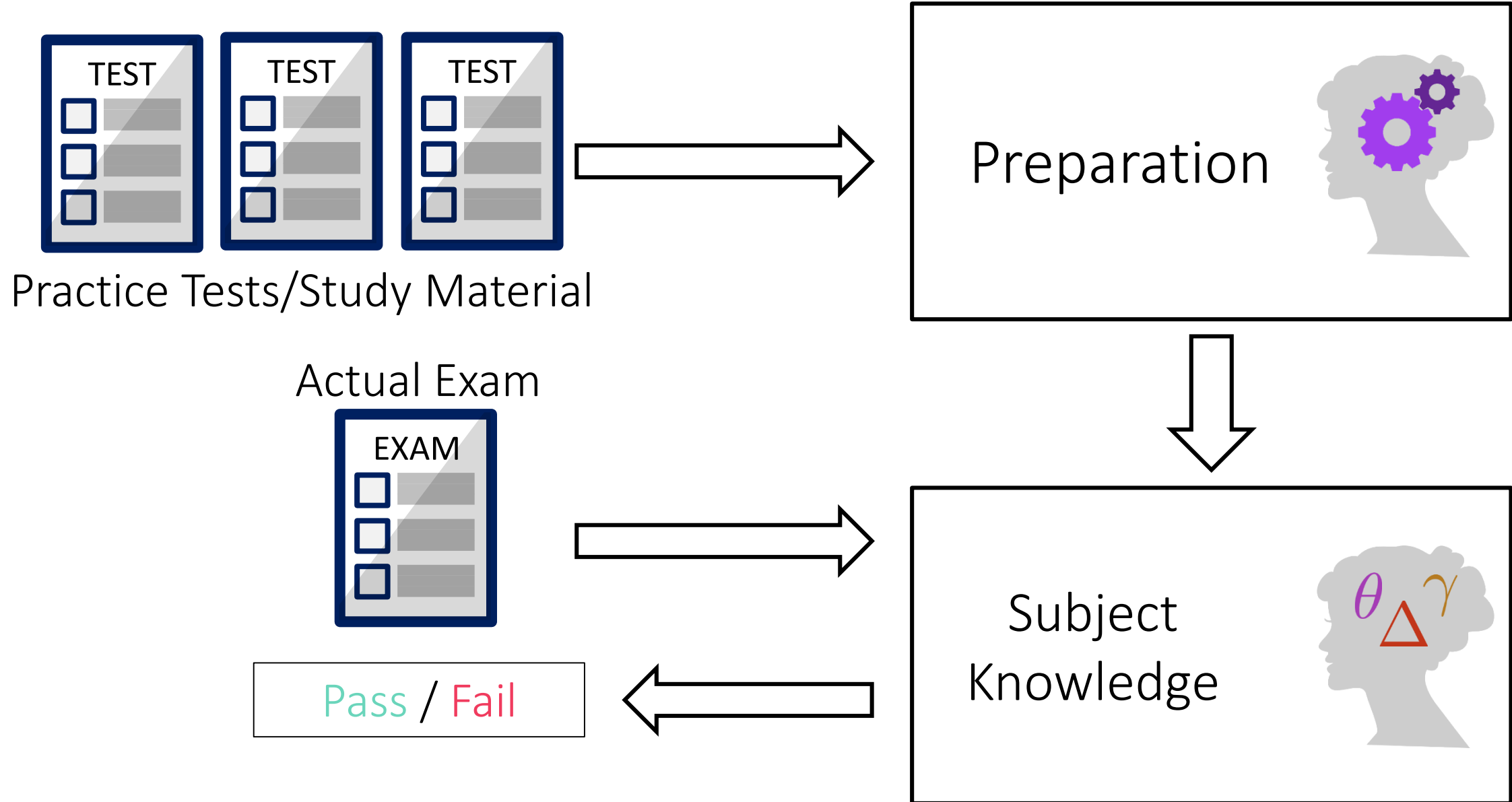
- Study similarity of ML with a student preparing for an exam
- Look at a toy ML problem
- Learn what is training data, test data?
- Learn what is a model?

Warning: lots of
oversimplifications
ahead!



A typical study cycle (e.g. in a course)

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Spam Filtering

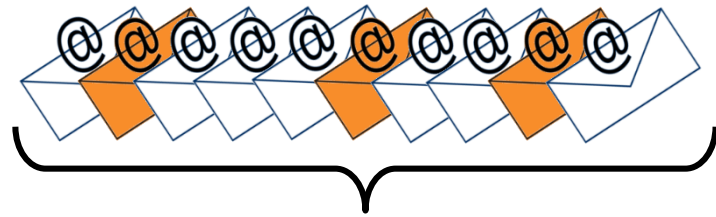


- Suppose Mary has already tagged several old emails as spam/non-spam, can we tag her new emails too?
- **Trick:** use the old tagged emails to try and understand what sort of emails does Mary think of as spam and which as non-spam!
- E.g. may find that emails about shopping always tagged as spam
- E.g. may find that emails from Jill are never tagged as spam
- These insights/patterns are what are stored in the spam filter
- Our spam filter helps us make predictions on new emails



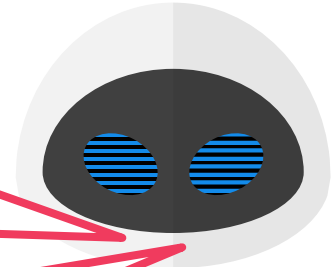
A typical ML workflow

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Old Emails

Ah! That is the fun (and artistic) bit about ML. We will learn tons of ways on how ML algos store patterns



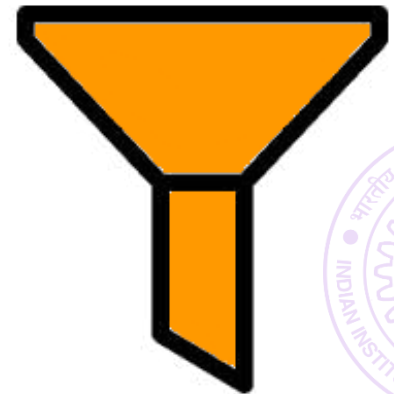
The spam filter stores information about your personal preferences about what looks spam to you

New Emails

How is this information stored?

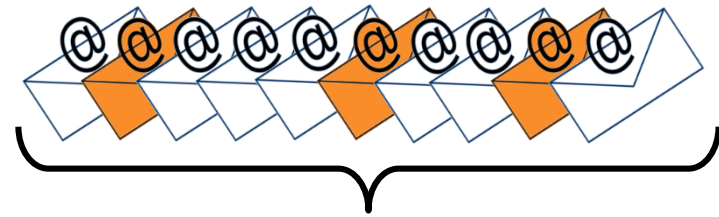
Spam/Non-spam

Spam Filter

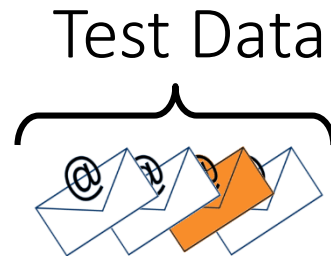
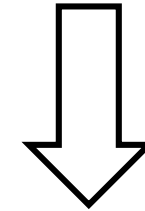
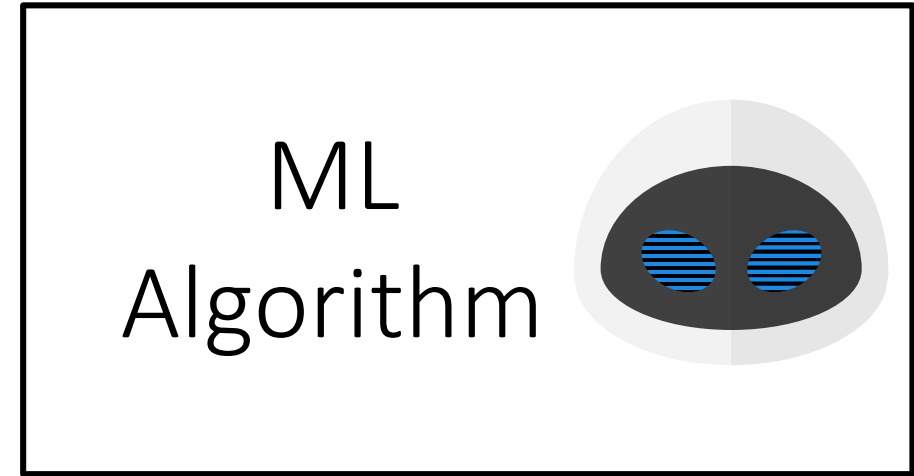
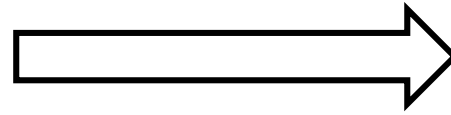


A typical ML workflow

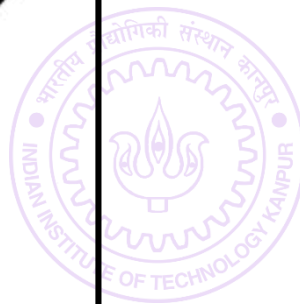
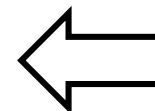
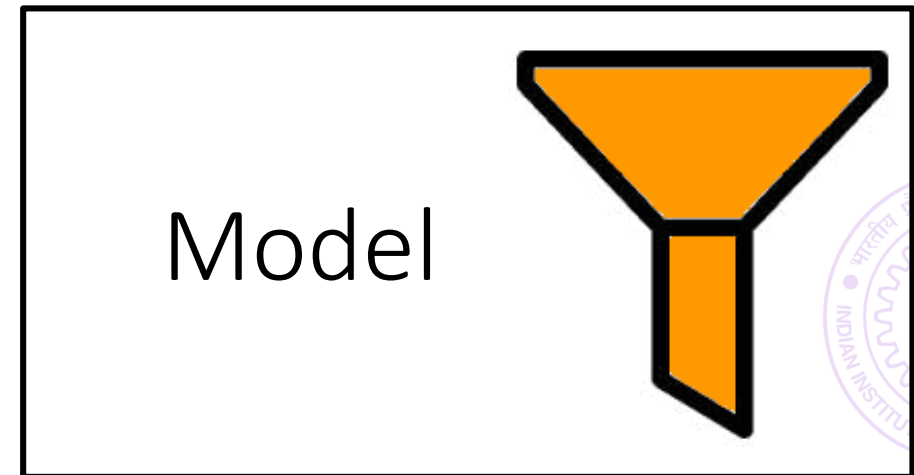
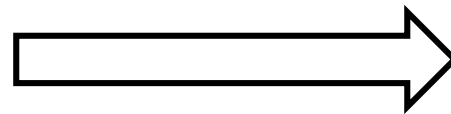
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Training Data

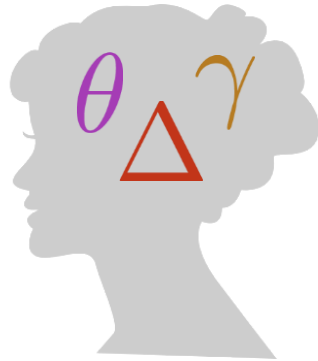


Test Data

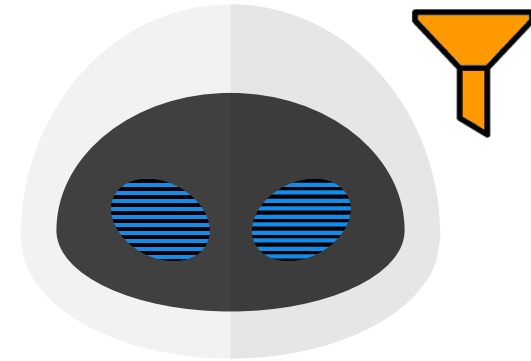


ML as an “examination”

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Our brain stores subject matter
Use subject matter to solve exam
Critical to do well on exam-day
Mock test results indicative
No out-of syllabus questions
Should not leak exam paper
before exam

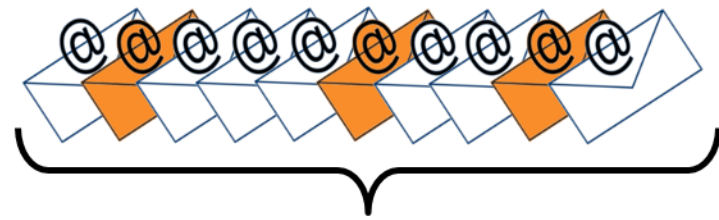


The model stores data patterns
Use model to predict on test data
Critical to do well on test data
Training accuracies indicative
Training/test data are similar
Should not look at test data while
training

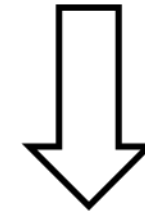
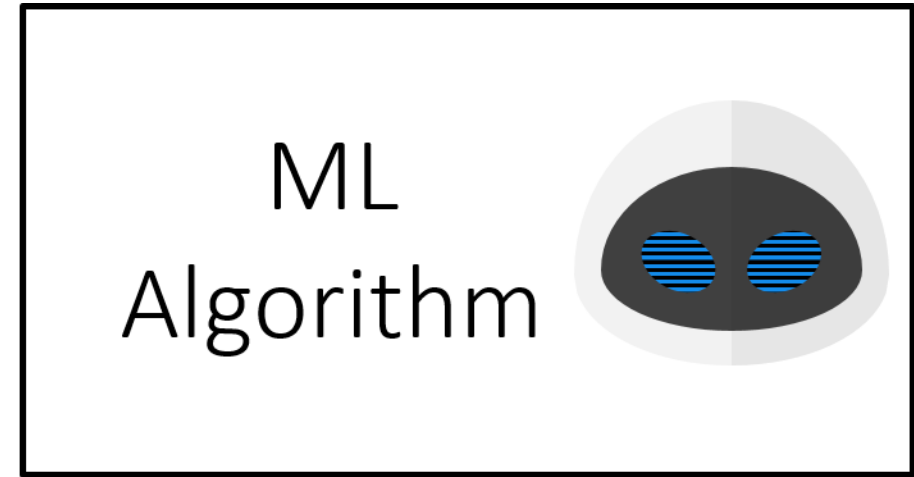
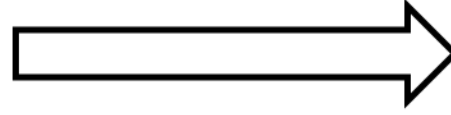


A typical ML workflow

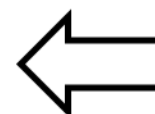
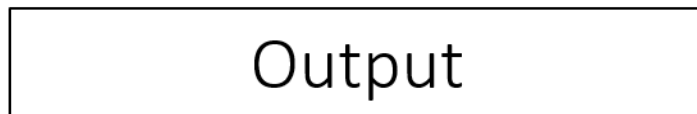
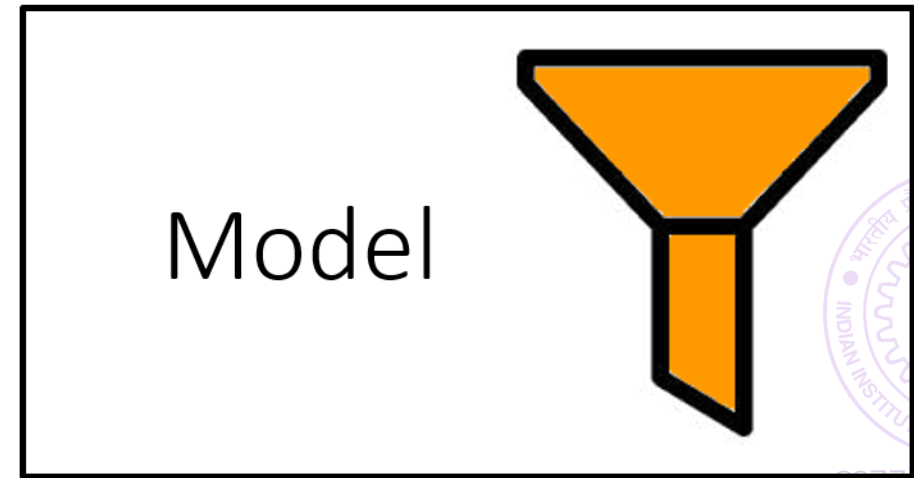
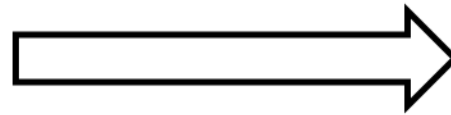
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Training Data

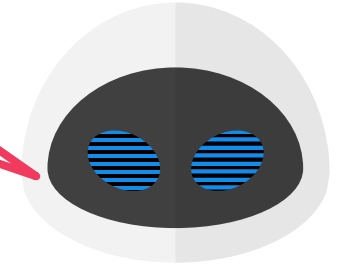


Test Data



ML can do lots of cool things with test data 9

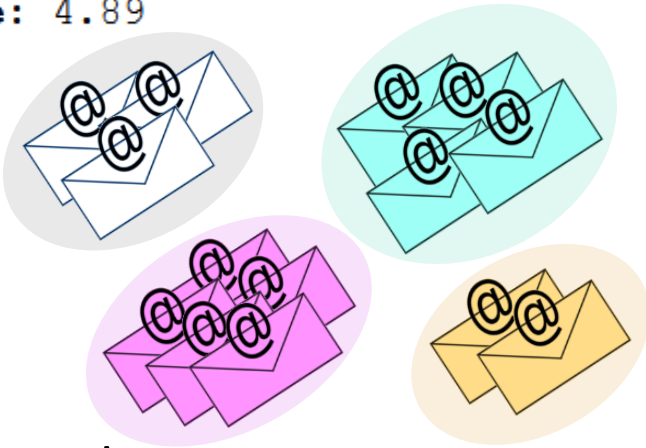
In this course, we will learn how to do most of these operations with test data



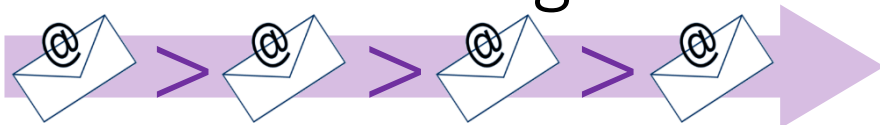
Regression

Subject: [****SPAM****] Free movie tickets every month
X-Barracuda-Spam-Score: 4.89

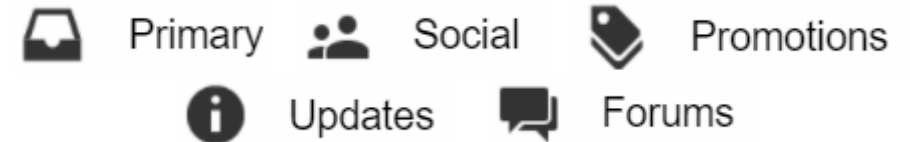
Clustering



Ranking



Multi-classification



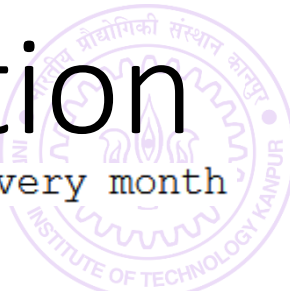
Tagging



URGENT,
OFFICIAL,
TAX

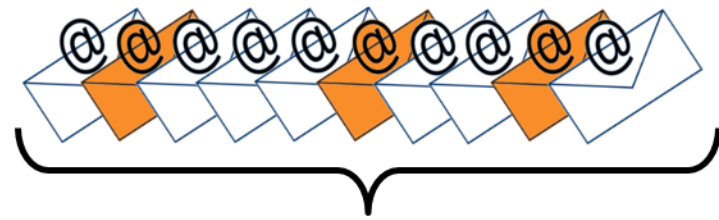
Binary Classification

Subject: [****SPAM****] Free movie tickets every month
X-Barracuda-Spam-Status: Yes

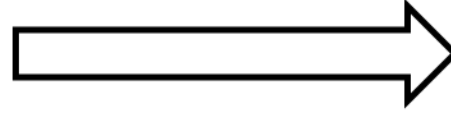


A typical ML workflow

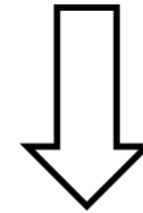
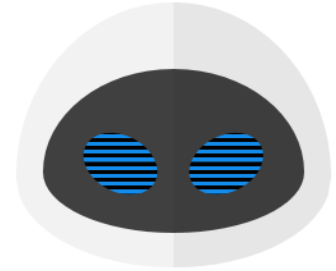
10



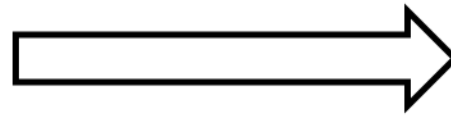
Training Data



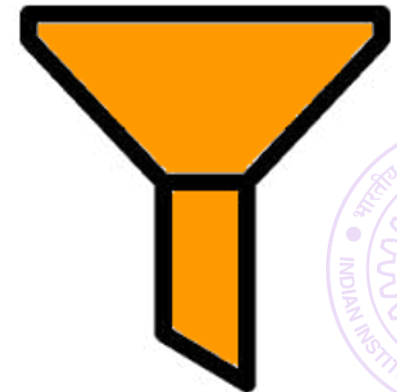
ML
Algorithm



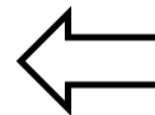
Test Data



Model

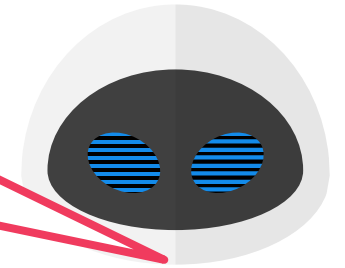


Output

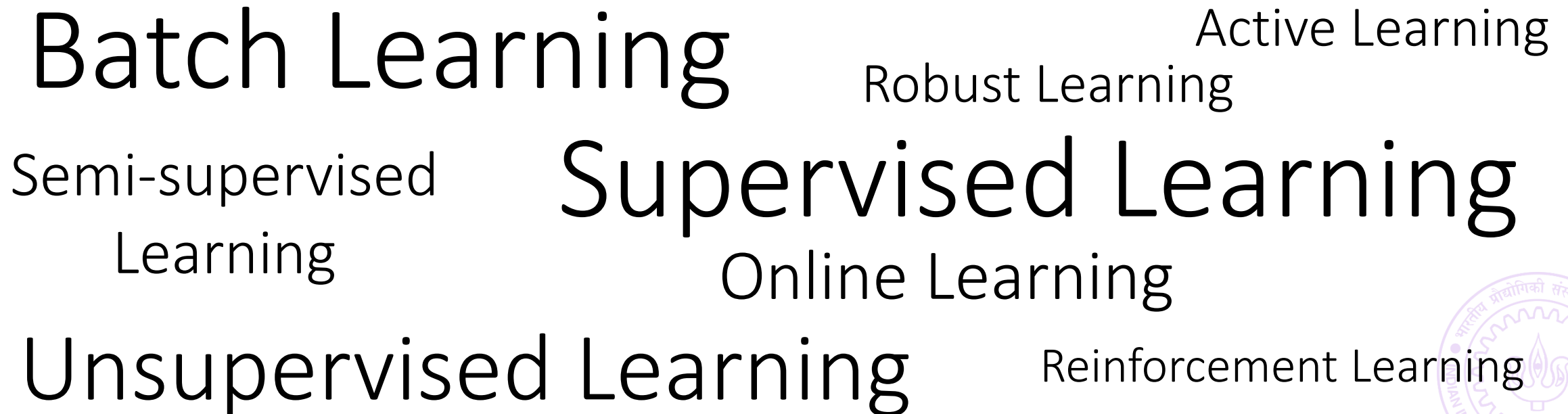


ML can take in lots of kinds of training data¹¹

We won't be able to cover all these training settings in this course – there are entire courses devoted to specific training settings e.g. CS773 (Online Learning)

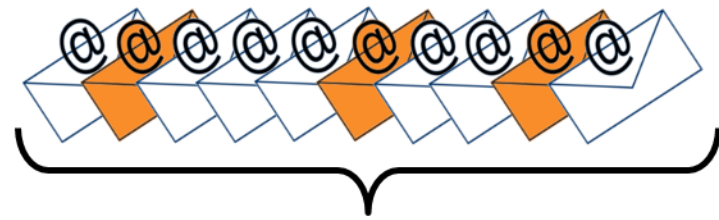


Training Data

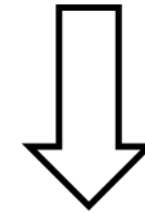
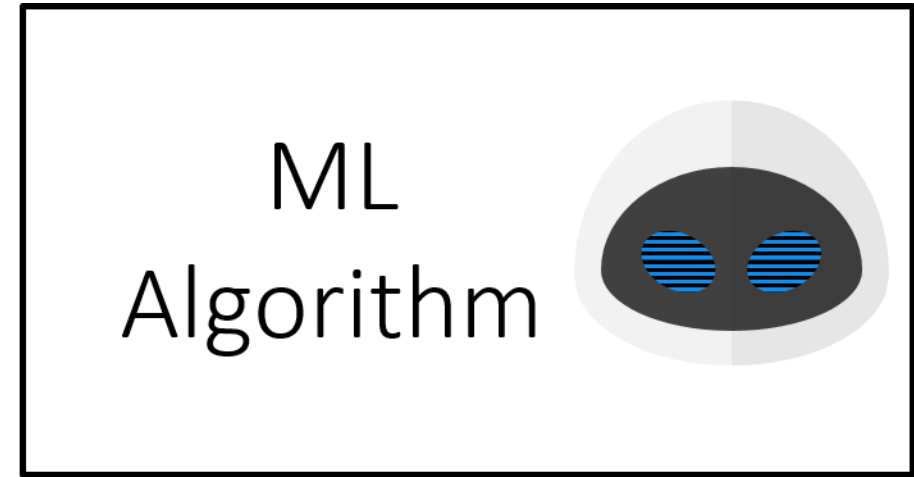
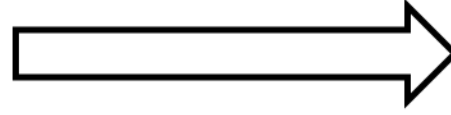


A typical ML workflow

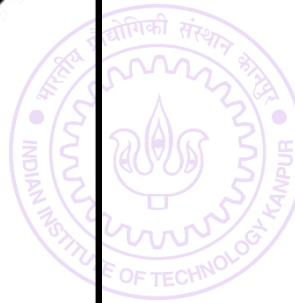
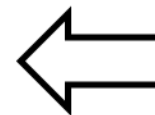
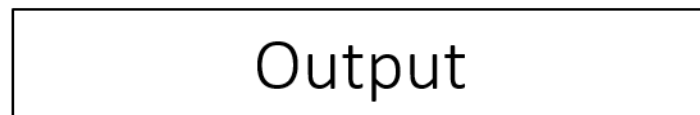
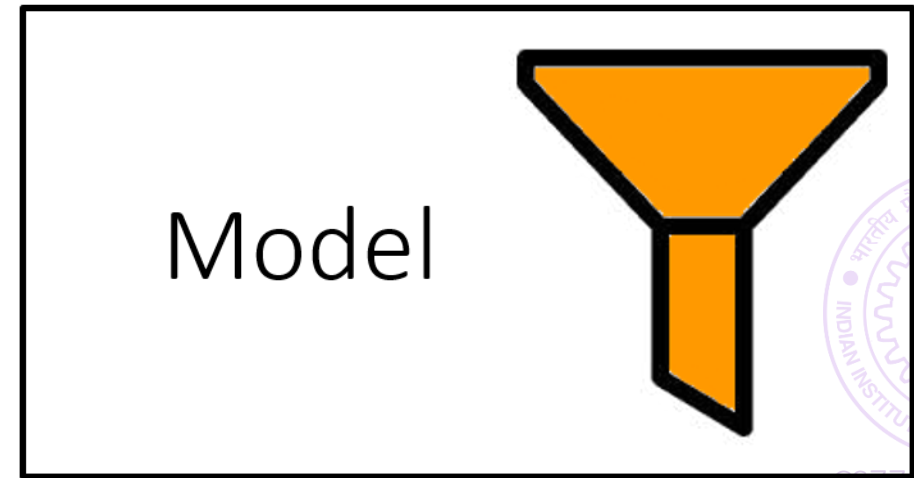
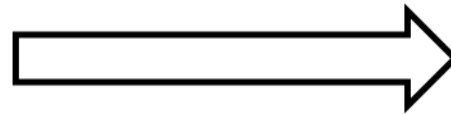
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Training Data



Test Data



ML can store info in lots of innovative ways 13



ML Models and Algorithms

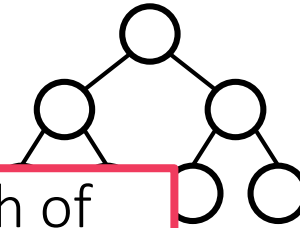
Linear/Opt

We can mix-n-match these methods too e.g. Bayesian Deep Learning or Kernel Nearest Neighbours (Local)

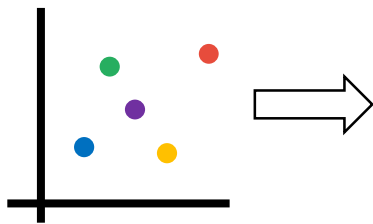
Neural/Deep



Local

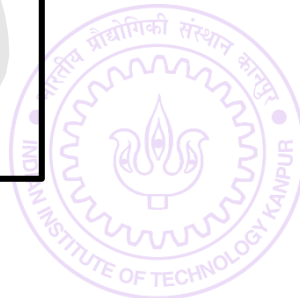
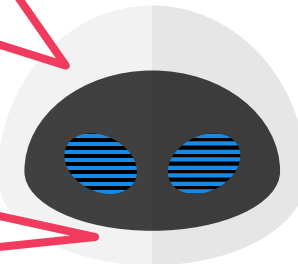


Kernel



We will learn how to use each of these techniques in the course, but a bit briefly. As before, there are entire courses devoted to each technique e.g. CS772 (Prob ML), CS774 (Opt)

Correct! But we will not be able to cover such advanced methods either



Fantastic Features

- ... and how to find them
- What are vectors
- How are vectors used in ML
- Useful operations on vectors



What are features

We could have – but it does not carry much information about spam/non-spam since it is such a common word!

Why did we not keep the word “to” as a feature?

Guys, something is wrong with our feature. The word “do” means different things in two emails

every new email (test data) must be converted into a vector

Do	You	Want	Go	Million	Dollars	Dinner	Today
1	1	1	1	0	0	1	0
1	1	1	0	1	1	0	0
1	0	0	0	1	0	0	1

Do you want to go for dinner?

Do you want to win a million dollars?

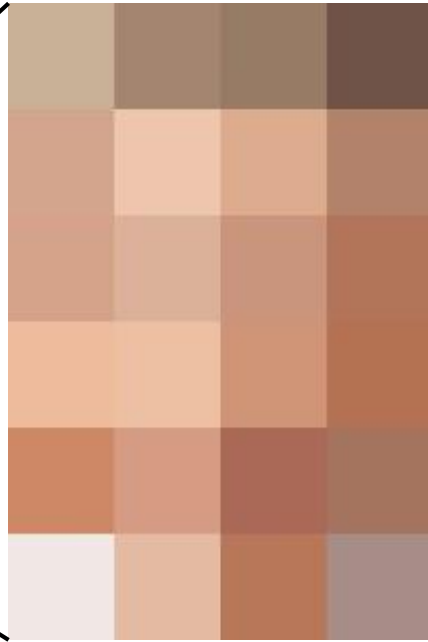
I have a million things to do today!

Since I am basically a computer program, I need you to convert your data into a nice set of numbers

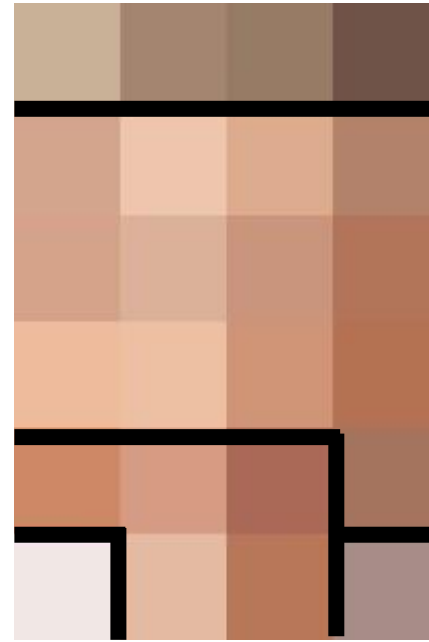
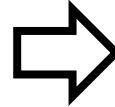
Good catch – this may not be the best feature representation!

What are features

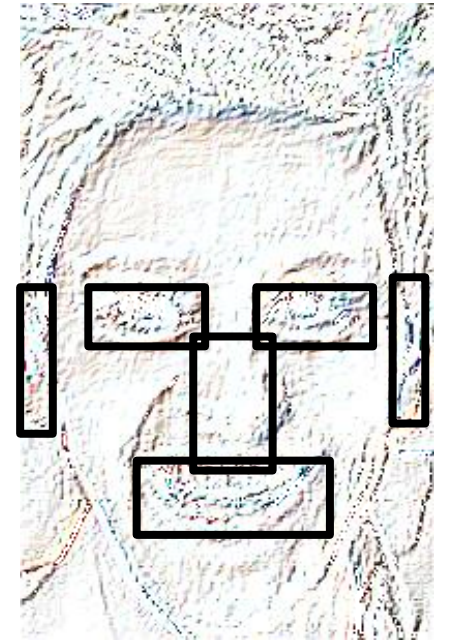
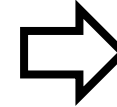
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May represent images
as a vector/matrix of
pixel RGB values



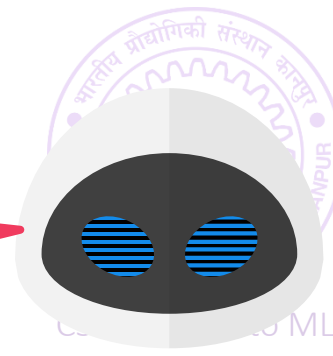
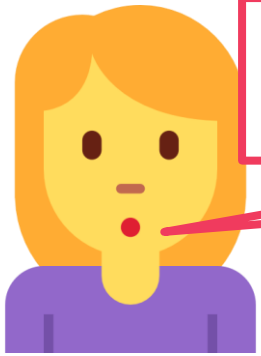
May instead encode
images using edges
present in them



May instead encode
images using presence
of eyes/noses/ears

Makes sense. Features are also a way for us to store what we know about data. If we throw away data, naturally doing anything becomes hard!

If your features are good, my job becomes twice as easy.
If not, then doing any ML may become impossible!



Types of Features

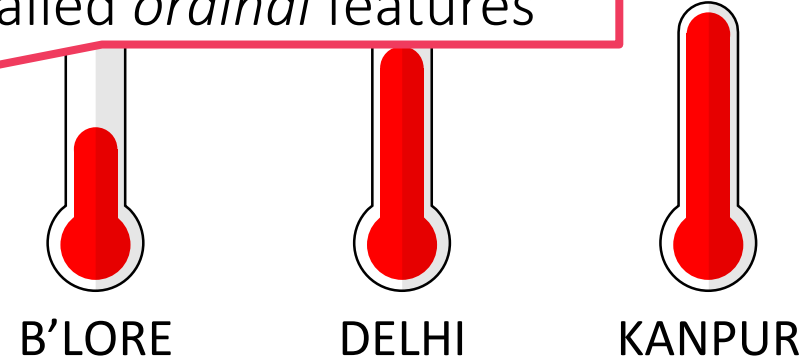
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Numerical Features

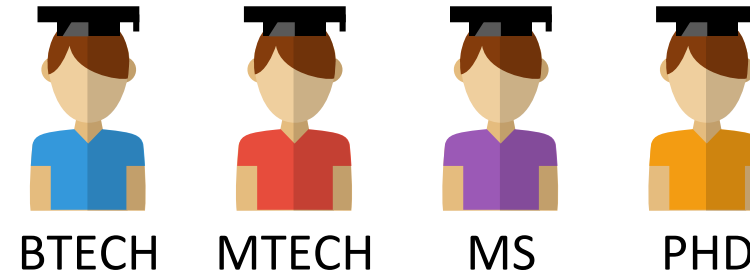
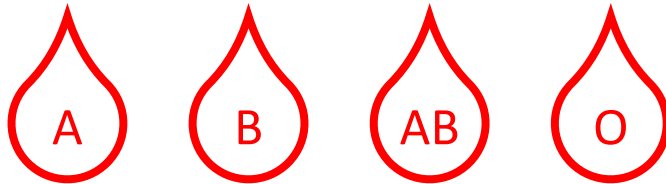
Dangal ★★★★★

Dhoom 3 ★★★

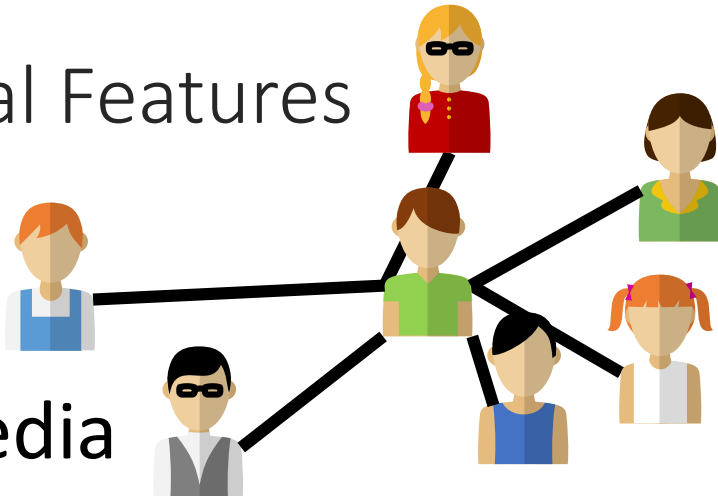
Discrete numerical features
often called *ordinal* features



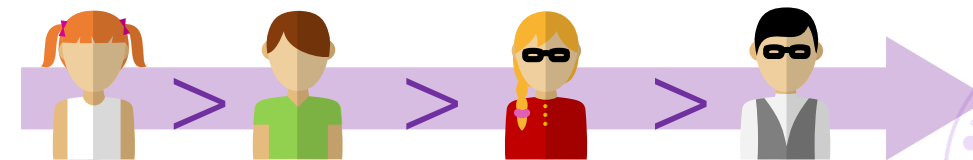
Categorical Features



Relational Features



Social Media



Ranking in Class



Derived Features

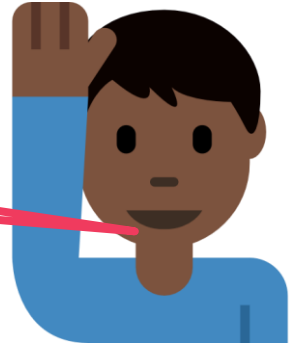
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Bagged/binning features



ESC101 (A), ESO207 (B), CS220 (B)
(C), MSO201 (A), CS771 (A)

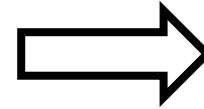
As we saw, the bag-of-words (also called BoW) is not always a very good feature (it confuses polysemous words). However, it is still extremely popular due to its simplicity



Pooled/aggregated features



ESC101 (A), ESO207 (B), CS220 (B), CS340
(C), MSO201 (A), CS771 (A)



10 (max), 8.67 (avg)

The way we represented emails in the spam problem is called the *bag-of-words* feature



Do you want to go for dinner?

Do you want to win a million dollars?

I have a million things to do today!

Do	You	Want	Go	Million	Dollars	Dinner	Today
1	1	1	1	0	0	1	0
1	1	1	0	1	1	0	0
1	0	0	0	1	0	0	1



Feature Selection??

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●	DIET (VEG/NON-VEG)
✗	EYE COLOR
●	TOTAL INCOME
●	EDUCATION LEVEL
●	FAMILY SIZE
✗	HOUSE NO (ODD/EVEN)
●	NO OF CHILDREN
●	RENTED/OWNED
✗	SURNAME

Useful for predicting expenditure

Not useful for predicting expenditure

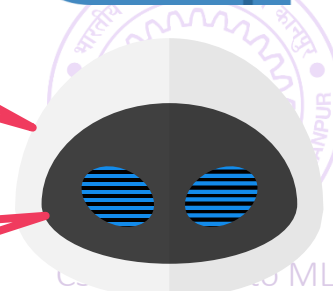


In fact, one reason for the success of deep learning is that it learns good features themselves!

Can we perform automatic feature selection?

Yes indeed, but those methods are a bit advanced for now!

True, but more on deep learning later! For now, back to basics.



A bit of caution with features

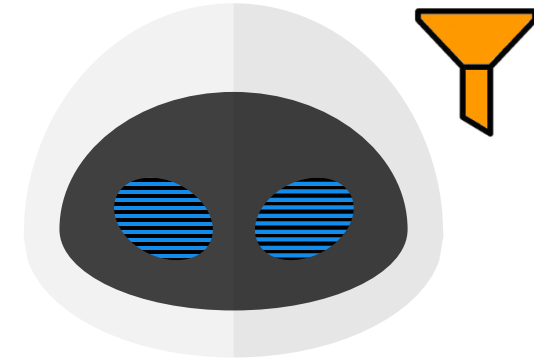
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Tricks, mnemonics lessen cognitive load, increase speed

Easy questions can be solved in one step with a mnemonic

Too many mnemonics can confuse you at time of exam



Derived features make learning easier, faster at test

What you are trying to predict is just another feature of the data!

However, not to worry. For most of this course, we will give you pre-made feature vectors 😊

In fact, one of the main challenges in deep learning is that it learns way too many features

