Machine Learning Deep Dive

Delta Analytics builds technical capacity around the world.

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Module 2:
Machine learning building blocks.

Course overview:

- ✓ Module 1: Introduction to Machine Learning
- ✓ Module 2: Machine Learning Deep Dive
- ❑ Module 3: Model Selection and Evaluation
- ❑ Module 4: Linear Regression
- ❑ Module 5: Decision Trees
- ❑ Module 6: Ensemble Algorithms
- ❑ Module 7: Unsupervised Learning Algorithms
- ❑ Module 8: Natural Language Processing Part 1
- ❑ Module 9: Natural Language Processing Part 2

Now let's turn to the data we will be using…

Module Checklist

- ❑ Model Development
  - ❑ Defining the machine learning task
  - ❑ Measuring performance of your model
  - ❑ Supervised vs. unsupervised learning methods
- ❑ Model Validation

Modeling Phase

Now we have our research question, we are able to start modeling!

Data Cleaning → Exploratory Analysis → Research Question → Modeling Phase

- Task
- Learning Methodology
- Performance

Research question from Module 1:

- How does loan amount requested vary by town?

Now we have our research question, we are able to start modeling!

Data Cleaning → Exploratory Analysis → Research Question → Modeling Phase

- Task
- Learning Methodology
- Performance

In this module we introduce the first two steps of modeling:

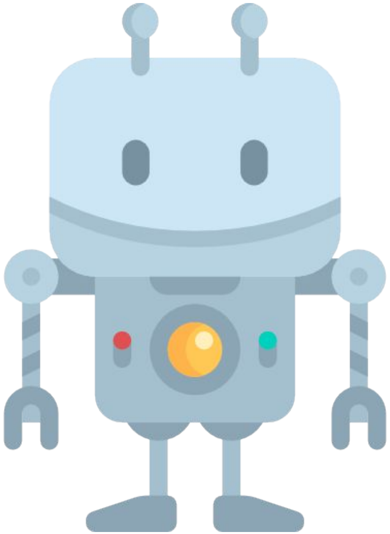
- Defining the machine learning task
- Understanding how the machine learns

We are here!

We will discuss model performance in the next module

Modeling Phase

Let's start at the basics. Why do we want to build a model?



Machine learning allows us to tackle tasks that are too difficult to code all possible approaches to on our own.

By allowing machines to learn from experience, we avoid the need for humans to specify all the knowledge a computer needs.

Source: Deep Learning Book - Chapter 5: Introduction to Machine Learning

Human Intuition

Based on our experience of the world, we have an understanding of relationships between features

Machine Learning Model

Computers acquire human intuition and quantify it, by extracting patterns from raw data

Machine learning models quantify and learn the patterns we observe in data.

Modeling Phase

All models have 3 key components: a task, a learning methodology and a performance measure

Task	What is the problem we want our model to solve?
Learning Methodology	ML algorithms can be supervised or unsupervised. This determines the learning methodology.
Performance Measure	Quantitative measure we use to evaluate the model's performance.

Source: Deep Learning Book - Chapter 5: Introduction to Machine Learning

Today we are looking closer at each component of the framework:

Task	What is the problem we want our model to solve?
Defining f(x)	What function will map our x (input) as close as possible to the true Y (output).
Feature engineering & selection	What is x? How do we decide what explanatory features to include in our model?
Is our f(x) correct for this problem?	What assumptions does our model make about the data? Do we have to transform the data?

Learning methodology: how does the model **learn** the function that best maps x to the true Y?

Learning Methodology	Is our model supervised or unsupervised; how does that affect the learning processing?
How does our ML model learn?	Overview of how the model teaches itself.
What is our loss function?	Every supervised model has a loss function it wants to minimize.
Optimization process	How does the model minimize the loss function.

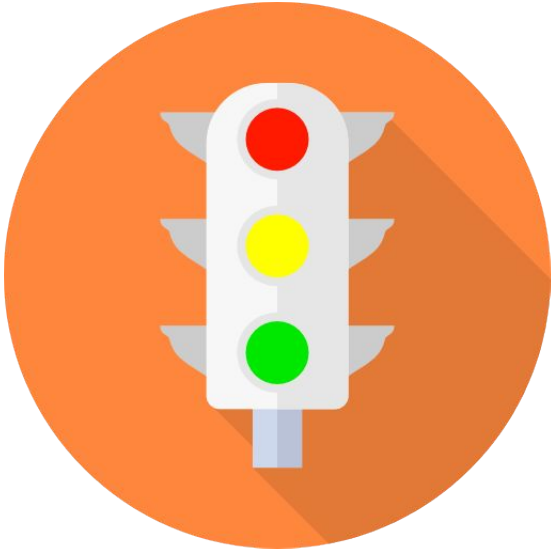
Performance: How do we evaluate how useful the model is, and how we can improve it?

Performance — Quantitative measure we use to evaluate the model's performance.

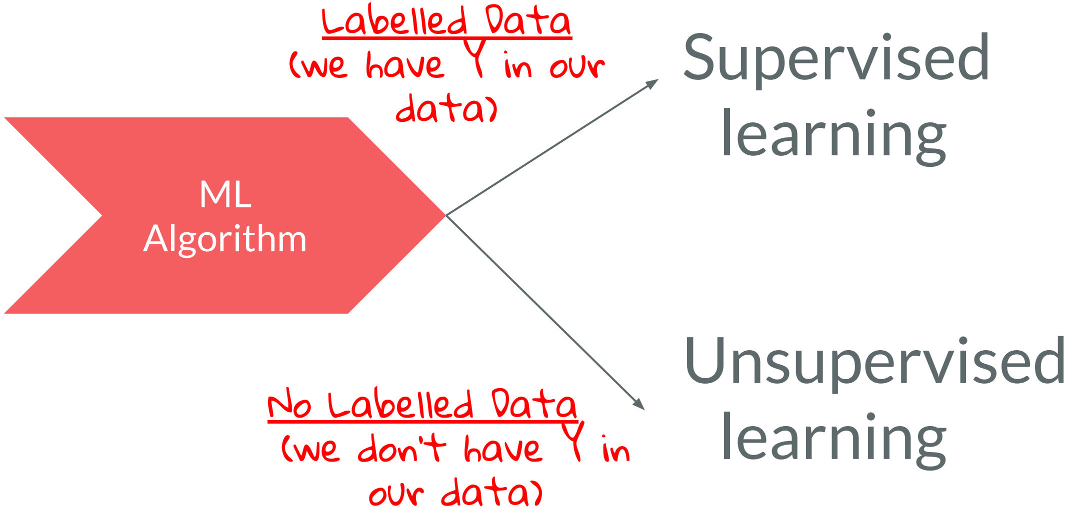
- **Measures of performance** — R2, Adjusted R2, MSE
- **Feature Performance** — Statistical significance, p-values
- **Ability to generalize to unseen data** — Overfitting, underfitting, bias, variance

Task and learning methodology

Hold on! Important disclosure:



For the next few slides, we will be introducing the intuition behind machine learning models using **supervised learning** examples. Later in this module, we will explore how unsupervised learning is different.



1. Task

Task

What is the problem we want our model to solve?

Research Question

Recap: How does loan amount requested on Kiva vary by town in Kenya?

We have KIVA data about loan amount requested by borrowers all over Kenya.

We want to know how the loan amount requested varies by town.

Task

Building a model involves turning your research question into a machine learning question.

Research question → Machine learning task

How does loan amount requested on Kiva vary by town? → ??

Task

Firstly, let's establish a common vocabulary to talk about the data.

Features

Observations

lender_count	loan_amount	location.country	location.country_code	location.geo.level	location.geo.pairs	location.geo.type	location.town
7	225	Kenya	KE	town	-1.166667 36.833333	point	Kiambu
14	350	Kenya	KE	town	0.516667 35.283333	point	Eldoret
33	1075	Kenya	KE	town	1 38	point	Kakamega North

Location.town is an example of a feature. Every column in our data set is a feature!

Every row of our dataset is an observation. When we include the observation in our model it is part of our training set.

Source: Subset of Kenyan loans dataset.

Task

A machine learning task has explanatory features and an outcome feature.

Explanatory features

Town borrower lives in

Outcome feature

Loan amount requested

An <u>outcome feature</u> is the **feature we expect to change** when the explanatory features are manipulated. In this example, we expect the loan amount to change when we change the location.

What would the outcome features and explanatory features be in the research questions below?

Try identifying some:

- What will the price of a stock be tomorrow?
- Does this patient have malaria?
- Would this person buy a car?

The outcome feature might be regression (e.g. $12) or a classification (e.g. Yes or No). We'll talk about this more later!

Solutions:

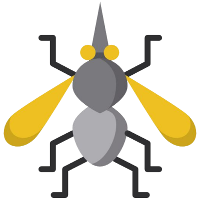
Explanatory features	Outcome feature
Price of a stock market index today	Company X's stock price tomorrow
Age, symptoms, travel history	Whether or not a patient has malaria
Income, location	Whether or not a person would buy a car

Task

Let's define our explanatory and outcome features for this task

***Problem*:**
I am the mayor of a 30,000 person town and need to justify spending budget on mosquito nets.

I want evidence on how the number of mosquito nets affects the number of cases of malaria. *Can you help?*

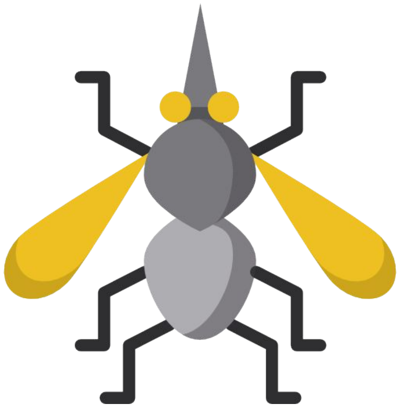


1.Research Question

2.Task

Let's start by identifying the research question!

The research question is what we want to find out from the data, formally stated.

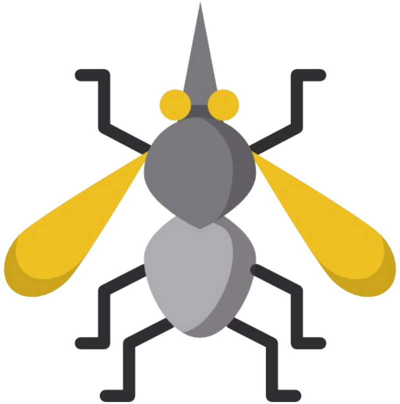


How does the number of cases of malaria change when the number of mosquito nets changes?

Task

Next let's define our task!

1. Define explanatory and outcome feature
2. Define f(x)
3. Bring it all together



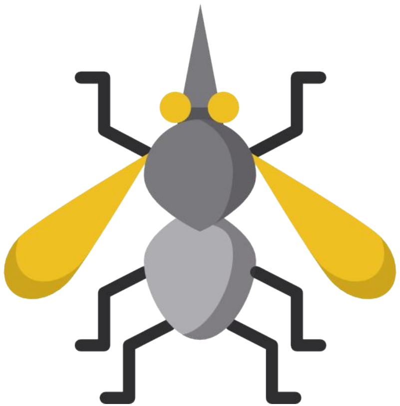
Define explanatory and outcome feature

How does the number of cases of malaria change when the number of mosquito nets changes?

explanatory feature(s)

x Number of mosquito nets

2007: 1000
2008: 2200
2009: 6600
2010: 12600



outcome feature

Y Number of people with malaria

2007: 80
2008: 40
2009: 42
2010: 35

We also call our explanatory features x, and our outcome feature Y.

Looks like as mosquito nets increase, the number of malaria cases decreases.

Task

What would you conclude from looking at this data? How many nets would you recommend?

X Number of mosquito nets

2007: 1000
2008: 2200
2009: 6600
2010: 12600

Y Number of people with malaria

2007: 80
2008: 40
2009: 42
2010: 35

You came to a conclusion by **recognizing a pattern in the data**. This is similar to how a machine learning algorithm would approach the same problem.

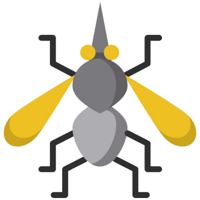
Task

Machine learning allows us to learn from historical patterns.

If Mr. Mayor had **no** machine learning methods to use, he could find an answer by trying a different # of nets year after year.

But this has an obvious **human cost**, and it would be very hard to update the model to account for, for example, new residents to his town.

Machine learning algorithms help answer questions without this human cost - we are **learning from data**, or in other words, **learning from history**!



Human Intuition

"Over four years, increasing number of mosquito nets decrease the number of malaria cases."

Machine Learning Model

An increase in x (mosquito nets) <u>causes</u> a decrease in Y (malaria cases).

- Humans form rules based upon observation and pattern recognition.
- ML model takes input x and maps it to the output Y.

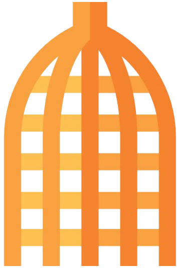
Define f(x)

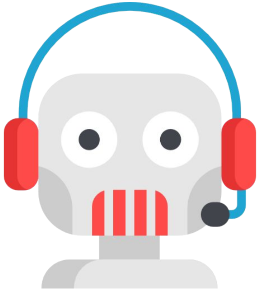
Our model f(x) is a function that maps our input x to a predicted Y*.

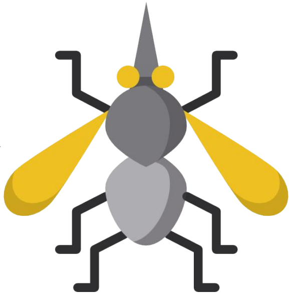
explanatory feature(s) | model | predicted outcome

x Number of mosquito nets → $f(x) + e$ → Y^* Predicted Number of people with malaria

irreducible error



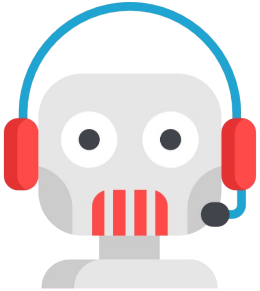




Define f(x)

The goal of f(x) is to predict a Y* as close to the true Y as possible.

My job is to make the predictions as **useful** as possible!



Our function f(x) maps an input x to a predicted Y, which we refer to as Y*. We want to choose an f(x) that will map x as close to the true Y as possible.

$$f(x) + e = Y^*$$

Predicted Number of people with malaria

e is <u>irreducible error</u>. This captures error caused by factors like measurement error, randomness in the data, and inappropriate model choice. No matter how well you optimize your model, this will never be reduced to 0.

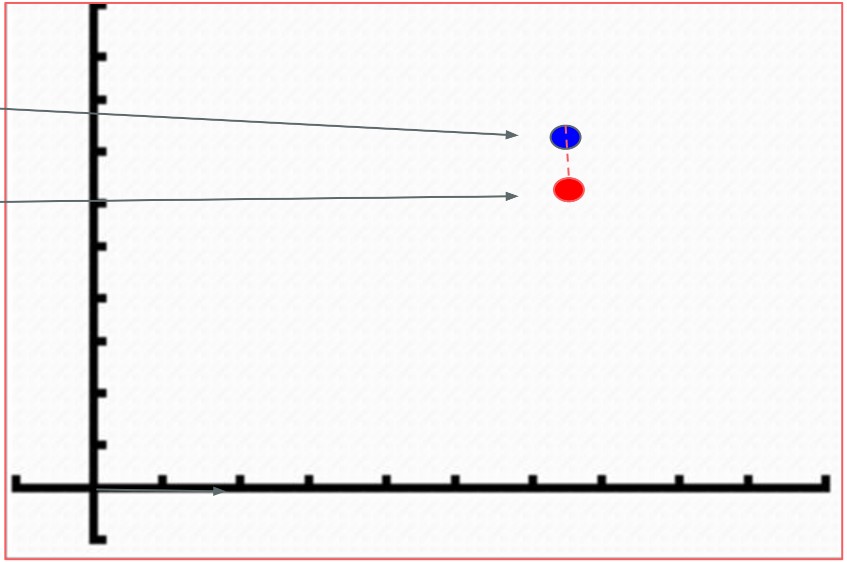
Define f(x)

We want Y* to be close to true Y because we want the function to output useful predictions.

In this example, predicted Y appears close to the true Y. We will talk about how to quantify this in the next section.

True Y

Y*=f(x)+e



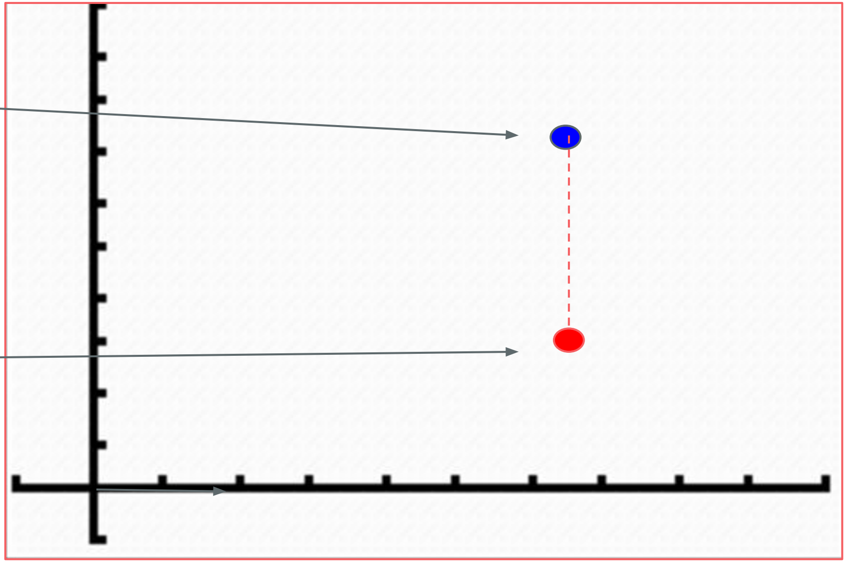
Define f(x)

We want Y* to be close to true Y because we want the function to output useful predictions.

In this example, predicted Y appears far from the true. ***This is probably not very useful***. We will talk about how to quantify this in the next section.

True Y

Y*=f(x)+e



Define f(x)

What is f(x)? It depends on the machine learning algorithm we choose.

x → **f(x)** → **Y***

<u>explanatory feature(s)</u>, like number of mosquito nets

<u>predicted outcome</u>, e.g. Number of people with malaria

Examples of f(x):

Supervised learning algorithms:

- Linear regression
- Decision tree
- Random forest
- ...

When you have labelled data

Unsupervised learning algorithms:

- K-means clustering
- Hierarchical clustering
- ...

When you don't have labelled data

Bring it all together

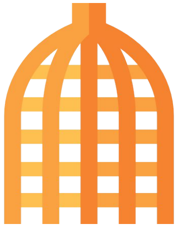
Let's bring everything together.

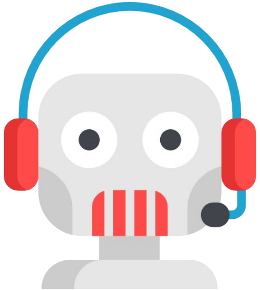
Research question

How does the number of cases of malaria change when the number of mosquito nets changes?

Machine learning task

x Number of mosquito nets → f(x) → Y* Number of people with malaria





Supervised learning task

The task function depends upon the data type you want to predict. Supervised learning problems fall into two main categories: regression & classification.

The Task

Regression

Continuous variable

A regression problem is when we are trying to **predict a numerical value**, such as “dollars” or “weight”.

Classification

Categorical variable

A classification problem is when we are trying to **predict whether something belongs to a category**, such as “red” or “blue” or “disease” and “no disease”.

Source: Andrew Ng, Stanford CS229 Machine Learning Course

2. Learning Methodology

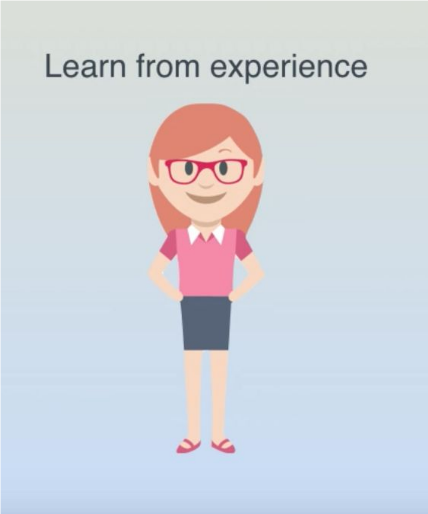
Learning Methodology

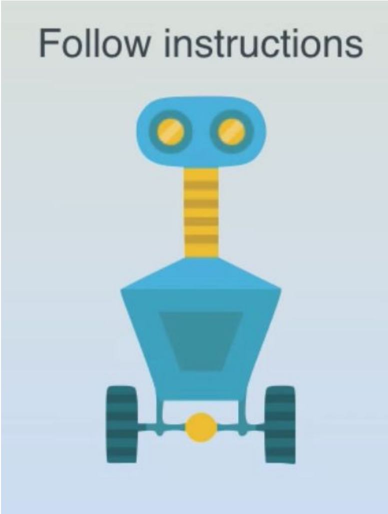
ML algorithms can be supervised or unsupervised. This determines the learning methodology.

Learning methodology: how does the model learn the function that best maps x to the true Y?

Learning Methodology	Is our model supervised or unsupervised? How does that affect the learning processing?
How does our ML model learn?	Overview of how the model teaches itself.
What is our loss function?	Every supervised model has a loss function it wants to minimize.
Optimization process	How does the model minimize the loss function?

Recall that machine learning is a subset of data science that allows machines to learn from raw data.





Machine learning

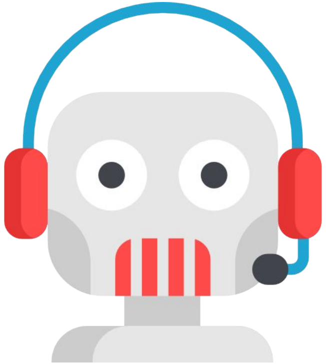
Traditional software programing involves giving machines instructions which they perform. **Machine learning involves allowing machines to learn from raw data so that the computer program can change when exposed to new data (learning from experience).**

Source: https://www.youtube.com/watch?v=IpGxLWOIZy4

Learning Methodology

What do we mean when we say a machine "learns from experience"?

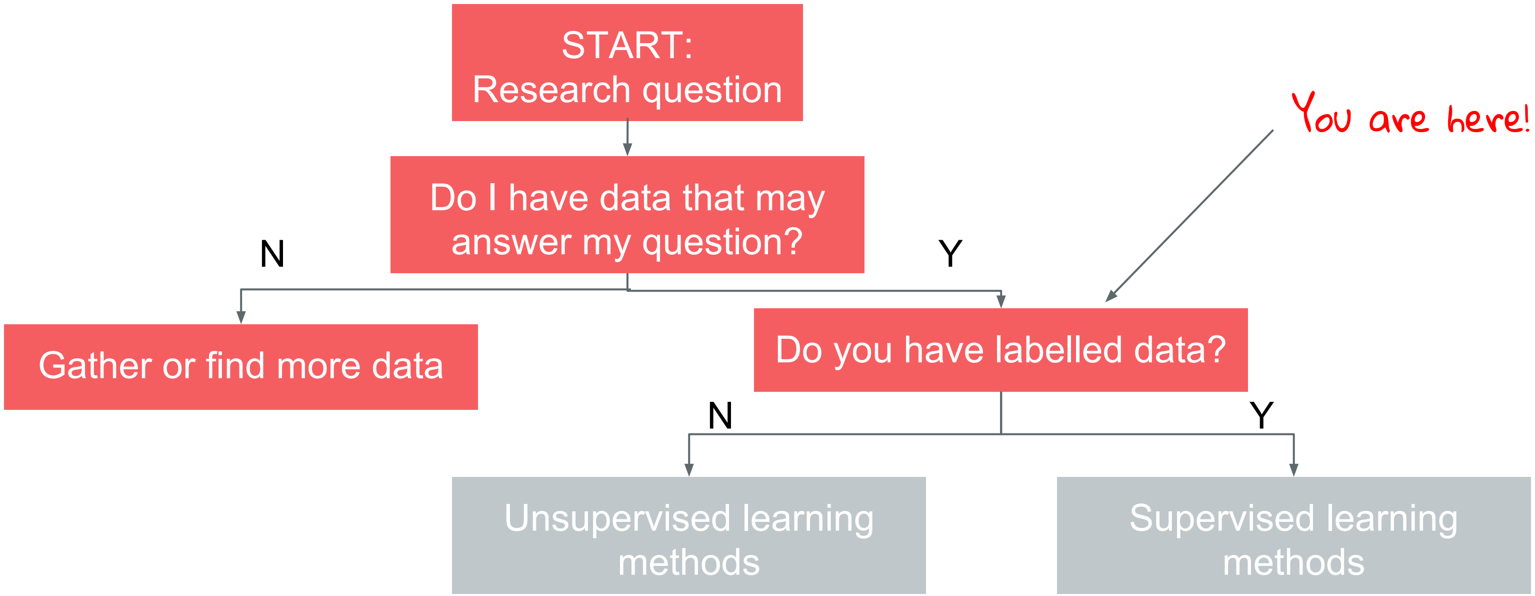
Machine learning is a subset of data science that allows machines to learn from raw data.



How does the model learn from raw data?

Learning Methodology

How the algorithm learns depends upon type of data you have.



Learning Methodology

What does labelled data mean?

Do you have labelled data?

Yes

The outcome feature (Y) you are interested in predicting is recorded in the data. If you have a labelled Y, you can use supervised learning methods.

Y=Number of people with malaria

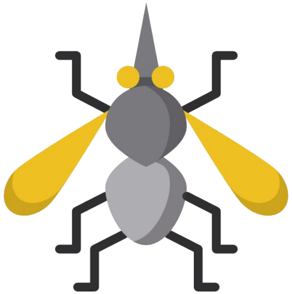
2007: 80
2008: 40
2009: 42
2010: 35

No

The outcome feature (Y) is not recorded in the data. You do not have a labelled Y.

Y=Number of people with malaria

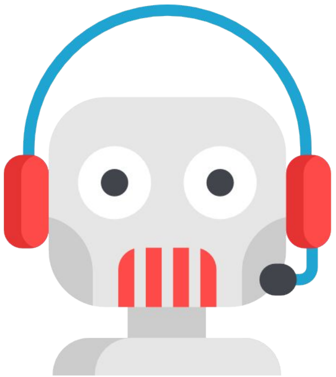
2007:
2008:
2009:
2010:



Learning Methodology

Whether or not you have labelled data determines whether it is a <u>Supervised</u> or <u>Unsupervised</u> Learning problem

$$f(x) + e = Y^*$$



Do you have labelled data?

Y is in your data

Yes

No

Y is not in your data

Supervised Learning

- For every x, there is a Y
- Goal is to **predict** Y using x

Unsupervised Learning

- For every x, there is no Y
- Goal is not to predict, but to **investigate** x

Most problems you will initially encounter are supervised algorithms.

How do supervised algorithms learn?

supervised learning

Intuitive explanation for how supervised algorithms learn:

Y Number of people with malaria

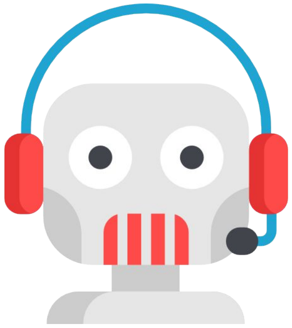
2007: 80
2008: 40
2009: 42
2010: 35

Imagine you are a teacher and you ask your students a question.

The labels Y provide the correct answer for the problem the students are trying to solve. **Since you know the correct answer, you can reward good student performance and punish poor performance.** This encourages ongoing learning!

supervised learning

Extending this example, you (the researcher) are the teacher and the Model is the student.



Model

I want to get the correct answer for predicting Y and be the best student in the class.

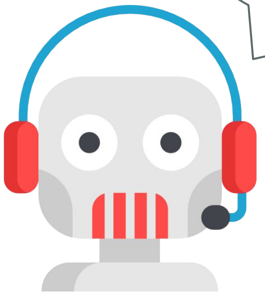
Great Mr. Model! Once you give me your answer I will let you know the correct answer.

Every time Mr. Model predicts Y*, you compare Y* to the true Y to see how well he did.

supervised learning

Our Model starts trying to provide an estimated Y* by guessing.

I have never seen this problem before! I'll just start by randomly guessing an answer and see what happens.



Model

Y*	Y
Predicted Number of people with malaria	Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

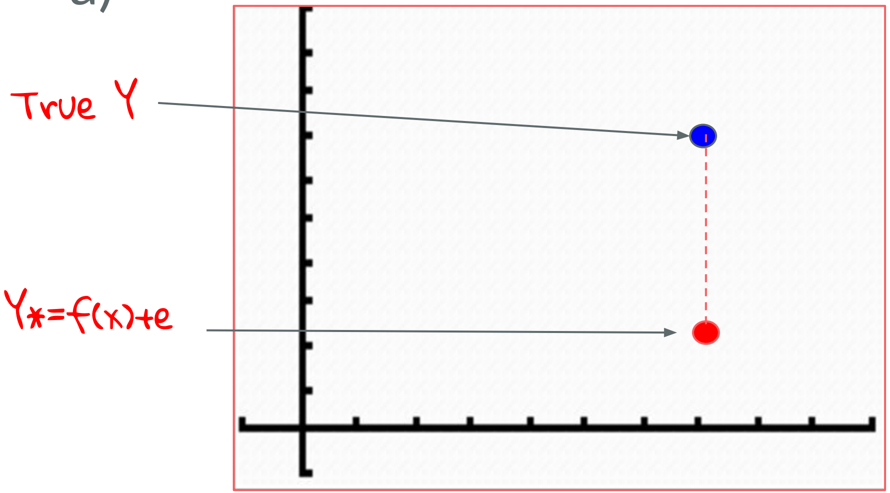
Unsurprisingly, the results appear terrible, judging from the fact that actual numbers are very different from the predicted numbers. ***To quantify how bad or good results are, we use Y-Y*.***

Learning Methodology

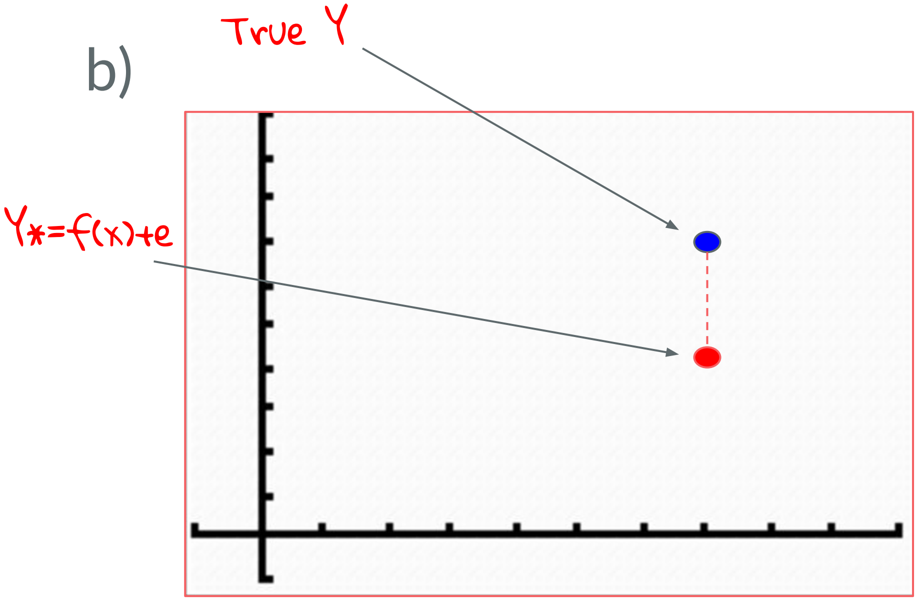
What is our loss function?

Which model is more useful at mapping x close to true Y?

a)



b)



Which prediction was worse, a) or b)?

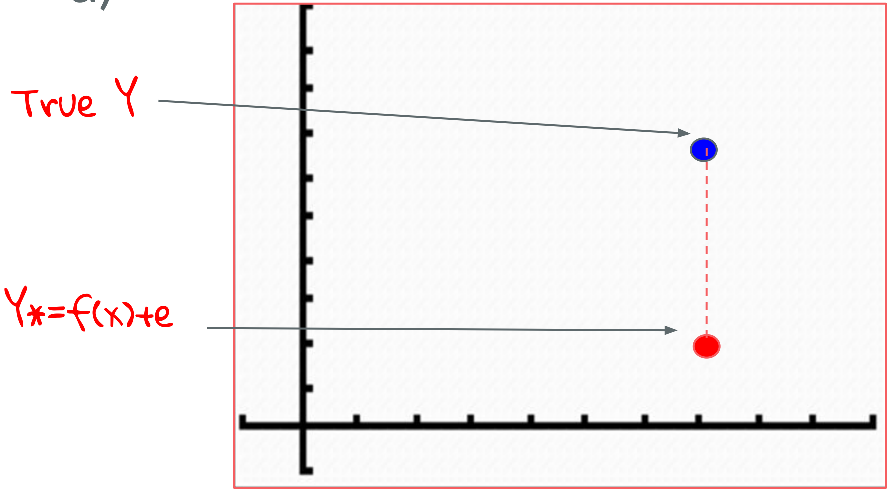
Learning Methodology

What is our loss function?

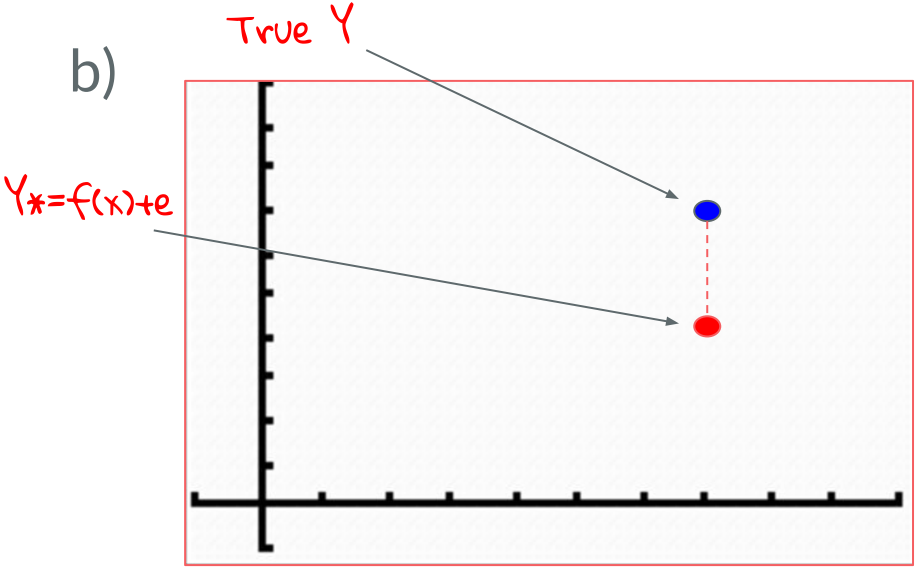
We can immediately tell that b is better!

We can see that the f(x) in b maps x to a Y* much closer to the true Y. A **loss function** allows us to quantify this difference.

a)

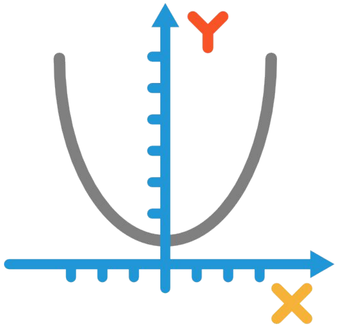


b)



A model's goal is to minimize the loss function.

The Task



The Loss Function

A loss function quantifies how unhappy you would be if you used f(x) to predict Y* when the correct output is y. It is what we want to minimize.

Another way to think about it is that a loss function quantifies how well our f(x) fits our data.

We have already seen one simple example: Y-Y*, or the difference between the predicted Y and the actual Y. Later, we will see more sophisticated loss functions.

Source: Stanford ML Lecture 1

supervised learning

Since I know the right answer, I can compare predicted Y* to the true Y to help guide Mr. Model.

Y*	Y
Predicted Number of people with malaria	Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

We first decide on how to measure how unhappy we are with these results. We call this our **loss function**. On the next slide, we show a few different possible loss functions we can use to assess Mr. Model.

Supervised learning task

Recall that there are two different types of tasks:

The Task

Regression

Continuous variable

Classification

Categorical variable

A regression problem is when we are trying to predict a numerical value given some input, such as "dollars" or "weight".

A classification problem is when are trying to predict whether something belongs to a category, such as "red" or "blue" or "disease" and "no disease".

Source: Andrew Ng, Stanford CS229 Machine Learning Course

Learning Methodology

What is our loss function?

The choice of loss function depends upon the type of task. We will discuss loss functions for both types of task.

Regression

Continuous variable

absolute error (L1)	least squares error (L2)

Including mean squared error (MSE), root mean squared error (RMSE)

Classification

Categorical variable

log loss	hinge loss

Source: Andrew Ng, Stanford CS229 Machine Learning Course

Learning Methodology

What is our loss function?

There are a few different loss functions we could choose from, depending on the problem we are trying to solve.

Regression

Continuous variable

absolute error (L1)

root mean squared error (RMSE)

least squares error (L2)

mean squared error (MSE)

Classification

Categorical variable

log loss

hinge loss

Regression loss functions

1. L1 norm (mean absolute error)
2. L2 norm (least squares error)
    - Mean squared error

Learning Methodology

What is our loss function?

Our outcome feature is continuous: the number of people who have malaria.

Outcome feature in data is continuous → Regression task → L1 or L2 loss function

Y

Number of people with malaria

2007: 80
2008: 40
2009: 42
2010: 35

Learning Methodology

What is our loss function?

L1 and L2 loss are two possible options for assessing how unhappy we are with Mr. Model's choice of f(x).

absolute error (L1)	least squares error (L2)	mean squared error
Also called L1 loss, this minimizes the **sum** of absolute errors between True Y and predicted Y*.	Also called L2 loss, this minimizes the **square** of the error between True Y and predicted Y*.	Takes the mean of the L2 loss over all observations.

$$S = \sum_{i=1}^{n} |y_i - f(x_i)|.$$

$$S = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

Source: L1 and L2

Learning Methodology

What is our loss function?

How bad were Mr. Model's initial results? Let's compute the L1 norm.

How well did Mr. Model's random guess perform?

$$S = \sum_{i=1}^{n} |y_i - f(x_i)|.$$

Y*	Y
Predicted Number of people with malaria	Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

absolute error (L1)

(|1-80|+|2000-40|+|300-42|+|40-35|)
= 2,302

Source: Intro to Stat - Introduction to Linear Regression

Learning Methodology

What is our loss function?

How bad where Mr. Model's initial results? Let's compute the L2 norm.

How did Mr. Model's initial random guess do?

$$S = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

Least squares error (L2)

Y^* Predicted Number of people with malaria	Y Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

(80-1)^2+(40-2000)^2+(42-300)^2
+(35-40)^2=3,914,430

Source: Intro to Stat -Introduction to Linear Regression

Learning Methodology

What is our loss function?

We can normalize our L2 loss by computing mean squared error or root mean squared error.

least squares error (L2)	mean squared error	root mean squared error
Also called L2 loss, minimizes the square of the error between True Y and predicted Y*.	Takes the mean of the L2 loss over all observations.	Takes the square root of the mean of the L2 loss.
$$S = \sum_{i=1}^{n}(y_i - f(x_i))^2$$	MSE = mean(S)	RMSE = sqrt(mean(S))

Source: L1 and L2,

Learning Methodology

What is our loss function?

Mean squared error takes the average L2 error per observation.

How did Mr. Model's initial random guess do?

Y*	Y
Predicted Number of people with malaria	Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

MSE = mean(S)

Mean squared error

((80-1)^2+(40-2000)^2+(42-300)^2
+(35-40)^2)/4
= 978,607.5

Source: Intro to Stat -Introduction to Linear Regression

Learning Methodology

What is our loss function?

Root mean squared error takes the square root of the average L2 error per observation.

How did the models initial random guess do?

RMSE = sqrt(mean(S))

Root mean squared error

Y*	Y
Predicted Number of people with malaria	Actual Number of people with malaria
2007: 1	2007: 80
2008: 2000	2008: 40
2009: 300	2009: 42
2010: 40	2010: 35

(((80-1)^2+(40-2000)^2+(42-300)^2+(35-40)^2)/4)^(½)
= 989.25

Source: Intro to Stat - Introduction to Linear Regression

Learning Methodology

We can compute for each loss functions how unhappy we are with models initial random guess.

Don't worry about these numbers. What's important is you understand how we are transforming them step by step.

absolute error (L1)	least squares error (L2)	mean squared error	root mean squared error
2,302	3,914,430	978,608	989
Also called L1 loss, minimizes the sum of absolute errors between True Y and predicted Y*.	Also called L2 loss, minimizes the square of the error between True Y and predicted Y*.	Takes the average L2 loss per observation in the data.	Takes the square root of the average L2 loss per observation in the data.
$S=\sum_{i=1}^{n}\lvert y_i-f(x_i)\rvert.$	$S=\sum_{i=1}^{n}(y_i-f(x_i))^2$	MSE = mean(S)	RMSE = sqrt(mean(S))

Source: L1 and L2

Learning Methodology

RMSE is the square root of the average L2 loss per observation.

Model

There are five steps to RMSE:

Y-Y*	For every observation in our dataset, measure the difference between true Y and predicted Y.
^2	Square each Y-Y* to get the absolute distance, so positive values don't cancel out negative ones when we sum.
Sum	Sum across all observations so we get the total error.
mean	Divide the sum by the number of observations we have.
root	Take the square root of the mean calculated above.

MSE

Source: Intro to Stat -[Introduction to Linear Regression]

Which loss function should we use?

1. L1 norm (mean absolute error)
2. L2 norm (least squares error)

Learning Methodology

What is our loss function?

Each loss function has important pros and cons.

absolute error (L1)

vs.

least squares error (L2)

	Robust?	Stable Solution?	How many solutions?
L1	Robust	Not stable	Multiple possible solutions
L2	Not very robust	Stable	One possible solution

MSE and RMSE are both normalized versions of L2 error. If we decide to use L2, we will choose MSE or RMSE.

Source: L1 and L2

Learning Methodology

What is our loss function?

If we decide to use least squares error (L2), we may decide to report RMSE OR MSE

MSE vs. RMSE

The key difference between RMSE and MSE is that taking the root in RMSE normalizes the error to the same units of measurement.

This makes the error term more interpretable.

Both MSE and RMSE amplify and severely penalize large errors more than small ones by squaring the error.

Classification loss functions

1. Log loss
2. Hinge loss

Define explanatory and outcome feature

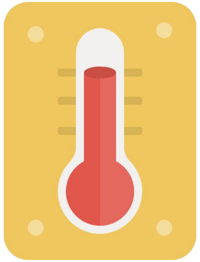
Let's define a slightly different task so we can discuss hinge and log loss.

Task: We want to predict whether or not a patient has malaria using their temperature.

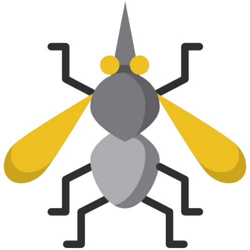
X Temperature of patient

Y Does the patient have malaria?

39.5°C
37.8°C
37.2°C
37.2°C



No
Yes
Yes
No



Learning Methodology

What is our loss function?

Our outcome feature is categorical: we want to predict whether or not someone has malaria. This is a binary classification problem.

This is a classification task, so we can use either log loss or hinge loss.

But first, what is a classification task?

Classify based upon probability threshold

Classification tasks output the **probability of belonging to a class**. Normally, based upon a threshold of 50% we then assign the predicted class.

outcome feature		predicted probability	predicted outcome	
Y	Does the patient have malaria?	What is the probability that the patient has malaria?	Y*	Does the model predict that the patient has malaria?
	No	0.55		Yes
	Yes	0.80		Yes
	Yes	0.85		Yes
	No	0.2		No

Classify based upon probability threshold

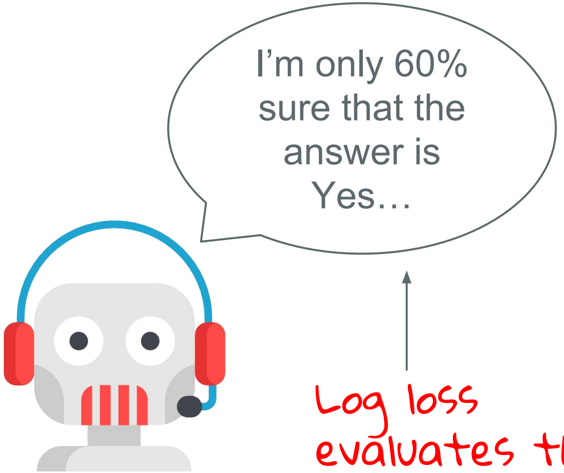
We can evaluate accuracy by looking just at **the predicted outcome vs. the actual outcome**. Here, accuracy is 75%!

outcome feature		predicted probability	predicted outcome	
Y	Does the patient have malaria?	What is the probability that the patient has malaria?	Y*	Does the model predict that the patient has malaria?
	No	0.55		Yes
	Yes	0.80		Yes
	Yes	0.85		Yes
	No	0.2		No

However, **we are missing out on using probability**, which is important information about how certain the model is about its prediction. Let's look at some loss functions that utilize this metric.

Log loss

For every prediction the model Makes, we can measure the logarithmic loss. **What is logarithmic loss?**



Model

Log loss evaluates the probability of belonging in a class

$$L = -\frac{1}{n}\sum_{i=1}^{n}[y_i log(\hat{y}_i) + (1-y_i)log(1-\hat{y}_i)]$$

- The smaller the log loss, the smaller the uncertainty, the better the model
  - A perfect classifier would have log loss = 0
- Log loss heavily penalizes classifiers that are confident about an incorrect classification

- Ways to improve log loss:
  - Are there problematic errors in dataset?
  - Do we want to smooth the probabilities?

Source: https://www.r-bloggers.com/making-sense-of-logarithmic-loss/

Hinge loss

For every prediction our model makes, we can also measure the hinge loss. **What is hinge loss?**

Hinge loss is the logical extension of the regression loss function, **absolute loss**.

Absolute loss: Y- Y*, where Y and Y* are integers.

Hinge loss: max(0,1-(Y*)(Y))

Where Y can equal -1 (no) or 1 (yes) for each class.

For each observation, if Y* == Y (both are 1 or both are -1), hinge loss = 0. If Y =/= Y*, hinge loss **increases**.

The cumulated hinge loss is therefore the upper bound of the number of mistakes made by the classifier.

Sources: https://en.wikipedia.org/wiki/Hinge_loss; http://scikit-learn.org/stable/modules/generated/sklearn.metrics.hinge_loss.html

How do we choose a loss function for a classification problem?

Log Loss

vs.

Hinge Loss

Leads to **more exact probabilities**, but at the cost of accuracy

Leads to **better accuracy**, but at the cost of exact probabilities

How do we choose a loss function for a classification problem?

Depends on the question you want to answer!

E.g. For a problem where we are trying to assess patient health, we know that *false positives* (the model predicts you do have malaria, but you actually don't) are safer and generally more preferable than *false negatives* (the model predicts you don't have malaria, but you actually do.)

Therefore it is probably safer to evaluate our output as a **probability** of whether or not you have malaria. We will use **log loss**.

A note on categorical loss functions …

We provide only a broad conceptual overview of log loss and hinge loss as we will not be using them in our coding lab. However, we encourage you to explore them further.

More resources can be found at the end of this module.

Our model computed an initial guess using RMSE.

How does he improve on his initial guess?

Learning Methodology

What is our loss function?

Our initial RMSE is very high. Our model tries a different f(x) and compares RMSE.

Oh no! That wasn't very good, let's try something else!

	1st initial guess	2nd update	3rd update
RMSE	1,000	1,300	800
# nets	300	100	400

If the new f(x) reduces the loss, **our model keeps changing the f(x) in that direction.** After every change, the model measures whether the loss has increased, decreased or stayed the same.

As the model updates the prediction at each step, we see that themodel is **learning** - it changes in response to a higher MSE.

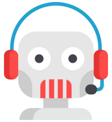
Source: Intro to Stat -Introduction to Linear Regression

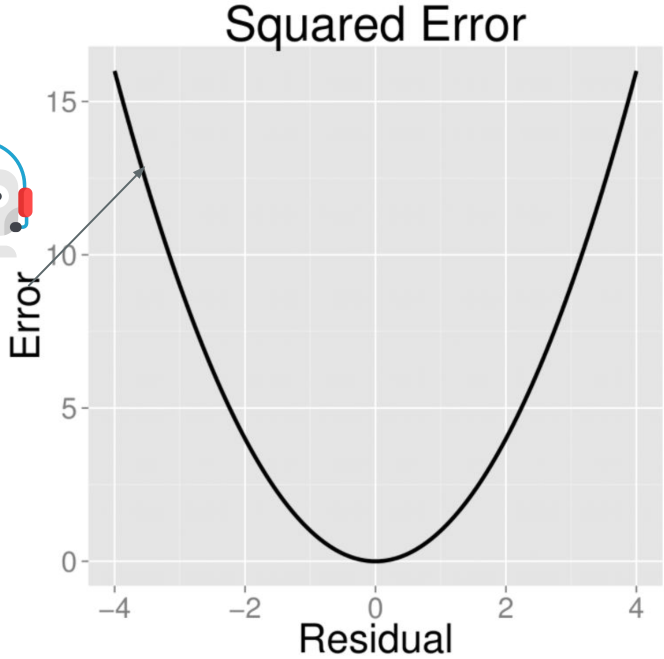
Learning Methodology

How does our ML model learn?

The process of changing f(x) to reduce the loss function is called **learning**. It is what makes ordinary least squares (OLS) regression a machine learning algorithm.

Our model's initial **random** f(x) gives us a high initial error





For every f(x) we choose there is an associated loss.

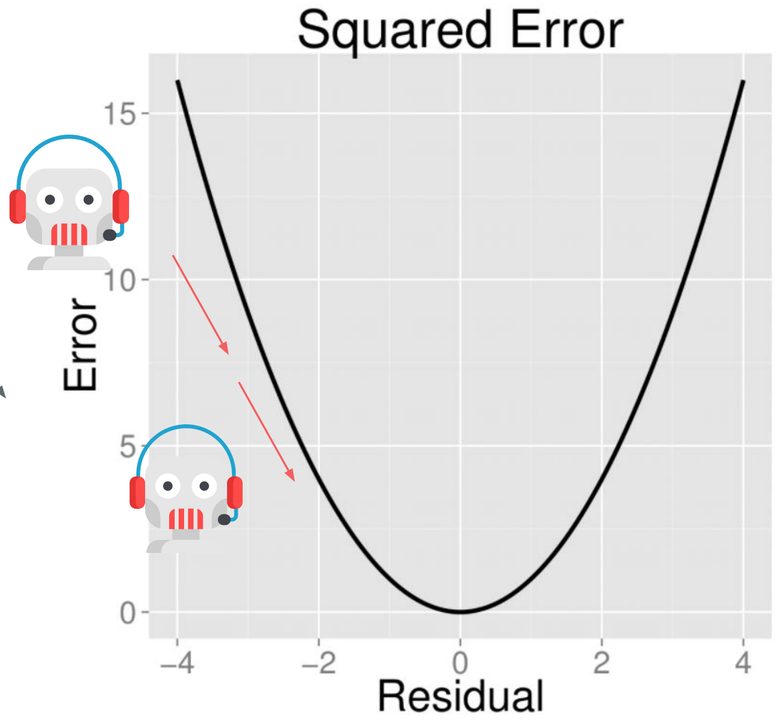
The learning process involves updating f(x) in order to reach the global minimum loss.

Learning Methodology

How does our ML model learn?

Our model starts with a **random** f(x) and update f(x) to make our loss as small as possible.

Our model's job is to change the parameters so that every time he changes f(x), the loss goes down.



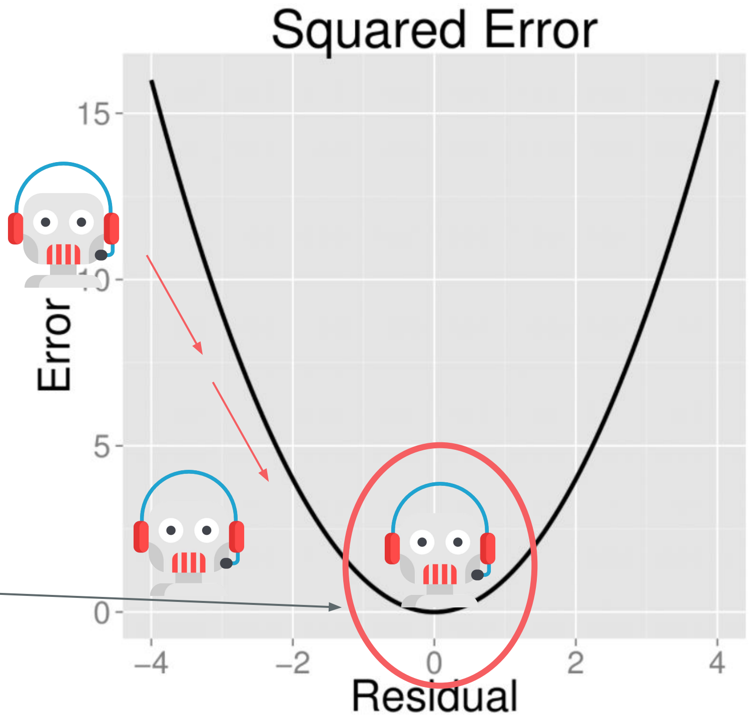
Our model succeeds when he reduces the error to its **minimum**.

Learning Methodology

How does our ML model learn?

When does our model stop?

Our model's job is to change the parameters so that every time he changes f(x), the loss goes down.



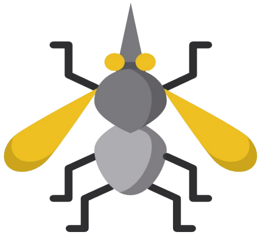
Our model succeeds when he reduces the error to its **minimum.**

Learning Methodology

How does our ML model learn?

What if we don't have labelled data?

Do you have labelled data?



Yes

The outcome feature (Y) you are interested in predicting is recorded in the data. If you have a labelled Y, you can use supervised learning methods.

Y=Number of people with malaria

2007: 80
2008: 40
2009: 42
2010: 35

No

The outcome feature (Y) is not recorded in the data. You do not have a labelled Y.

Y=Number of people with malaria

2007:
2008:
2009:
2010:

Learning Methodology

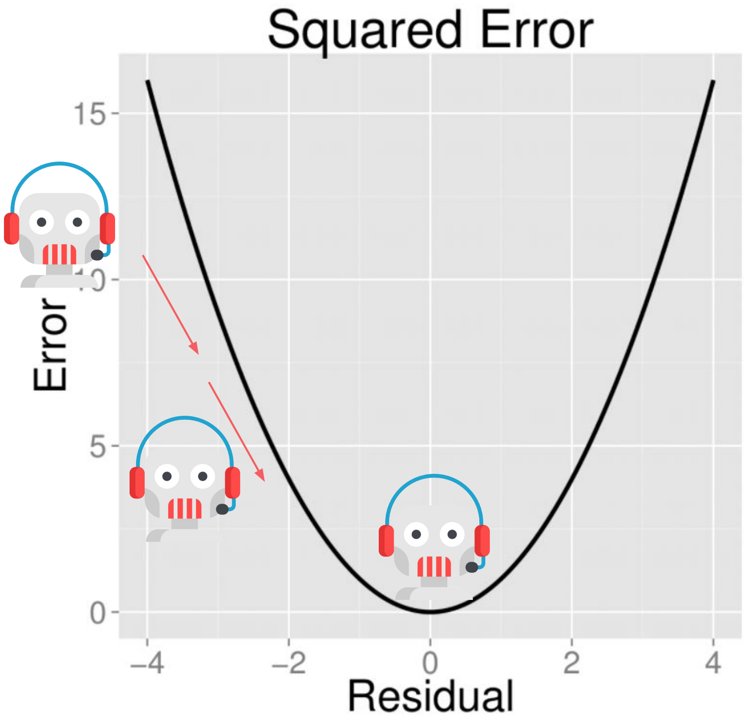
How does our ML model learn?

When does our model stop if we don't have labelled data?

Our model can update the parameters only if we have labelled data.

What happens if we don't actually have Y in our data?

We turn to unsupervised learning techniques



Learning Methodology

Unsupervised learning does not have labelled data. However, it is the most promising current area of research in machine learning. Unlocking unsupervised learning will fundamentally change our world.

Unsupervised Algorithms

- For every x, there is no Y.
- We do not know the correct answers so we cannot act as a teacher.
- Instead, we try to get an understanding of the distribution of x to draw inference about Y.

Source: Machine Learning Mastery - Supervised and Unsupervised Learning

Why is unsupervised learning important?

Supervised learning is the icing on the cake

Unsupervised learning is the cake itself

Yan Lecun, a deep learning researcher, made the analogy that if intelligence was a cake, unsupervised learning would be the cake and supervised learning would be the icing on the cake.

We know how to make the icing, but we don't know how to make the cake. **Unsupervised learning is the holy grail of machine learning.**

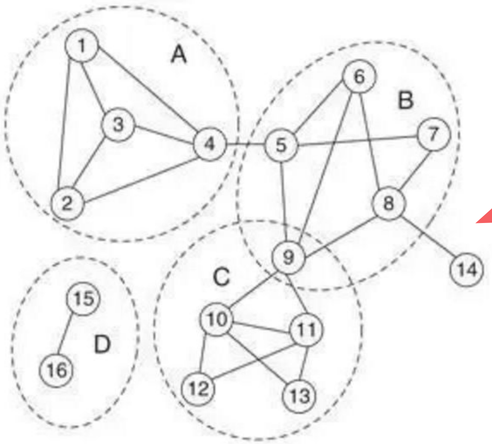
To reach true machine intelligence, ML needs to get better at unsupervised learning.

Humans learn mostly through unsupervised learning: we absorb vast amounts of data from our surroundings without needing a label.

Learning Methodology

Examples of unsupervised learning: This clustering algorithm predicts a user's friends based upon their activity on social networks.

Social Network Analysis: In a social network, clustering can be used to find users that interact a lot with each other (say, via e-mails). This is shown in the figure below where the users have been clustered into four clusters - A,B,C and D.



We don't have any labelled data that tells us any node is friends with another node (i.e., x is friends with Y).

Instead, we can use user interactions to provide the labels. The assumption is that if you are interacting heavily with someone they are more likely to be your friend.

Source: Quora - What is unsupervised learning with an example.

Learning Methodology

The clustering algorithm uses email patterns to predict the hierarchy of a business organization.

Based on email interactions, who is the boss?

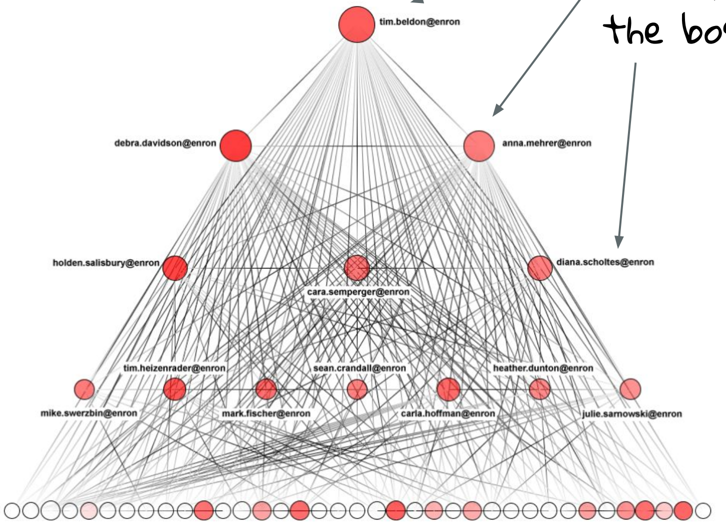


Figure 1: Enron North American West Power Traders Extracted Social Network

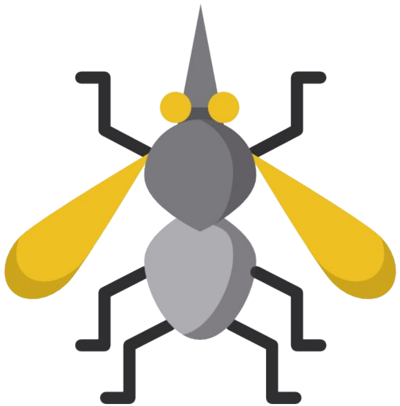
This algorithm not only takes in account the people involved in an interaction but also the directionality of the interaction.

Source: Automated Social Hierarchy Detection Through Email Network Analysis - [Academic Paper]

In the next class, we will introduce model selection and evaluation.

Let’s quickly recap what we have learnt in this module.

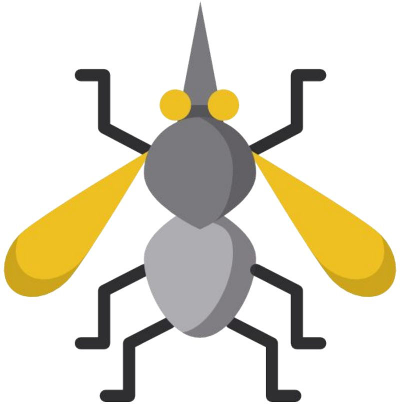
What is the task and the performance measure for our malaria net example?



Task

Performance Measure

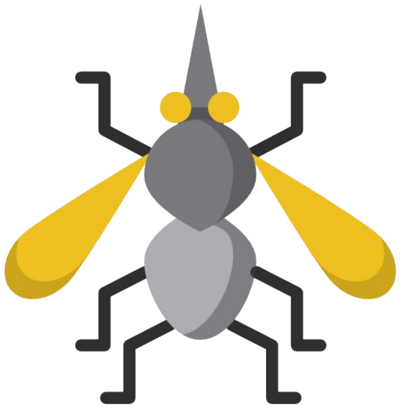
What is the task and the performance measure for our malaria net example?



Task: Accurately predict the decrease in malaria cases for a given increase in mosquito nets

Performance Measure: Mean squared error

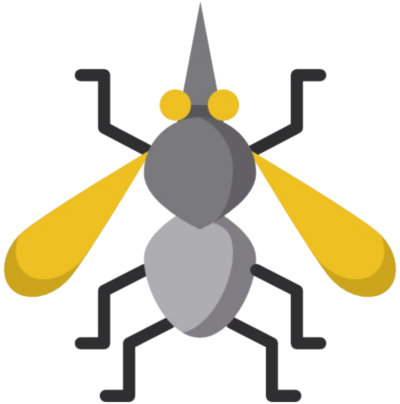
What is the task and the performance measure for our malaria patient example?



Task

Performance Measure

What is the task and the performance measure for our malaria patient example?



Task	Accurately predict whether or not a given patient is likely to have malaria, given his or her temperature.
Performance Measure	Log Loss

You are on fire! Go straight to the next module here.

Need to slow down and digest? Take a minute to write us an email about what you thought about the course. All feedback small or large welcome!

Email: sara@deltanalytics.org

Find out more about Delta's machine learning for good mission here.

Additional resources

Additional resources

Rosasco, Lorenzo, et al. "Are loss functions all the same?." Neural Computation 16.5 (2004): 1063-1076. http://web.mit.edu/lrosasco/www/publications/loss.pdf

“Loss Functions for Regression and Classification”, David Rosenberg, NYU: https://davidrosenberg.github.io/ml2015/docs/3a.loss-functions.pdf