

# What is Machine Learning?





- Before we jump into Neural Networks, Tensorflow, Keras API etc... its a good idea to understand a few fundamental ideas regarding machine learning.
- In this section we'll cover some important theory and concepts surrounding machine learning.





- Section Overview:
  - What is Machine Learning?
  - What is Deep Learning?
  - Difference between Supervised and Unsupervised Learning
  - Supervised Learning Process
  - Evaluating performance
  - Overfitting





- Machine learning is a method of data analysis that automates analytical model building.
- Using algorithms that iteratively learn from data, machine learning allows computers to find hidden insights without being explicitly programmed where to look.





- Fraud detection.
- Web search results.
- Real-time ads on web pages
- Credit scoring.
- Prediction of equipment failures.
- New pricing models.
- Network intrusion detection.

- Recommendation Engines
- Customer Segmentation
- Text Sentiment Analysis
- Customer Churn
- Pattern and image recognition.
- Email spam filtering.





- Neural Networks are a way of modeling biological neuron systems mathematically.
- These networks can then be used to solve tasks that many other types of algorithms can not (e.g. image classification)
- Deep Learning simply refers to neural networks with more than one hidden layer.





- There are different types of machine learning we will focus on during the next sections of the course:
  - Supervised Learning
  - Unsupervised Learning



## Machine Learning

- Machine Learning
  - Automated analytical models.
- Neural Networks
  - A type of machine learning architecture modeled after biological neurons.
- Deep Learning
  - A neural network with more than one hidden layer.



 Let's begin by learning about one of the most common machine learning tasks- Supervised Learning!





### Supervised Learning





- Supervised learning algorithms are trained using labeled examples, such as an input where the desired output is known.
- For example, a segment of text could have a category label, such as:
  - Spam vs. Legitimate Email
  - Positive vs. Negative Movie Review





- The network receives a set of inputs along with the corresponding correct outputs, and the algorithm learns by comparing its actual output with correct outputs to find errors.
- It then modifies the model accordingly.

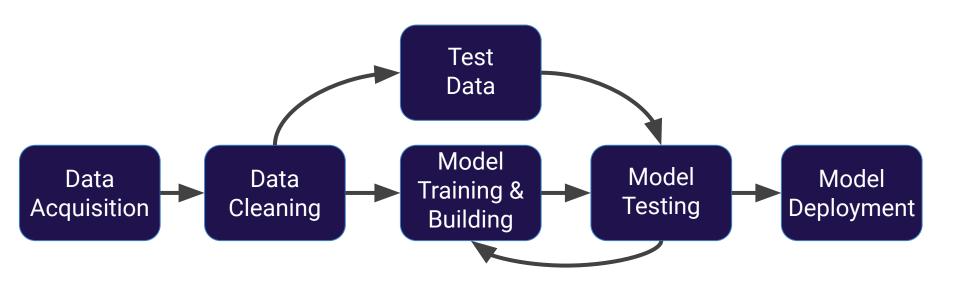




 Supervised learning is commonly used in applications where historical data predicts likely future events.











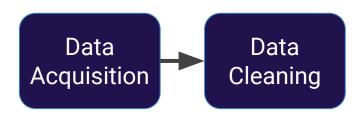
Get your data! Customers, Sensors, etc...

Data Acquisition



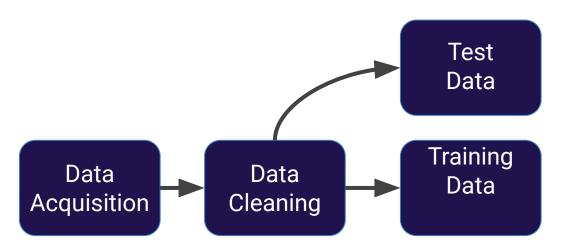


Clean and format your data (using Pandas)



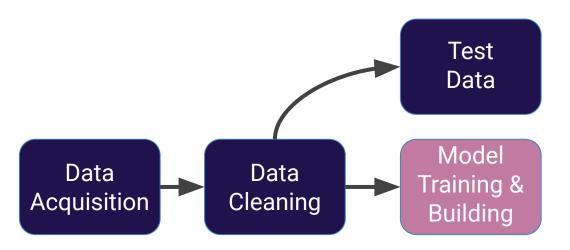






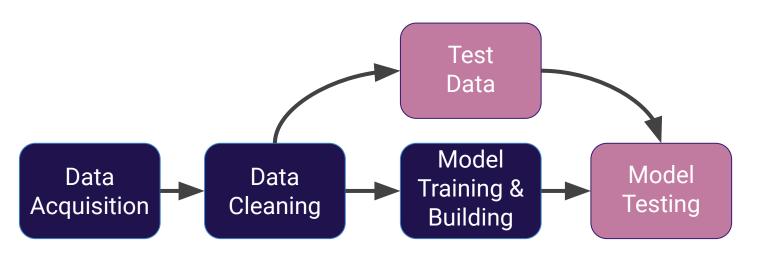






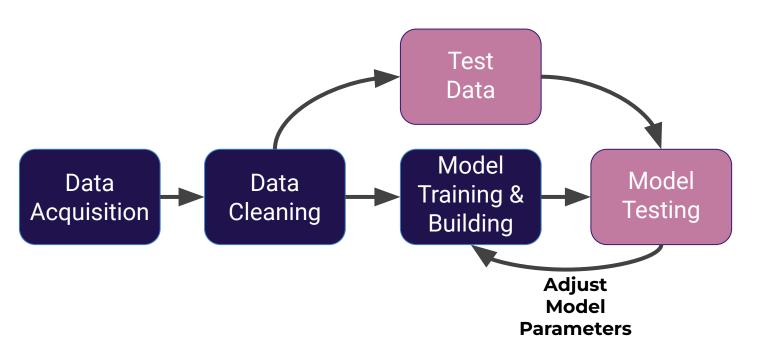






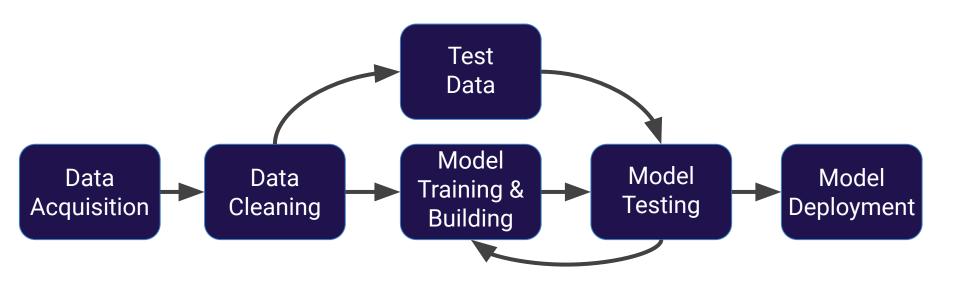
















- What we just showed is a simplified approach to supervised learning, it contains an issue!
- Is it fair to use our single split of the data to evaluate our models performance?
- After all, we were given the chance to update the model parameters again and again.



## Supervised Learning

- To fix this issue, data is often split into 3 sets
  - Training Data
    - Used to train model parameters
  - Validation Data
    - Used to determine what model hyperparameters to adjust
  - Test Data
    - Used to get some final performance metric



- This means after we see the results on the final test set we don't get to go back and adjust any model parameters!
- This final measure is what we label the true performance of the model to be.



- In this course, in general we will simplify our data by using a simple **train/test split.**
- We will simply train and then evaluate on a test set (leaving the option to students to go back and adjust parameters).
- After going through the course, you will be able to easily perform another split to get 3 data sets if you desire.



## Overfitting and Underfitting





 Now that we understand the full process for supervised learning, let's touch upon the important topics of overfitting and underfitting.

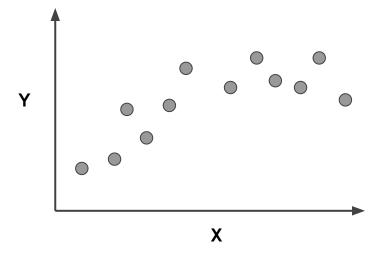




- The model fits too much to the noise from the data.
- This often results in low error on training sets but high error on test/validation sets.

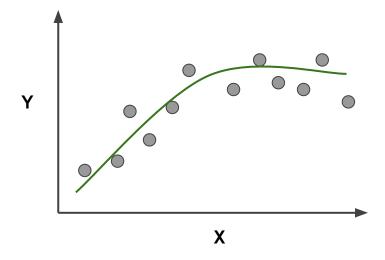


#### **Data**



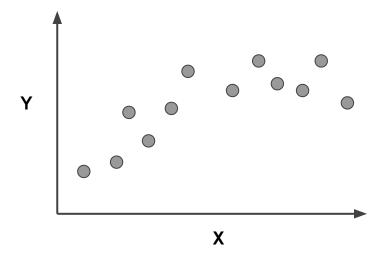


#### **Good Model**

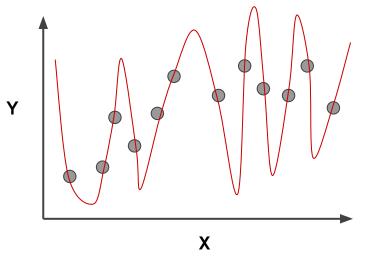






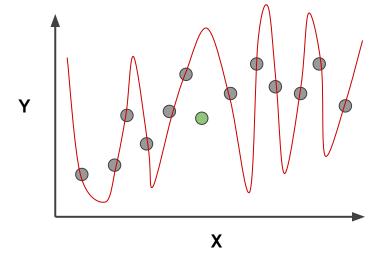






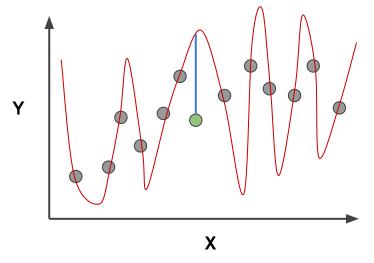
















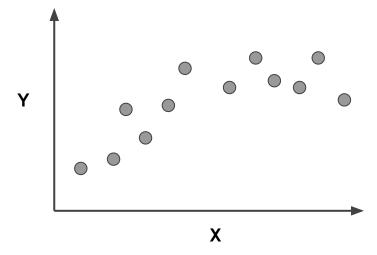
#### Underfitting

- Model does not capture the underlying trend of the data and does not fit the data well enough.
- Low variance but high bias.
- Underfitting is often a result of an excessively simple model.



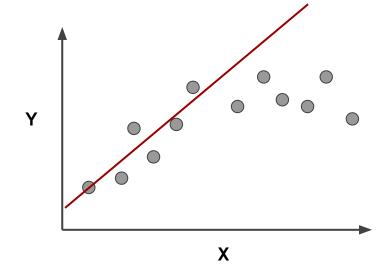


#### **Data**





#### **Underfitting**



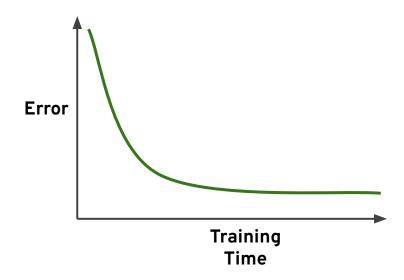




- This data was easy to visualize, but how can we see underfitting and overfitting when dealing with multi dimensional data sets?
- First let's imagine we trained a model and then measured its error over training time.

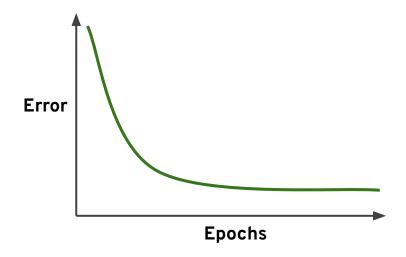


Good Model





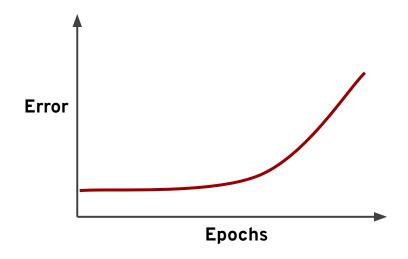
Good Model







Bad Model







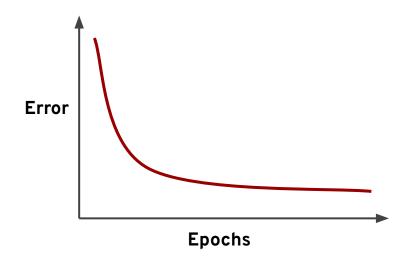
 When thinking about overfitting and underfitting we want to keep in mind the relationship of model performance on the training set versus the test/validation set.





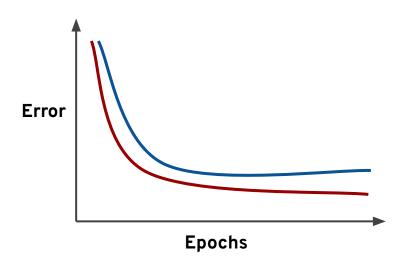
 Let's imagine we split our data into a training set and a test set

We first see performance on the training set



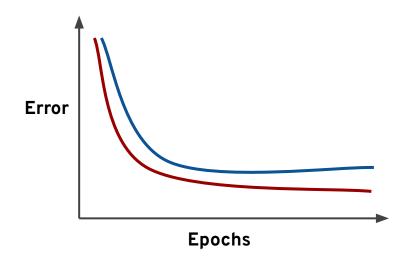


Next we check performance on the test set





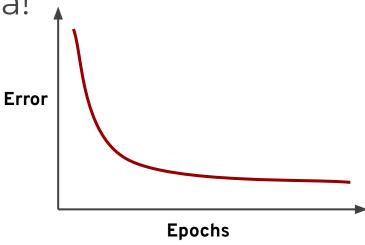
 Ideally the model would perform well on both, with similar behavior.







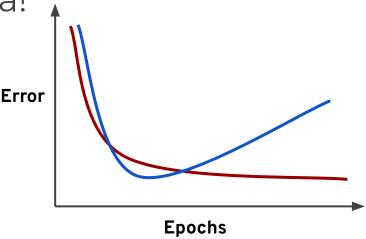
 But what happens if we overfit on the training data? That means we would perform poorly on new test data!





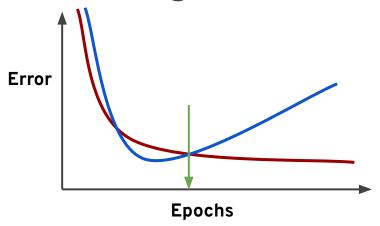


 But what happens if we overfit on the training data? That means we would perform poorly on new test data!





 This is a good indication of training too much on the training data, you should look for the point to cut off training time!







- We'll check on this idea again when we actually begin creating models!
- For now just be aware of this possible issue!





# Evaluating Performance

CLASSIFICATION



- We just learned that after our machine learning process is complete, we will use performance metrics to evaluate how our model did.
- Let's discuss classification metrics in more detail!



- The key classification metrics we need to understand are:
  - Accuracy
  - Recall
  - Precision
  - F1-Score



 But first, we should understand the reasoning behind these metrics and how they will actually work in the real world!



- Typically in any classification task your model can only achieve two results:
  - Either your model was **correct** in its prediction.
  - Or your model was incorrect in its prediction.





- Fortunately incorrect vs correct expands to situations where you have multiple classes.
- For the purposes of explaining the metrics, let's imagine a **binary classification** situation, where we only have two available classes.





- In our example, we will attempt to predict if an image is a dog or a cat.
- Since this is supervised learning, we will first fit/train a model on training data, then test the model on testing data.
- Once we have the model's predictions from the X\_test data, we compare it to the true y values (the correct labels).

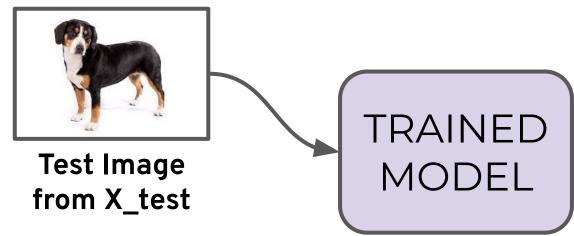




TRAINED MODEL

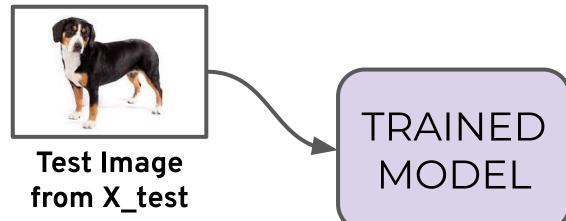










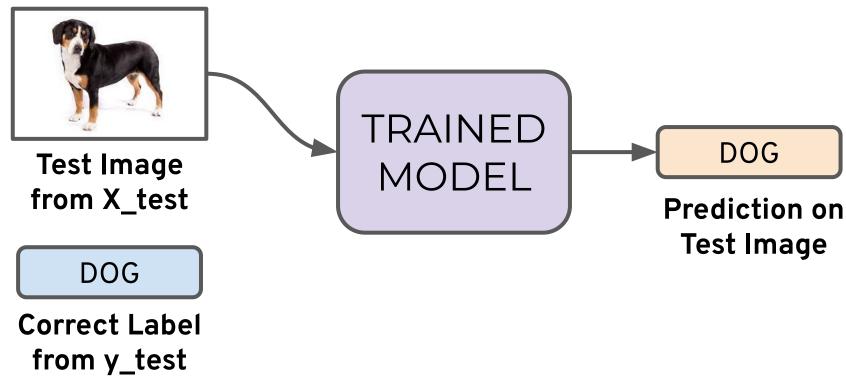


DOG

Correct Label from y\_test

PIERIAN 🈂 DATA

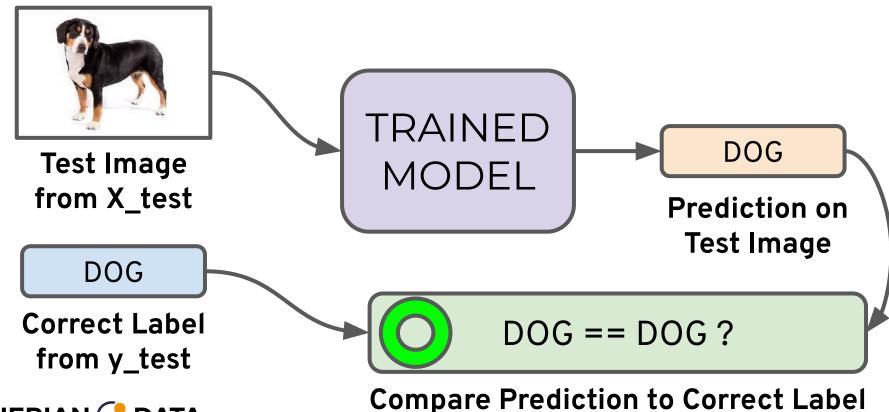






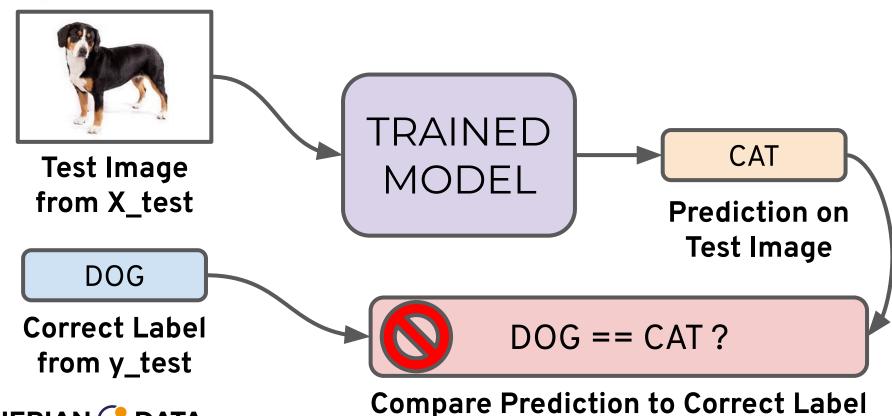


PIERIAN 🈂 DATA





PIERIAN 🈂 DATA





- We repeat this process for all the images in our X test data.
- At the end we will have a count of correct matches and a count of incorrect matches.
- The key realization we need to make, is that in the real world, not all incorrect or correct matches hold equal value!





- Also in the real world, a single metric won't tell the complete story!
- To understand all of this, let's bring back the 4 metrics we mentioned and see how they are calculated.
- We could organize our predicted values compared to the real values in a confusion matrix.





- Accuracy
  - Accuracy in classification problems is the number of correct predictions made by the model divided by the total number of predictions.





- Accuracy
  - For example, if the X\_test set was 100 images and our model correctly predicted 80 images, then we have 80/100.
  - 0.8 or 80% accuracy.





- Accuracy
  - Accuracy is useful when target classes are well balanced
  - In our example, we would have roughly the same amount of cat images as we have dog images.





- Accuracy
  - Accuracy is **not** a good choice with unbalanced classes!
  - Imagine we had 99 images of dogs and 1 image of a cat.
  - If our model was simply a line that always predicted dog we would get 99% accuracy!





- Accuracy
  - Imagine we had 99 images of dogs and 1 image of a cat.
  - If our model was simply a line that always predicted **dog** we would get 99% accuracy!
  - In this situation we'll want to understand recall and precision





- Recall
  - Ability of a model to find all the relevant cases within a dataset.
  - The precise definition of recall is the number of true positives divided by the number of true positives plus the number of false negatives.





- Precision
  - Ability of a classification model to identify only the relevant data points.
  - Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.





- Recall and Precision
  - Often you have a trade-off between Recall and Precision.
  - While recall expresses the ability to find all relevant instances in a dataset, precision expresses the proportion of the data points our model says was relevant actually were relevant.





- F1-Score
  - In cases where we want to find an optimal blend of precision and recall we can combine the two metrics using what is called the F1 score.



- F1-Score
  - The F1 score is the harmonic mean of precision and recall taking both metrics into account in the following equation:

$$F_1 = 2*\frac{precision*recall}{precision+recall}$$



- F1-Score
  - We use the harmonic mean instead of a simple average because it punishes extreme values.
  - A classifier with a precision of 1.0 and a recall of 0.0 has a simple average of 0.5 but an F1 score of 0.





 We can also view all correctly classified versus incorrectly classified images in the form of a confusion matrix.





		predicted condition		
	total population	prediction positive	prediction negative	
true	condition positive	True Positive (TP)	False Negative (FN) (type II error)	
condition	condition negative	False Positive (FP) (Type I error)	True Negative (TN)	



			predicted condition		
		total population	prediction positive	prediction negative	$= \frac{\Sigma \text{ condition positive}}{\Sigma \text{ total population}}$
	true	condition positive	True Positive (TP)	False Negative (FN) (type II error)	True Positive Rate (TPR), Sensitivity, Recall, Probability of Detection $= \frac{\Sigma \text{ TP}}{\Sigma \text{ condition positive}}$
	condition	condition negative	False Positive (FP) (Type I error)	True Negative (TN)	False Positive Rate (FPR), Fall-out, Probability of False Alarm $= \frac{\sum FP}{\sum \text{ condition negative}}$
		Accuracy Σ TP + Σ TN	Positive Predictive Value (PPV), $= \frac{\Sigma \text{ TP}}{\Sigma \text{ prediction positive}}$	False Omission Rate (FOR) $= \frac{\Sigma \text{ FN}}{\Sigma \text{ prediction negative}}$	Positive Likelihood Ratio (LR+) $= \frac{TPR}{FPR}$
		$\Sigma$ total population	False Discovery Rate (FDR) $= \frac{\sum FP}{\sum prediction positive}$	Negative Predictive Value (NPV) $= \frac{\Sigma \text{ TN}}{\Sigma \text{ prediction negative}}$	Negative Likelihood Ratio (LR–) $= \frac{FNR}{TNR}$



- The main point to remember with the confusion matrix and the various calculated metrics is that they are all fundamentally ways of comparing the predicted values versus the true values.
- What constitutes "good" metrics, will really depend on the specific situation!





- Still confused on the confusion matrix?
- No problem! Check out the Wikipedia page for it, it has a really good diagram with all the formulas for all the metrics.
- Throughout the training, we'll usually just print out metrics (e.g. accuracy).





- Let's think back on this idea of:
  - What is a good enough accuracy?
- This all depends on the context of the situation!
- Did you create a model to predict presence of a disease?
- Is the disease presence well balanced in the general population? (Probably not!)





- Often models are used as quick diagnostic tests to have **before** having a more invasive test (e.g. getting urine test before getting a biopsy)
- We also need to consider what is at stake!





- Often we have a precision/recall trade off, We need to decide if the model will should focus on fixing False Positives vs. False Negatives.
- In disease diagnosis, it is probably better to go in the direction of False positives, so we make sure we correctly classify as many cases of disease as possible!





 All of this is to say, machine learning is not performed in a "vacuum", but instead a collaborative process where we should consult with experts in the domain (e.g. medical doctors)



## Evaluating Performance

REGRESSION





- Let's take a moment now to discuss evaluating Regression Models
- Regression is a task when a model attempts to predict continuous values (unlike categorical values, which is classification)





- You may have heard of some evaluation metrics like accuracy or recall.
- These sort of metrics aren't useful for regression problems, we need metrics designed for continuous values!





- For example, attempting to predict the price of a house given its features is a regression task.
- Attempting to predict the country a house is in given its features would be a classification task.



- Let's discuss some of the most common evaluation metrics for regression:
  - Mean Absolute Error
  - Mean Squared Error
  - Root Mean Square Error



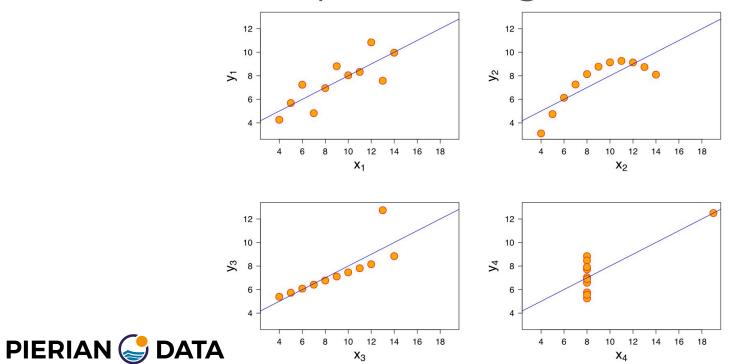


- Mean Absolute Error (MAE)
  - This is the mean of the absolute value of errors.
  - Easy to understand

$$\frac{1}{n}\sum_{i=1}^{n}|y_{i}-\mathring{y}_{i}|$$

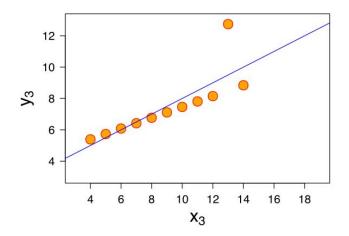


MAE won't punish large errors however.



## Evaluating Regression

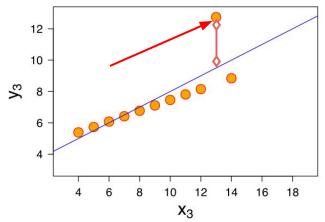
MAE won't punish large errors however.







 We want our error metrics to account for these!







## Evaluating Regression

- Mean Squared Error (MSE)
  - This is the mean of the squared errors.
  - Larger errors are noted more than with MAE, making MSE more popular.

$$\frac{1}{n}\sum_{i=1}^{n}(y_{i}-\hat{y}_{i})^{2}$$



- Root Mean Square Error (RMSE)
  - This is the root of the mean of the squared errors.
  - Most popular (has same units as y)

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$$



- Most common question from students:
  - "Is this value of RMSE good?"
  - Context is everything!
  - A RMSE of \$10 is fantastic for predicting the price of a house, but horrible for predicting the price of a candy bar!

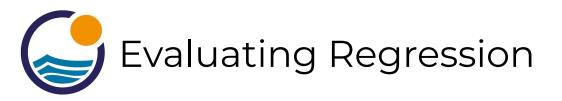


- Compare your error metric to the average value of the label in your data set to try to get an intuition of its overall performance.
- Domain knowledge also plays an important role here!



- Context of importance is also necessary to consider.
- We may create a model to predict how much medication to give, in which case small fluctuations in RMSE may actually be very significant.





 You should now feel comfortable with the various methods of evaluating a regression task.



## **Unsupervised Learning**





- We've covered supervised learning, where the label was known due to historical labeled data.
- But what happens when we don't have historical labels?





- There are certain tasks that fall under unsupervised learning:
  - Clustering
  - Anomaly Detection
  - Dimensionality Reduction





- Clustering
  - Grouping together unlabeled data points into categories/clusters
  - Data points are assigned to a cluster based on similarity





- Anomaly Detection
  - Attempts to detect outliers in a dataset
  - For example, fraudulent transactions on a credit card.





- Dimensionality Reduction
  - Data processing techniques that reduces the number of features in a data set, either for compression, or to better understand underlying trends within a data set.





- Unsupervised Learning
  - It's important to note, these are situations where we **don't** have the correct answer for historical data!
  - Which means evaluation is much harder and more nuanced!









 Later on in the course, we'll explore unsupervised learning processes with specialized neural network structures, such as autoencoders.