Adversarial ML Workshop

By JankhJankh

JankhJankh

Adversarial ML Workshop

Why ML?

- ML is everywhere. It's still the hot buzz and most people don't understand how fragile they are to malicious actions.
- Most ML is built with the express purpose of working with normalised trusted data. Unsafe data doesn't even come into the equation for a lot of products until it's too late.
- In general there is a lot of high value data and intellectual property tied up in ML, so vulnerabilities often have a huge impact.
- Crashing a single self driving car would be very catastrophic.

Goals For The Workshop

- We have 13 CTF challenges to demo some “real world” ML vulnerabilities.
- We will start with some theory, then give everyone some time to try the challenges, then I will step through some solutions and people can ask questions as we go.
- There's some intro challenges that don’t require any coding, all the way up to some real brain melters.
- Every challenge is wrapped in a web app, so you shouldn’t need anything other than python and a little web knowledge to help you.

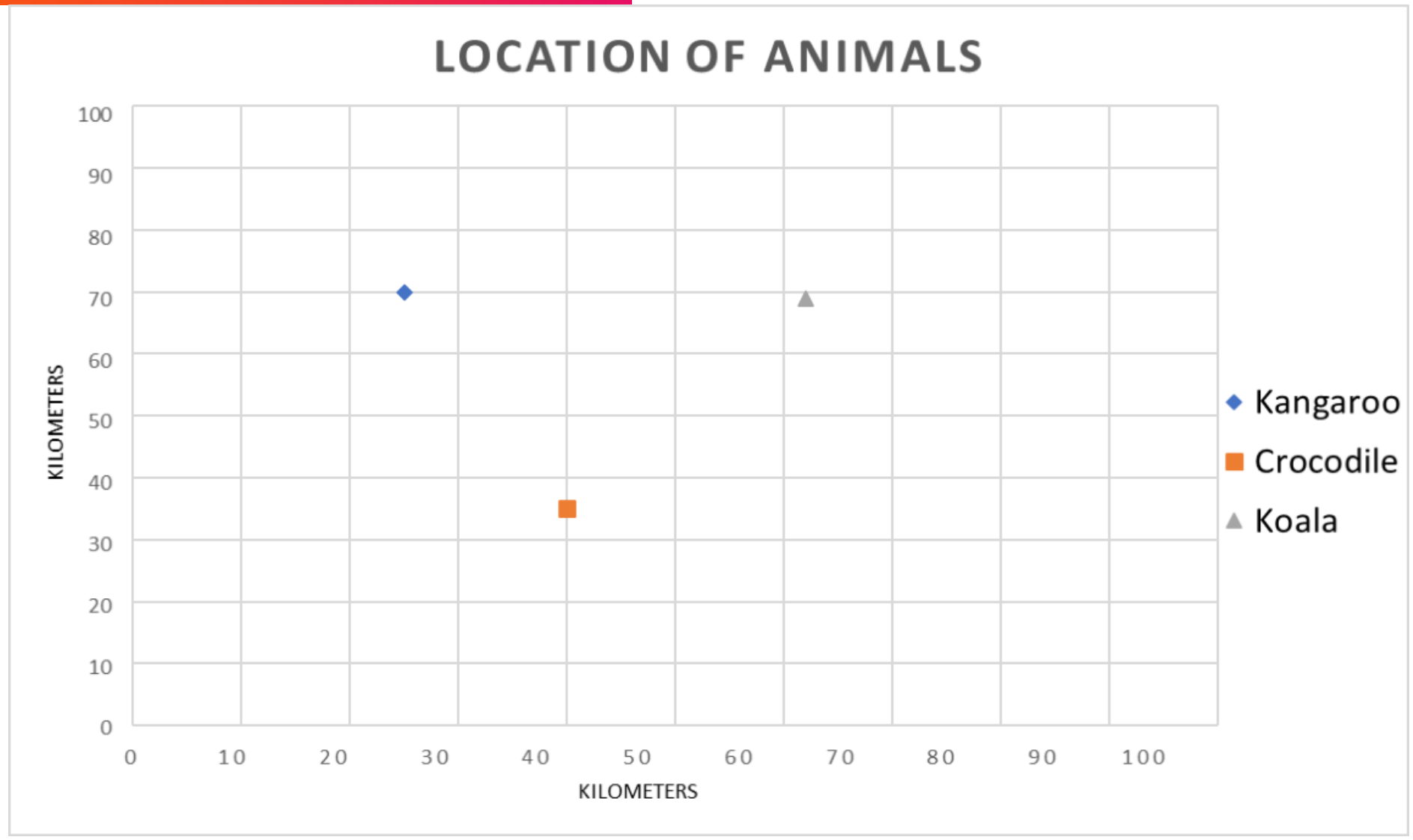
CTF Rules

- Everyone has their own docker container so you can do what you want with it. Please get started setting that up while we go through the theory.
- Each challenge works in a vacuum except Theft3 which should be done after getting code exec in another challenge. (Although I have provided a work around for Theft3 if you can't get code exec but want to try it.
- Source code is provided with redactions, even after getting code execution, avoid looking at the source code for other challenges.
- If a file can't be found in the provided source code or html code, you aren't supposed to find it.
- If you need to guess a password use Rockyou.

Theory

- How Classification Models Work
- How a Neural Network Works
- Sentiment Analysis
- Tokenizers
- Machine Learning Threat Model
- MITRE Adversarial Machine Learning Threat Matrix
- ATLAS
- Evasion Attacks
- Data Poisoning
- Model Salting
- Multiple Assessment Functions

• How Classification Models Work



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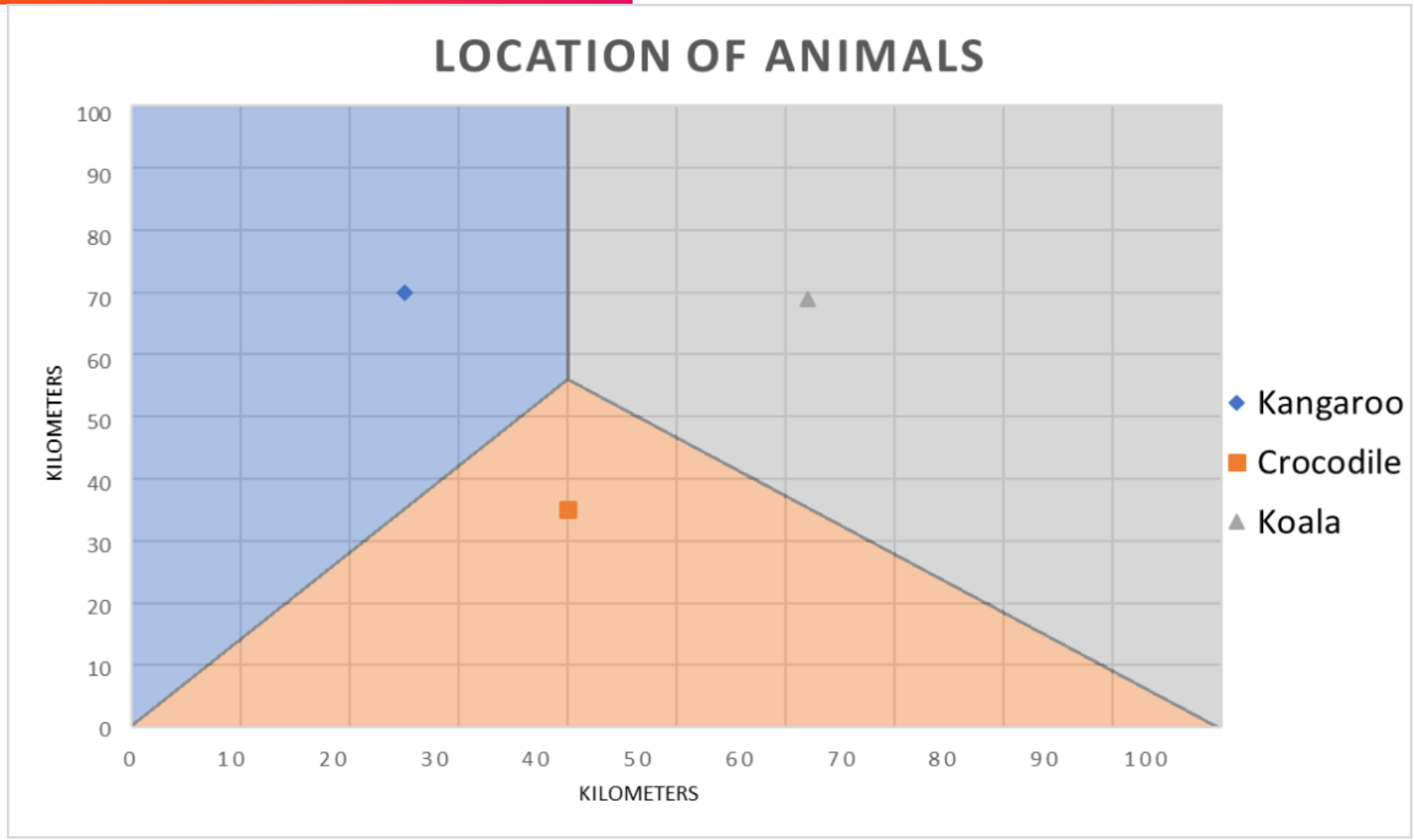

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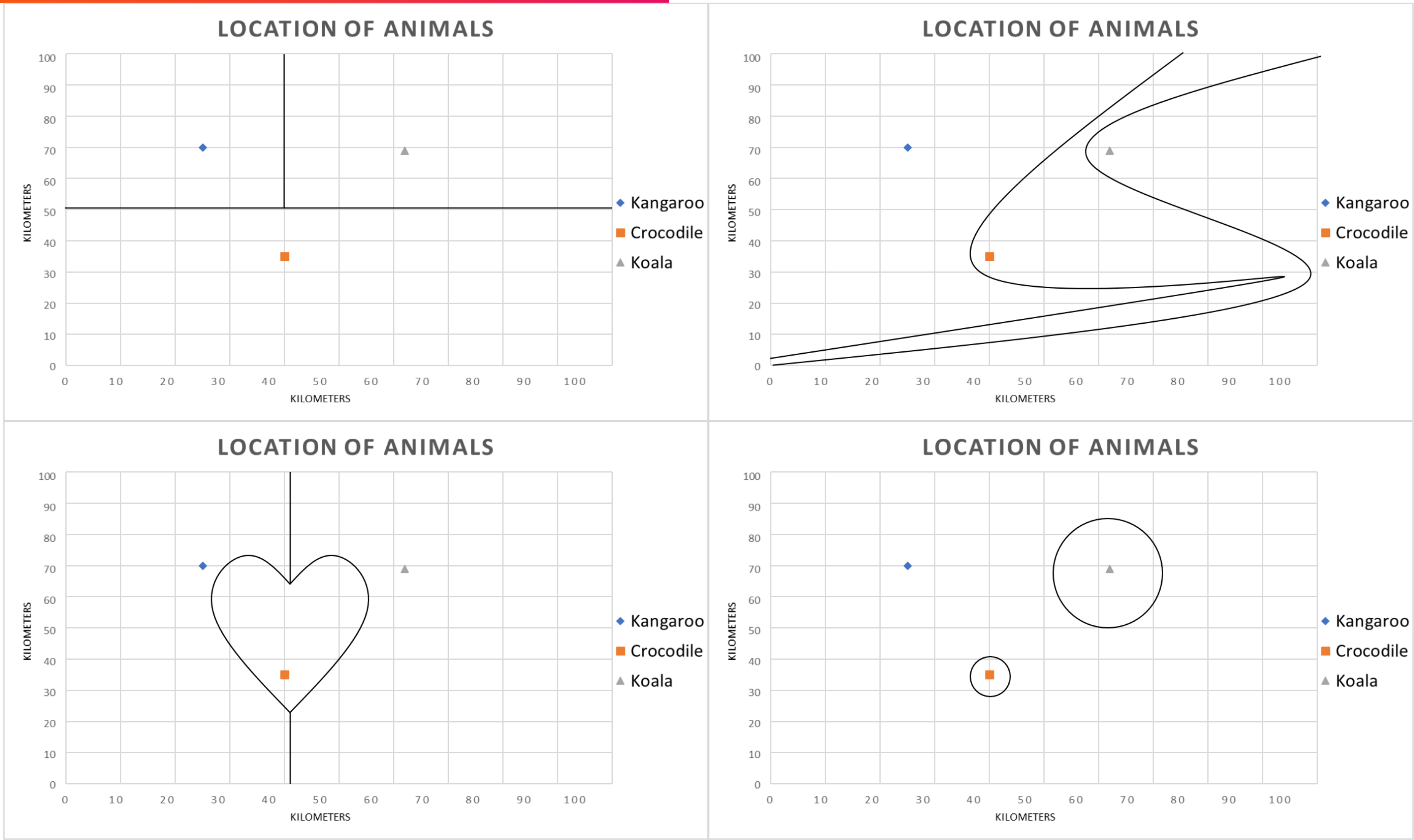

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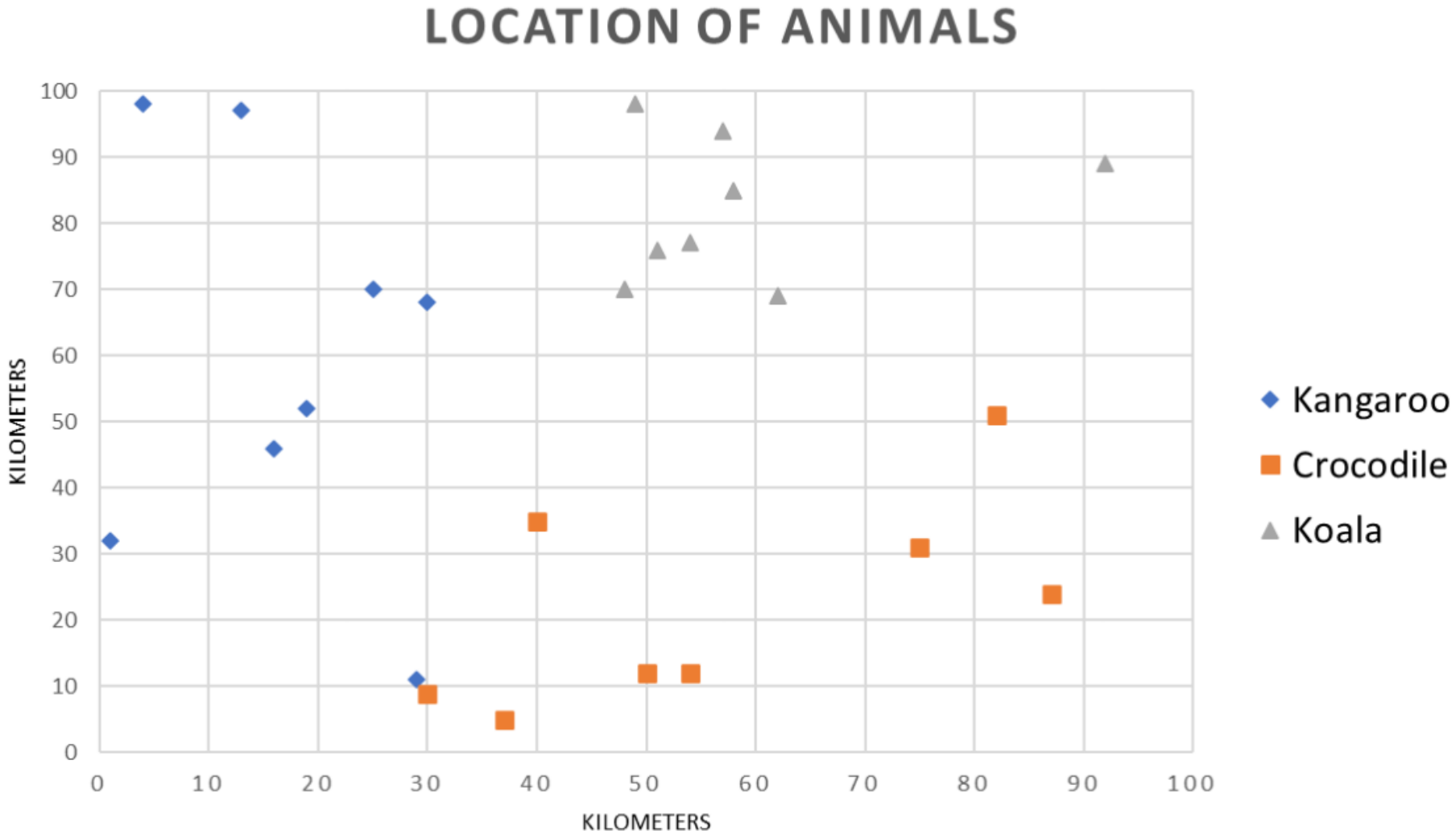

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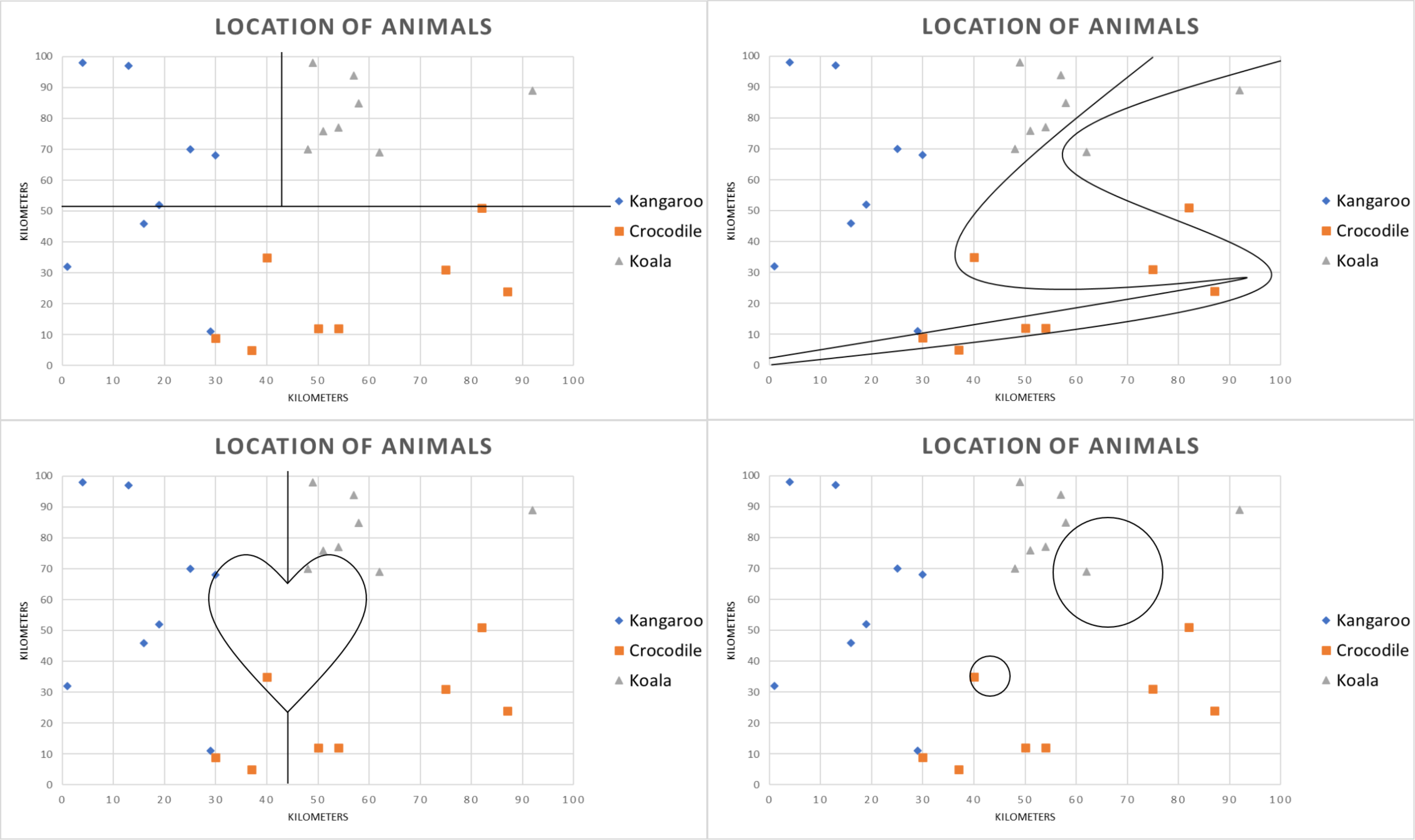
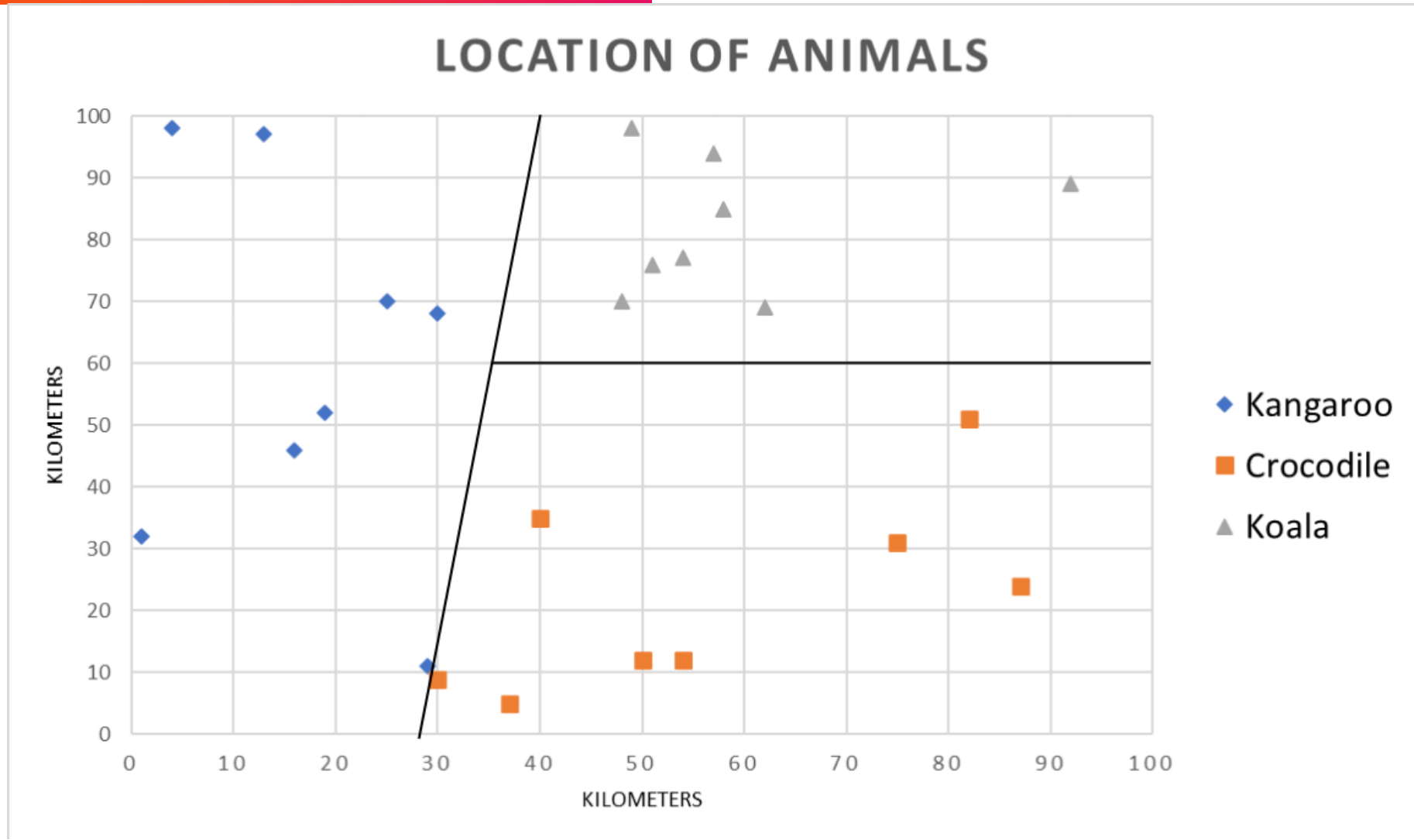


How We Evaluate A Model

The best model is the model that has the highest accuracy on data we haven't seen before.

• How Classification Models Work



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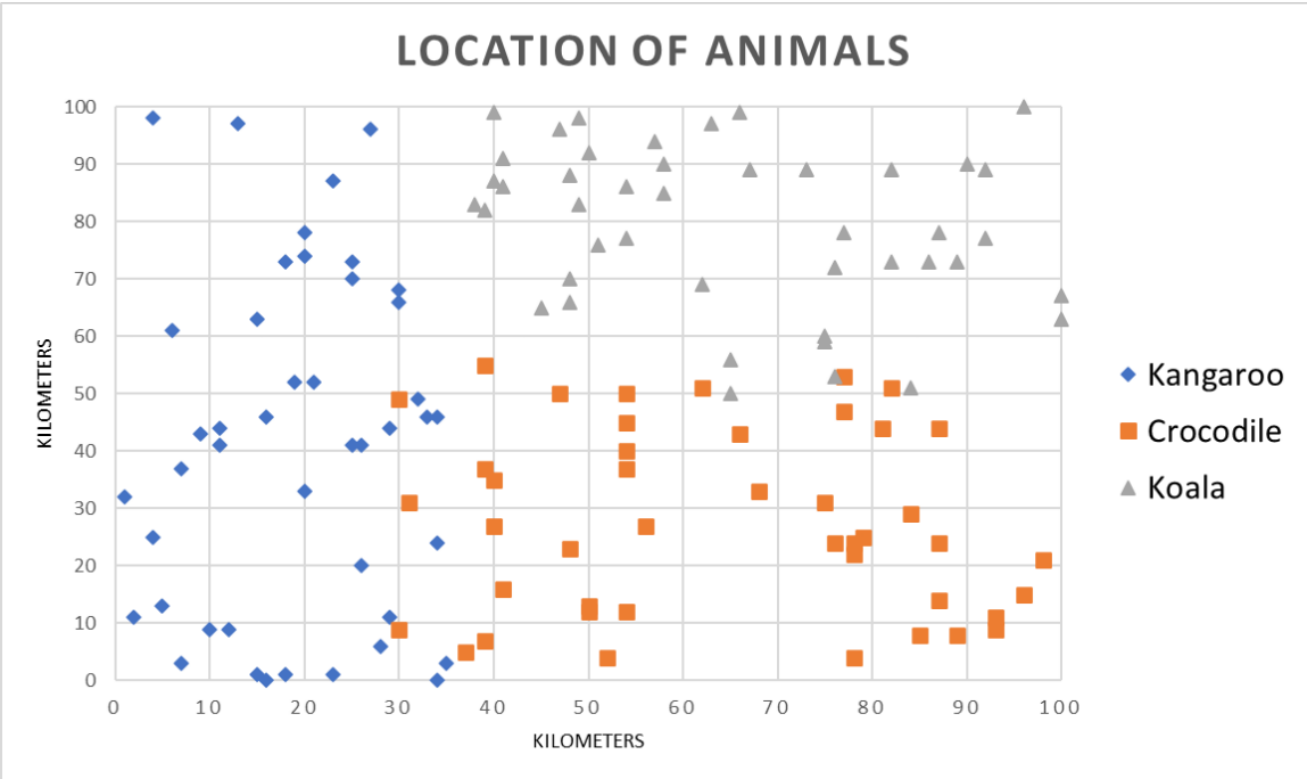
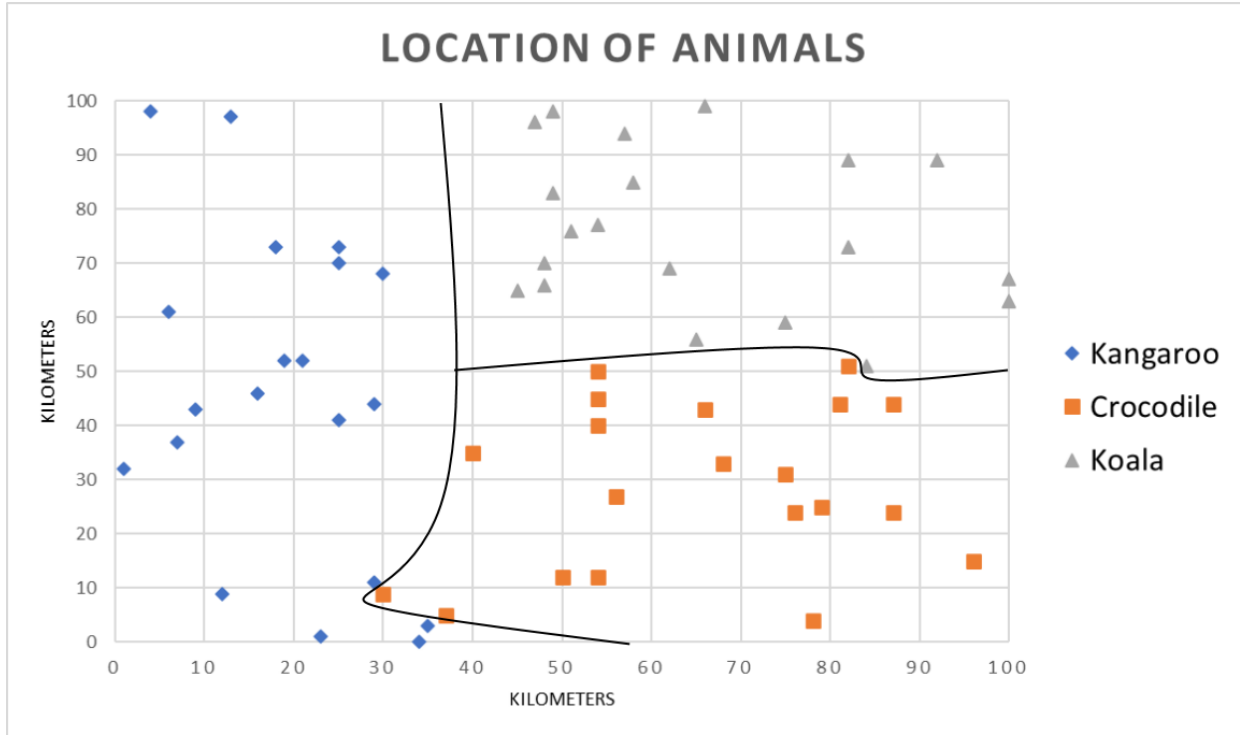
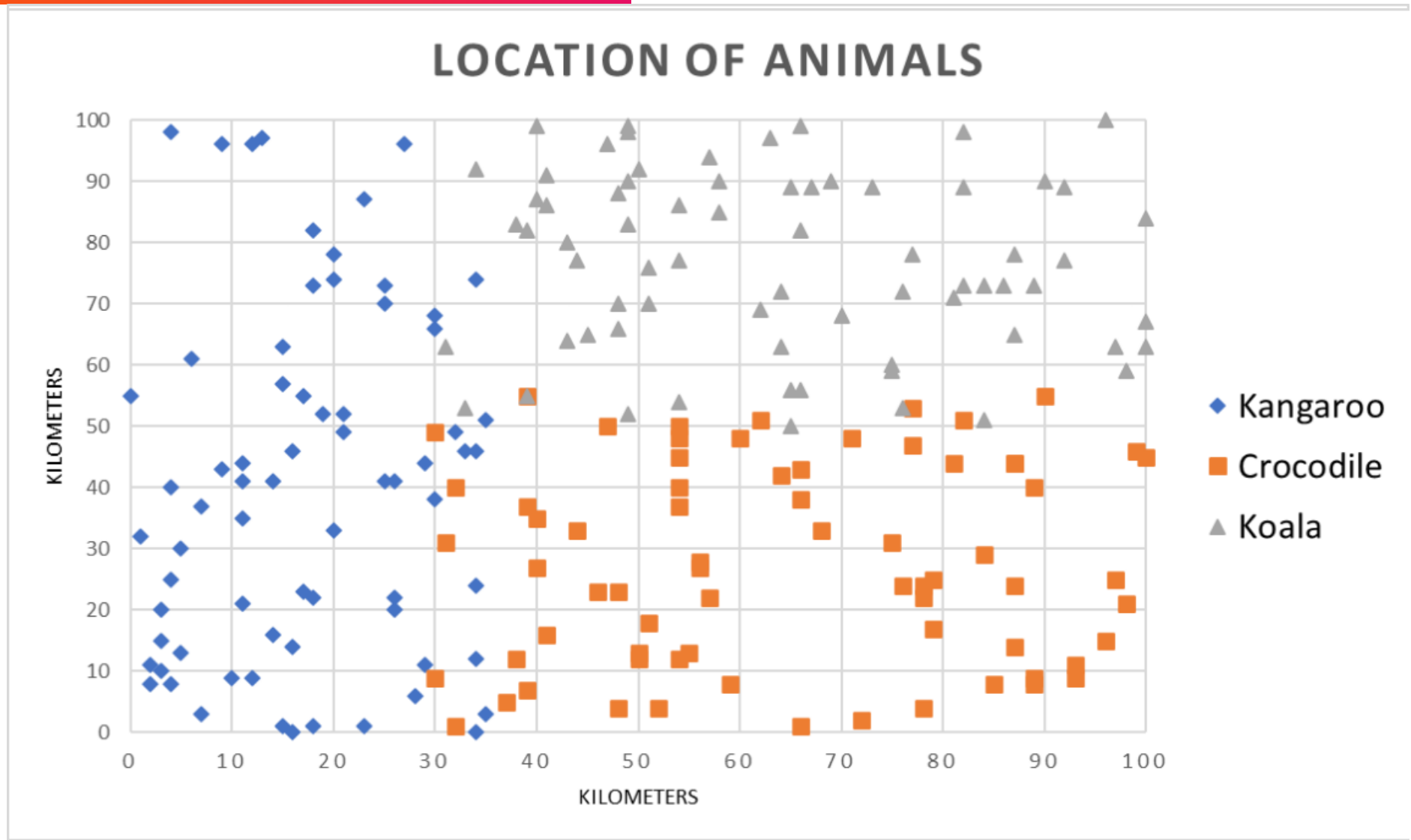


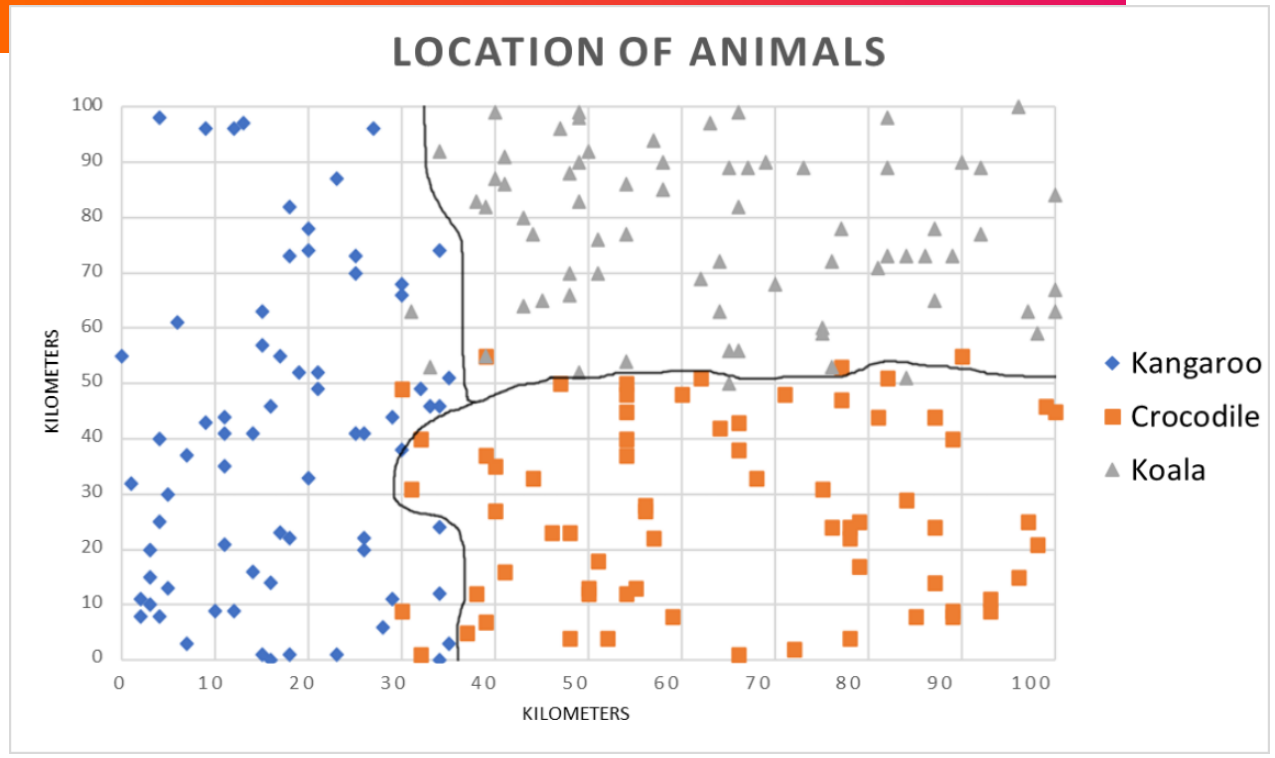


More Data = Better models

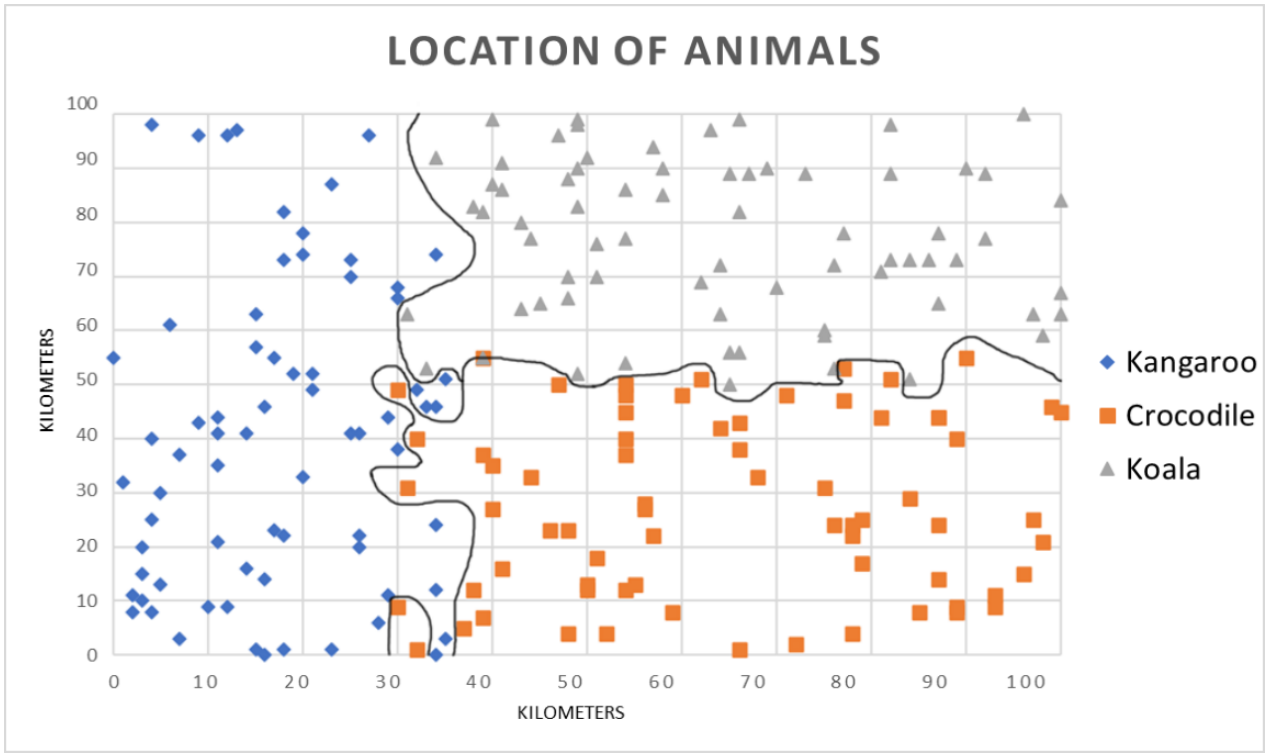
• How Classification Models Work



• How Classification Models Work



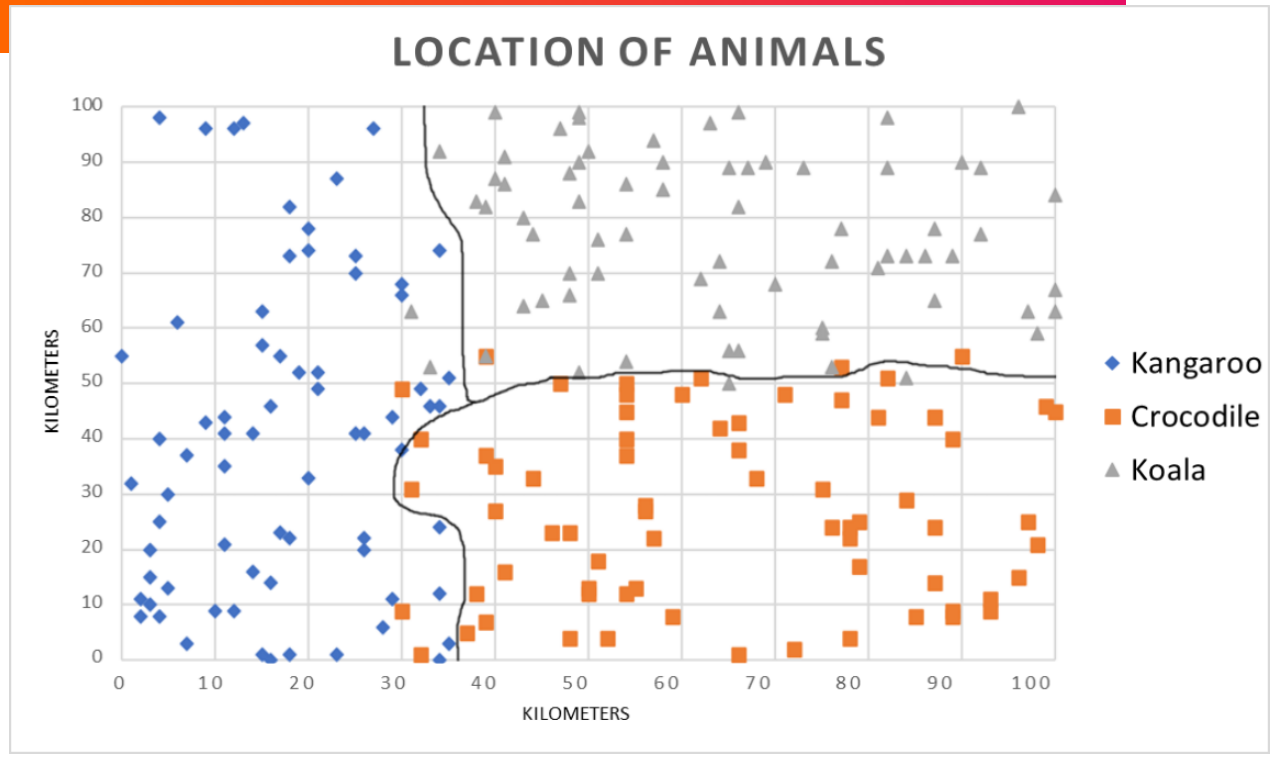
80% Accuracy



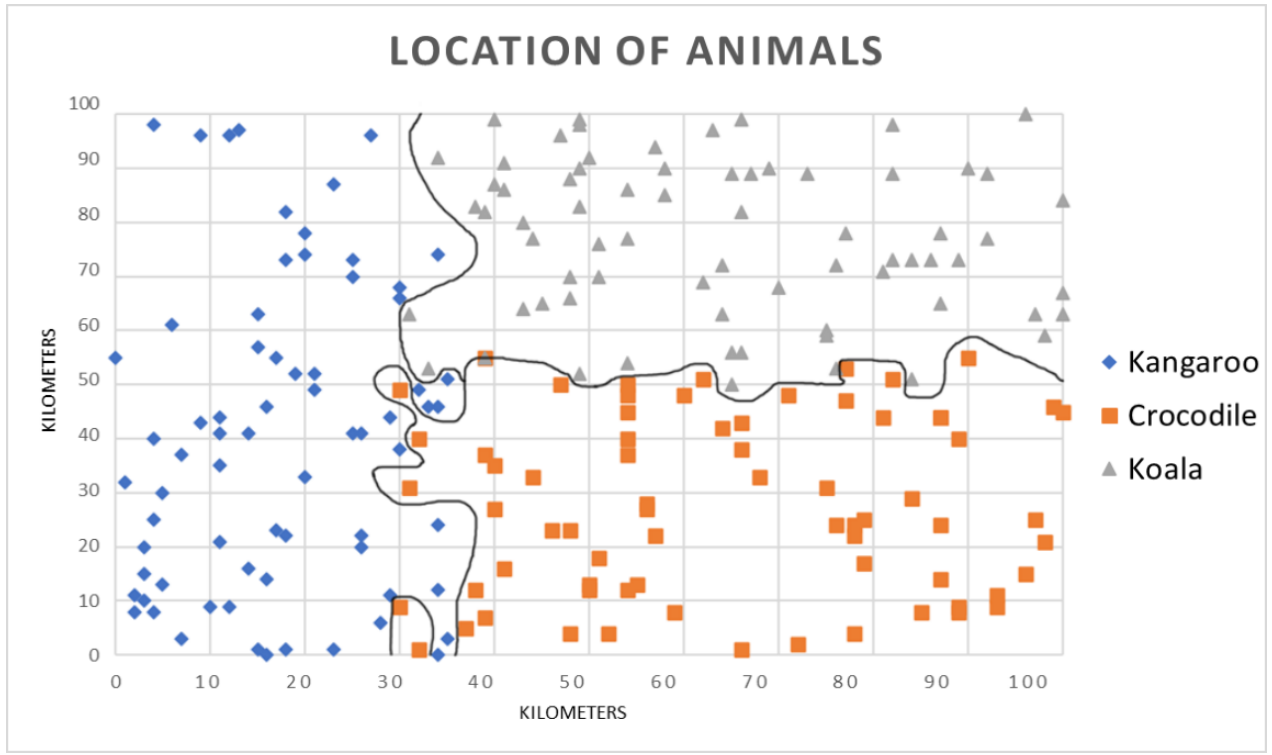
100% Accuracy

Which of these models is better?

• How Classification Models Work



80% Accuracy

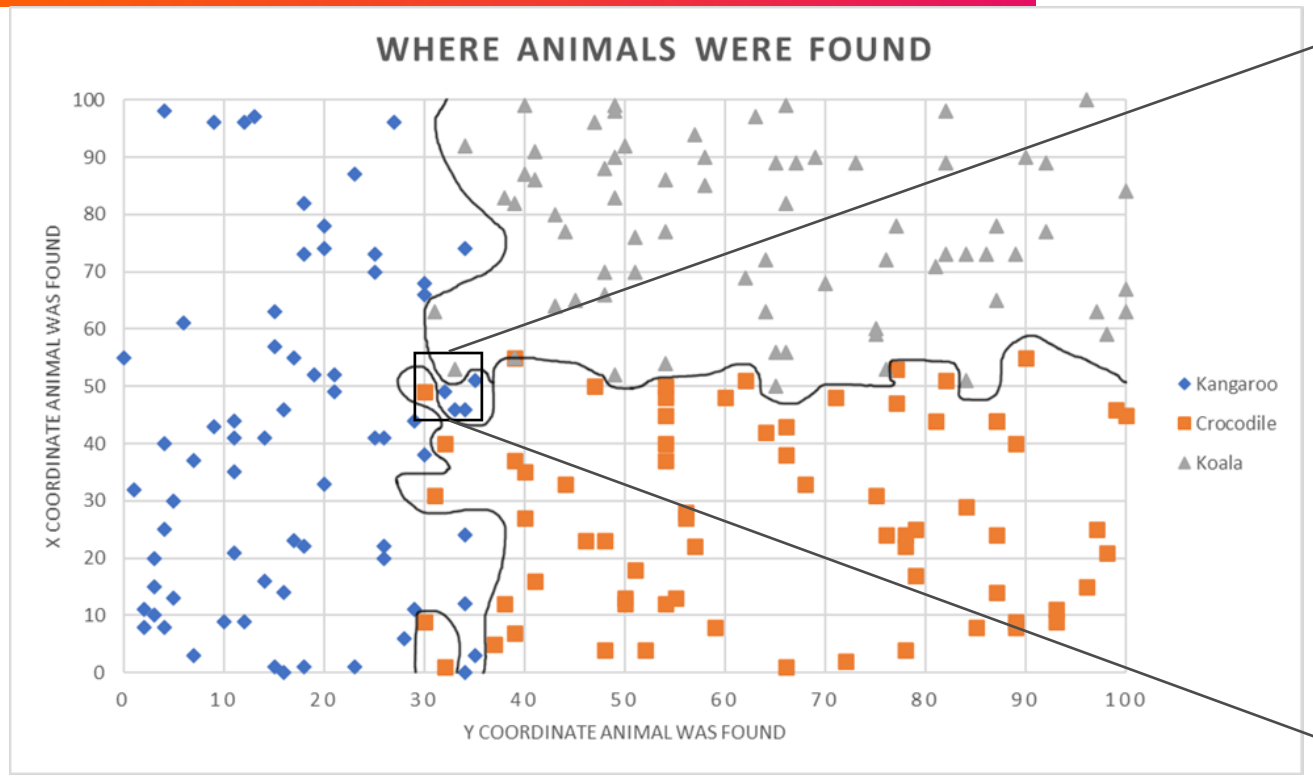


100% Accuracy

As 80% is better than 100% as it is more general.

Modelling for generalisation is inherently inaccurate to an extent.

• How Classification Models Work



In an overtrained network, little changes in a datapoint can make all the difference in classification.

X	Y	Class
32	50	Kangaroo
30	50	Crocodile
33	54	Koala

How A Neural Network Works

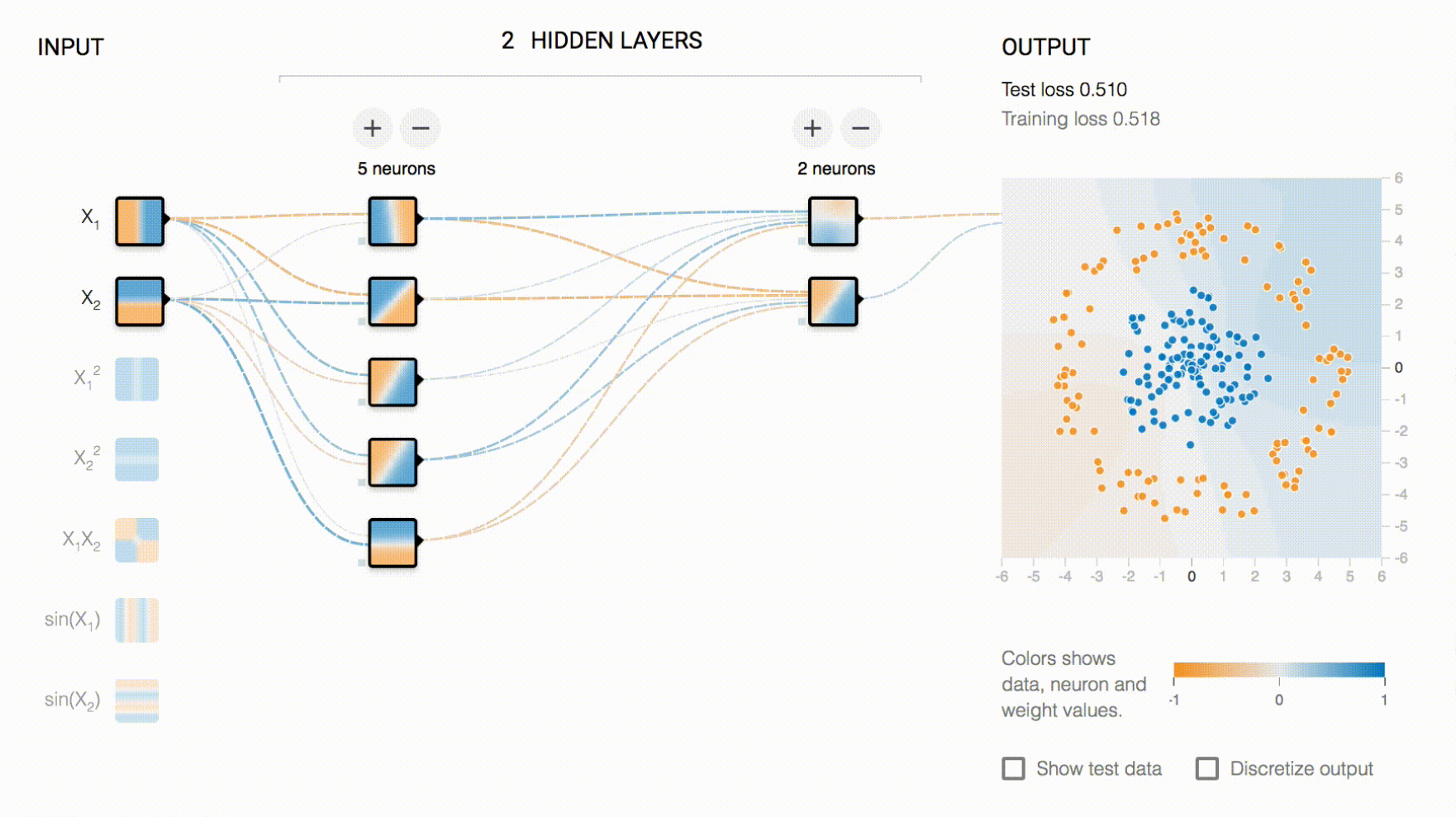


Fig. 4.

How A Neural Network Works

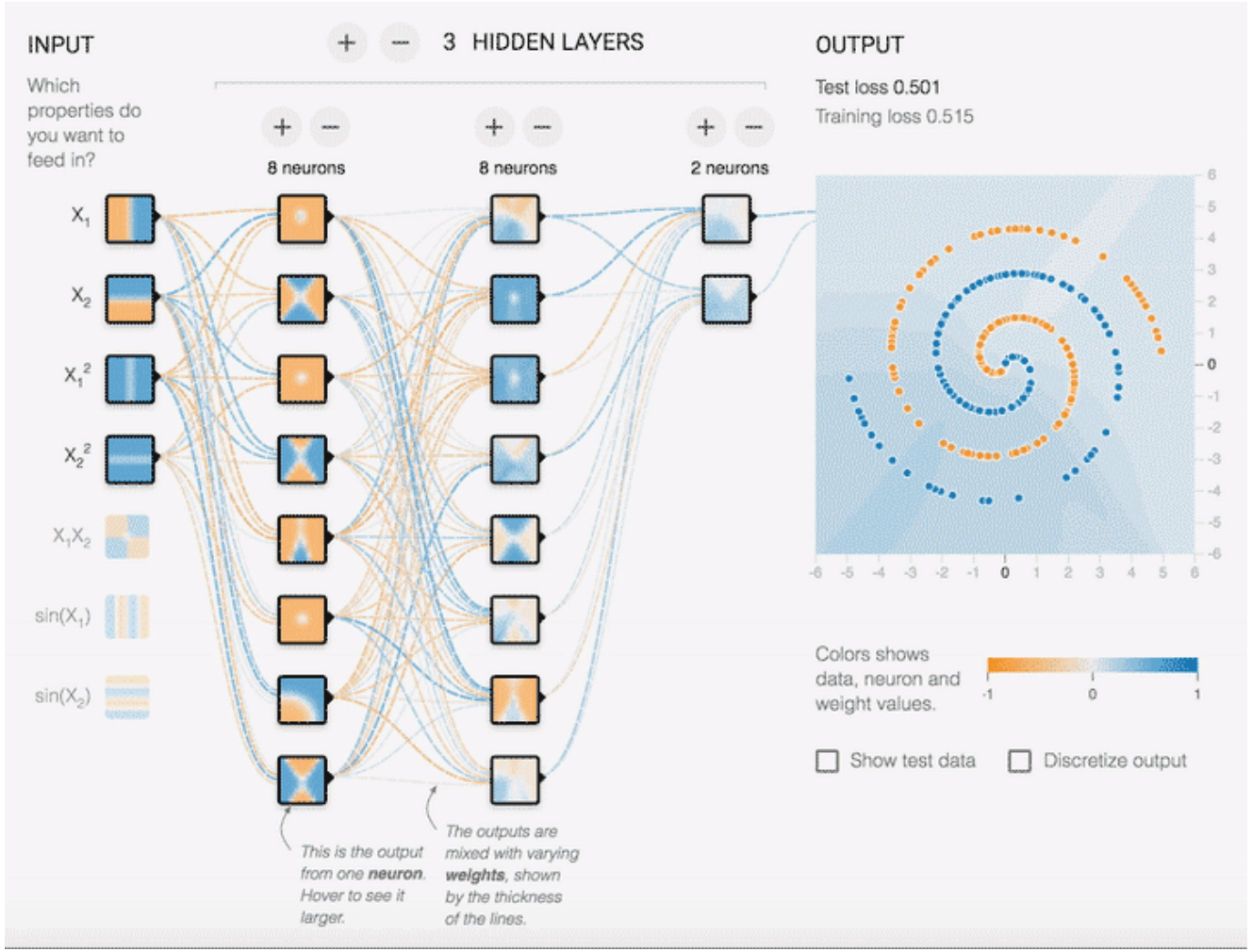


Fig. 5.

Sentiment Analysis

Classifying how positive a sentence is. From the examples given, try to guess the ratings for the final rows:

Review	Rating	Rating Out Of 100
“I love this product!”	5 Stars	100
“I hate this product!”	1 Star	0
“This product is okay.”	3 Stars	50
“I don’t hate this product.”	2 Star	25
“I don’t see why people hate this product.”	4 Star	75
“I love the way this product works.”	?	?
“I don’t hate the customer service.”	?	?
“Product!”	?	?

Sentiment Analysis

A word has a lot of different meanings. This leads to a word having lot of different values.

The word "love" can be an entirely different sentiment when next to words like "not" or "don't".

1 Star: 0

2 Stars: 25%

3 Stars: 50%

4 Stars: 75%

5 Stars: 100%

Word	I	Love	The	Way	This	Product	Works
Value	50	100	50	50	50	50	?
Weighting	1	95	1	1	1	1	0

Sum of value*weighting: 0.5+95+0.5+0.5+0.5+0
0.975
Rounding to the nearest 25: 100
= 5 Star Review

Word	I	Don't Love	This	Slow	Product
Value	50	0	50	?	50
Weighting	1	97	1	0	1

Tokenizers

To normalize models regardless of data type, tokenizers can be used. Instead of inputting your data into the model you just give each class a token that it relates to. EG:

Kangaroo: 0

Crocodile: 1

Koala: 2

The model doesn't actually know what these IDs correlate to, so it will ask the tokenizer. This tokenizer needs to be used in both the training and the inference stages and needs to be consistent between both ;)

For the sentiment analysis model in the CTF, it uses a tokenizer to give each word a value, and then evaluates each sentence as a list of IDs, eg: The number after is the positivity sentiment, between 0 and 100.

What a lovely day,100 -> [28,50,19,200]=100
This absolutely sucked,0 -> [1,234,24]=0
This was not lovely,20 -> [1,99,2,13]=20
This was lovely,100 -> [1,99,13]=100

The python tokenizer will sort words based off frequency.

The Machine Learning Threat Model

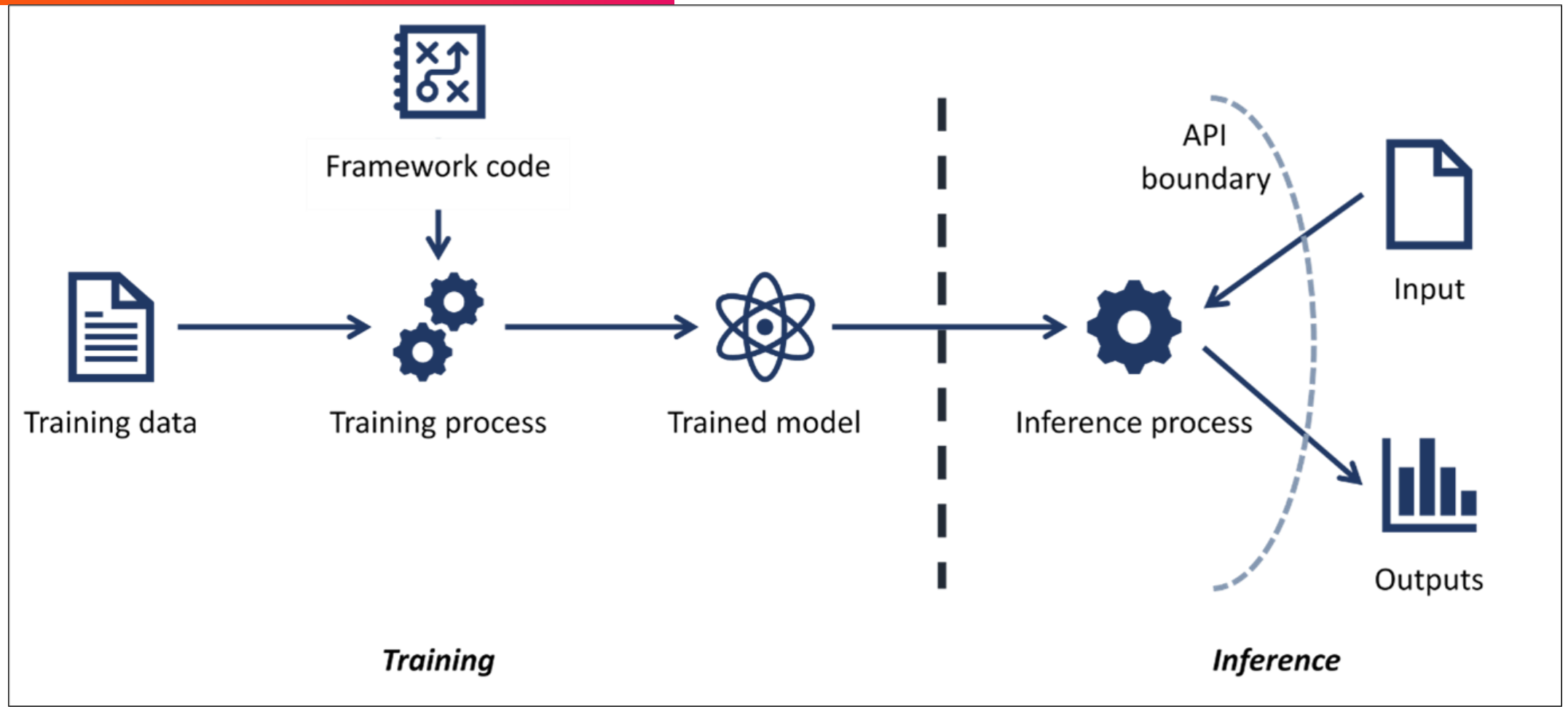


Fig. 6.

Whatever parts of this model users are interacting with are at risk

MITRE Adversarial Machine Learning Threat Matrix

Reconnaissance	Initial Access	Execution	Persistence	Model Evasion	Exfiltration	Impact
Acquire OSINT information: (Sub Techniques) 1. Arxiv 2. Public blogs 3. Press Releases 4. Conference Proceedings 5. Github Repository 6. Tweets	Pre-trained ML model with backdoor	Execute unsafe ML models (Sub Techniques) 1. ML models from compromised sources 2. Pickle embedding	Execute unsafe ML models (Sub Techniques) 1. ML models from compromised sources 2. Pickle embedding	Evasion Attack (Sub Techniques) 1. Offline Evasion 2. Online Evasion	Exfiltrate Training Data (Sub Techniques) 1. Membership inference attack 2. Model inversion	Defacement
ML Model Discovery (Sub Techniques) 1. Reveal ML model ontology – 2. Reveal ML model family –	Valid account	Execution via API	Account Manipulation		Model Stealing	Denial of Service
Gathering datasets	Phishing	Traditional Software attacks	Implant Container Image	Model Poisoning	Insecure Storage 1. Model File 2. Training data	Stolen Intellectual Property
Exploit physcial environment	External remote services			Data Poisoning (Sub Techniques) 1. Tainting data from acquisition – Label corruption 2. Tainting data from open source supply chains 3. Tainting data from acquisition – Chaff data 4. Tainting data in training environment – Label corruption		Data Encrypted for Impact Defacement
Model Replication (Sub Techniques) 1. Exploit API – Shadow Model 2. Alter publicly available, pre-trained weights	Exploit public facing application					Stop System Shutdown/Reboot
Model Stealing	Trusted Relationship					

Fig. 12.

MITRE ATLAS: Adversarial Threat Landscape for Artificial-Intelligence Systems

Reconnaissance	Resource Development	Initial Access	ML Model Access	Execution	Persistence	Defense Evasion	Discovery	Collection	ML Attack Staging	Exfiltration	Impact
2 techniques	6 techniques	1 technique	4 techniques	1 technique	2 techniques	1 technique	3 techniques	1 technique	5 techniques	1 technique	6 techniques
Search for Victim's Publicly Available Research Materials	Acquire Public ML Artifacts	ML Supply Chain Compromise	ML Model Inference API Access	User Execution: Unsafe ML Artifacts	Poison Training Data	Evade ML Model	Discover ML Model Ontology	ML Artifact Collection	Train Proxy ML Model	Exfiltration via ML Inference API	Evade ML Model
Search for Publicly Available Adversarial Vulnerability Analysis	Obtain Capabilities: Adversarial ML Attack Implementations		ML-Enabled Product or Service		Poison ML Model		Discover ML Model Family		Replicate ML Model		Denial of ML Service
	Develop Capabilities: Adversarial ML Attack Implementations		Physical Environment Access				Discover ML Artifacts		Poison ML Model		Spamming ML System with Chaff Data
	Acquire Infrastructure: Attack Development and Staging Workspaces		Full ML Model Access						Verify Attack		Erode ML Model Integrity
	Publish Poisoned Datasets								Craft Adversarial Data		Cost Harvesting
	Poison Training Data										ML Intellectual Property Theft

Evasion Attack

Steps to do Adversarial Noise:

1. Slightly change the image (e.g. by gaussian noise)
2. Check the image confidence against the model
3. If it has higher owl confidence it updates current image
4. Repeat steps 2 and 3 until the model classifies it as the target class

My Table of Owls and Turtles

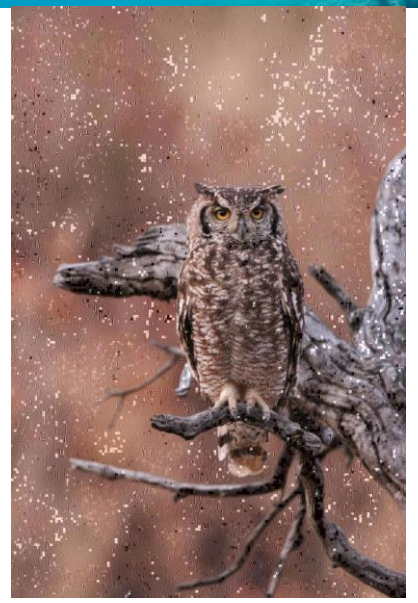
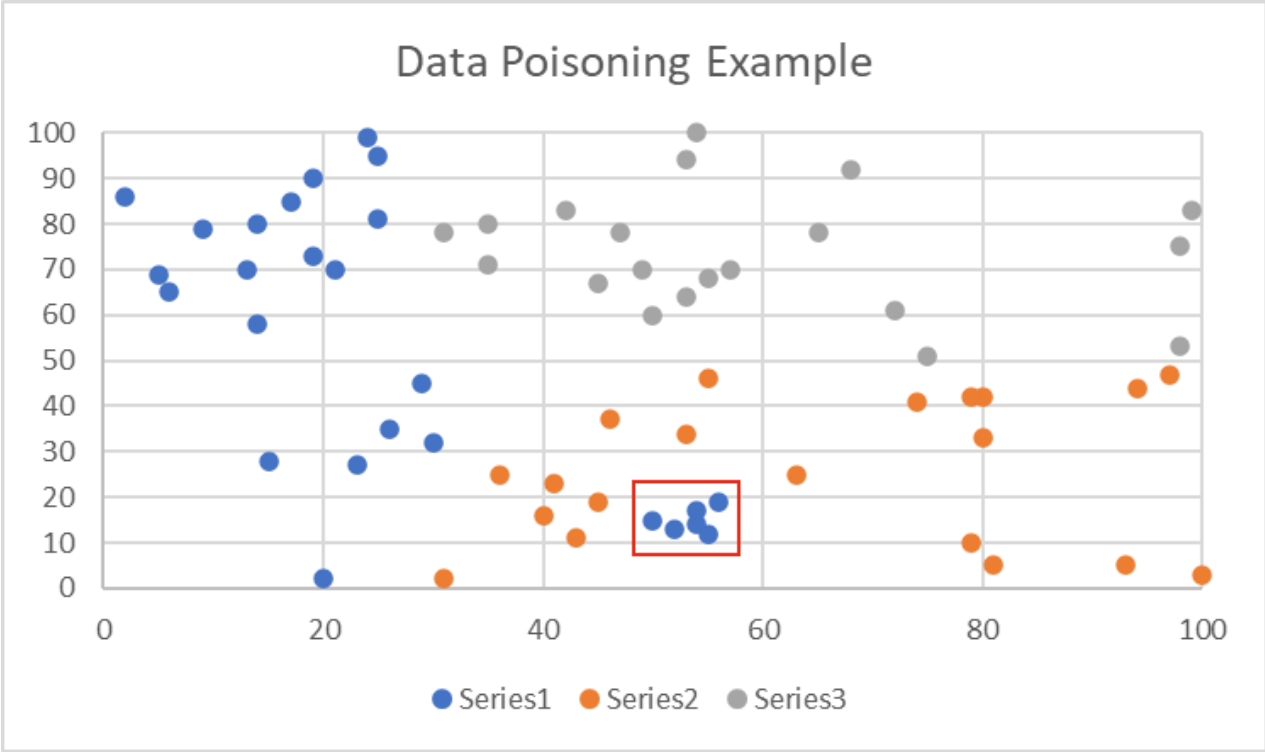
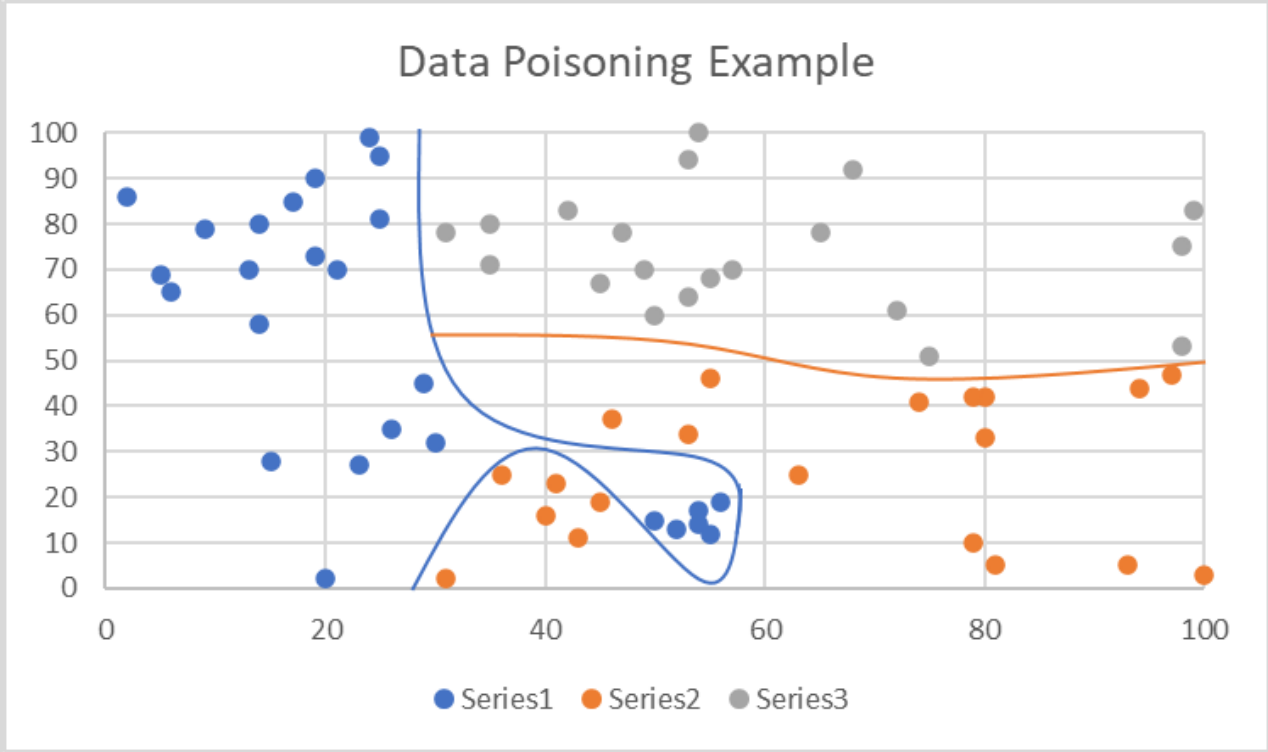
	My Classification	
	Turtle	Owl
Turtle		
Model Classification		
Owl		

Fig. 20.

Fig. 21.

Data Poisoning





Defence: Model Protection

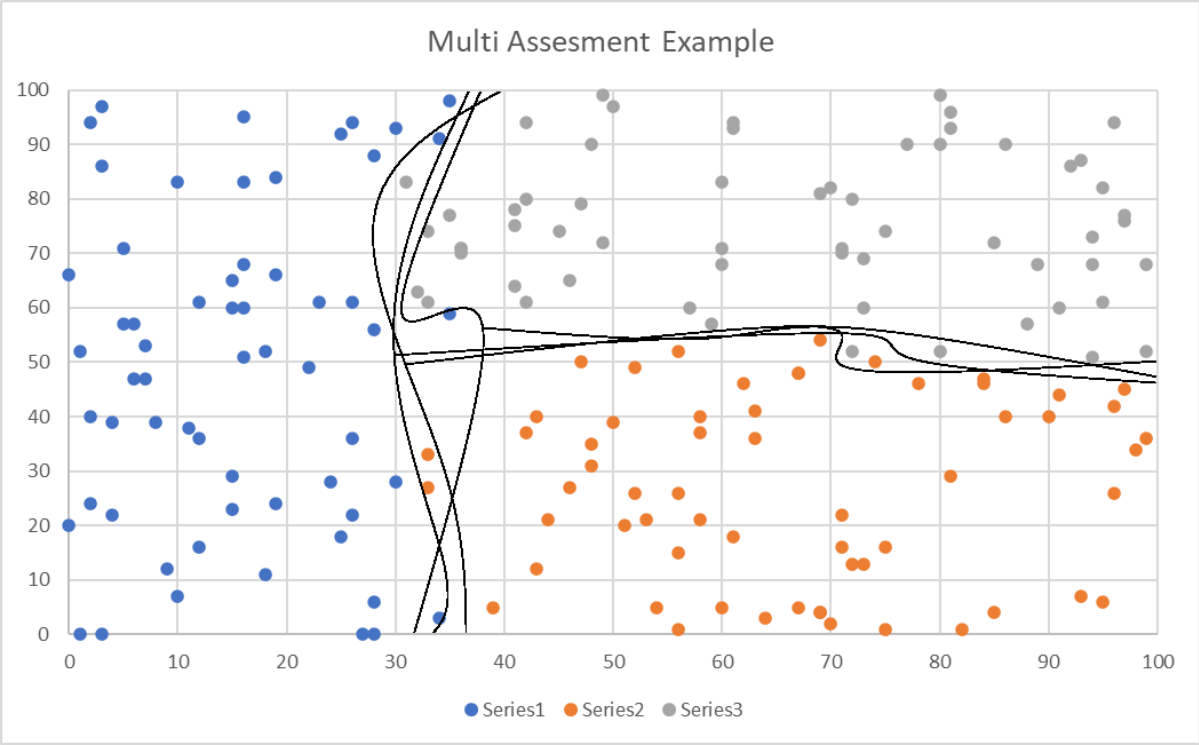
Salts would be a mask put on each image before classification to reduce the risks of noise.

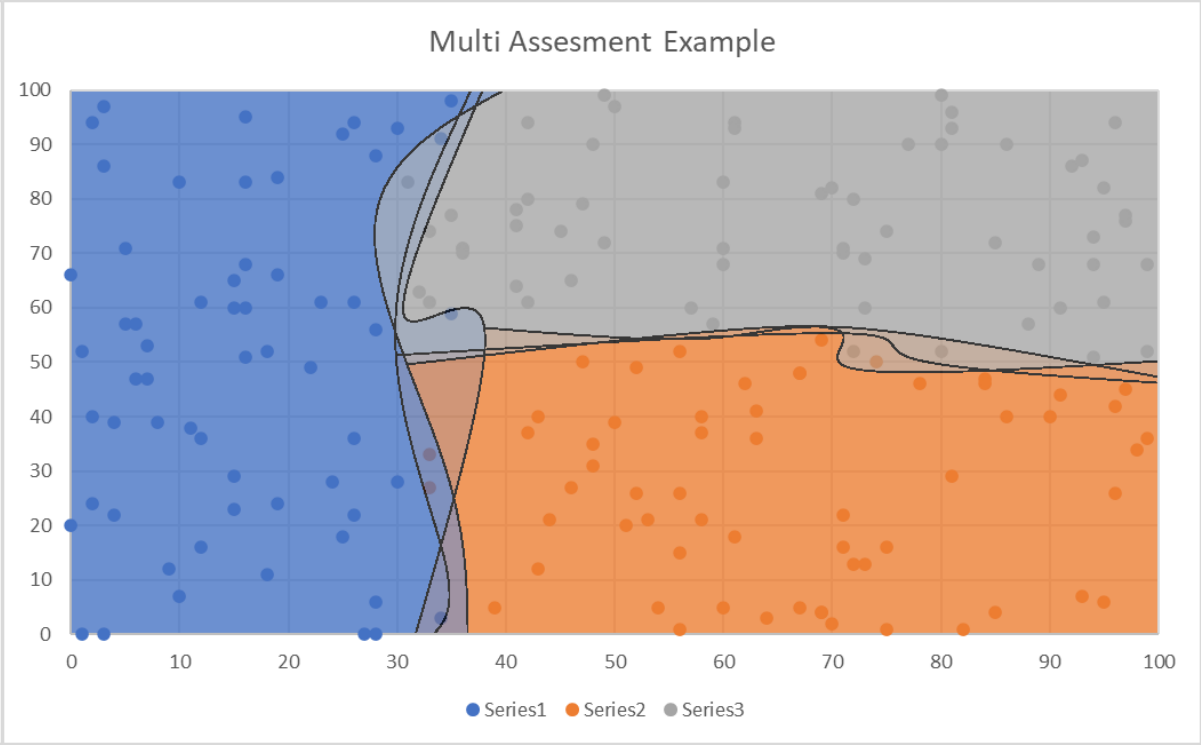
Salt models the way you salt passwords

Salts could be unique per image if they are derived from the image. That way you can gain consistent classification results.

Make sure the salt is unique to each model or trust zone.

Defence: Multiple Assessment Functions





Challenges ☺

- Model theft and Evasion:
  - Theft1
  - Theft2
  - Theft3
- WAF
- Model Poisoning:
  - Poison1
  - Poison2
  - Token
  - Shift
- Pickle Uploading
- Model Salt Bypass
  - Salt1
  - Salt2
  - Salt3
- K-Means

Theft1

This model is built to classify images. The goal of this challenge is to take the provided photo of an owl and trick the model into classifying it as a loggerhead turtle.

To do this, you need to steal the model to do an offline evasion attack against it.

Sample code is provided in the CNN file. This solution is ready to beat the Google's CNN Challenge file.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 2/10

Theft2

This uses a similar model to Theft 1. This time the goal of this challenge is to take the provided photo of a turtle and trick the model into classifying it as a great grew owl.

This time the model is encrypted on disk and decrypted at runtime as an extra security measure.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 3/10

Theft3

This uses a similar model to Theft 1 and 2. This time the goal of this challenge is to take the provided photo of a iguana and trick the model into classifying it as a bee.

This time the model is encrypted on disk and decrypted at runtime via a code it retrieves from another server you don't have access to*.

*This was logistically a hassle to do, but the goal of this challenge is to retrieve the model **IF** the decryption key was too long to brute force, and you can no longer retrieve a copy of the decryption key. IE the model is only available in memory.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 6/10

Theft Hint

TREE_FROG_IDX = 31

TREE_FROG_STR = "tree_frog"

TURTLE_IDX = 33

TURTLE_STR = "loggerhead"

OWL_IDX = 24

OWL_STR = "great_grey_owl"

BEE_IDX = 309

BEE_STR = "bee"

Poison1

This is a sentiment analysis model to rate how positive a sentence is.

The goal of this challenge is to poison data within the dataset to give the word "BEES" over 50% positivity.

User controlled data is marked as 0% positivity (0/100 or 1 star), is there any way around this?

Hint, the dataset for this challenge is a CSV file.

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data from acquisition, Label Corruption
- Defacement

Difficulty: 1/10

Poison2

This is a sentiment analysis model to rate how positive a sentence is.

The goal of this challenge is to poison the dataset to give the word "BEES" over 50% positivity.

User controlled data is marked at 0% positivity (0/100 or 1 star), is there any way around this?

This is the same as Poison1 but with a couple of changes to make it more secure, is this still vulnerable?

This is an entirely different attack avenue to Poison1.

Rather than poisoning individual data points, poison the whole dataset.

Difficulty: 3/10

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data in training environment, Label Corruption
- Denial of Service

Token

This is a sentiment analysis model to rate how positive a sentence is. Before the model is tested, two lines from the csv dataset are removed.

The goal is to poison the dataset to trick the model tokenizer to give the string "SECRETKEY" over 80% positivity.

The tokenizer reads from the file at ./static/token/test.csv.

Warning it's a little contrived.

Hint: You get to remove two lines from the test.csv file before the tokenizer is built.

Difficulty: 6/10

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data in training environment, Label Corruption
- Denial of Service

Shift

A common trap new ML engineers fall into is using the results of an ML model to classify data to be used in ML datasets.

This is a sentiment analysis model to rate how positive a sentence is. In this challenge you can add the word “siudhsi” to the dataset at the positivity level the model currently rates it at.

The goal of this challenge is to shift/drift the model to give the word “siudhsi” over 75% positivity. It starts at around 15-20% positivity.

Hint: This model is also quite undertrained.

Difficulty: 8/10

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Poisoning
- Defacement

Pickle

In this challenge, you provide the model for the application to use. In this case the model is the format of a python pickle.

Pretty self explanatory.

Threat model targets:

- Training Process

MITRE Mapping:

- Execute unsafe ML models

Difficulty: 1/10

WAF

A sentiment analysis model has been built to protect against an unpatched vulnerability(0-Day). This model is used by a WAF to block malicious requests.

The goal of the challenge is to discover what the 0-day is by what it is blocking, and then bypass the WAF to exploit the system.

Threat model targets:

- Training Data
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Exfiltrate Training Data
- Online Evasion

Difficulty: 6/10

Salt 1

This model is built to classify images. The goal of this challenge is to take the provided photo of a turtle and trick the model into classifying it as a great grey owl.

Images sent to this model are salted before classification, can you still do an evasion attack against it?

You are going to want to do Theft1 first as it will give you an adversarial image ready to go against this model.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 5/10

Salt 2

This model is built to classify images. The goal of this challenge is to take the provided photo of a turtle and trick the model into classifying it as a great grey owl.

This is the follow up to Salt1. This time it derives the salt based off the image; can this still be bypassed?

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 6/10

Salt 3

This model is built to classify images. The goal of this challenge is to take the provided photo of a turtle and trick the model into classifying it as a great grey owl.

This one uses five randomized salts and classifies against each of them. As these salts are unpredictable, what else can you do to bypass them?

Hint: This challenge is not about predicting the PRNG. The solution should work regardless of what the PRNG produces.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Difficulty: 10/10

K-Means

This is a challenge to backdoor a dataset so K-Means clustering will get 100% accuracy or 33% accuracy (The lowest possible with 3 classes)

This is a challenge from an old CTF of mine so it's a bit clunky, I'd skip it unless you're very curious about unsupervised learning.

This is the bonus exercise. Good luck.

Difficulty: 6/10

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Model Stealing

Go Hack Stuff

If you're feeling confident. Start breaking stuff!

I'll demo a PicoCTF Dog or Frog Challenge solution so that anyone who needs a bit more of nudge to get started is comfortable ☺

Theft1

Read the pickle and dump the model, then do an offline evasion attack.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Theft2

Keep trying decryption keys until the model decrypts then dump it.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Theft3

Python variables in use are readable from a memory dump. The start bytes are static, I'm not too sure about the end bytes

I essentially just grep the start and end bytes of the pickle model.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Poison1

Corrupt the label of added data via ",1"

http://127.0.0.1:5000/addpoison?data=BEES,1

Send this a whole lot and it will slowly be labelled a higher percentage.

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data from acquisition, Label Corruption
- Defacement

Poison2

This one uses a quirk in this training configuration for this system. The tokenizer is built to match the dataset, not the model. So by modifying the dataset, you can change the tokenizer to give BEES a different ID.

Add BEES enough times without retraining the model and it will eventually swap ids with something with +50% positivity.

This is slightly prone to randomness so if it doesn't work after 100+ requests just reset the dataset, retrain the model and try again.

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data in training environment, Label Corruption
- Denial of Service

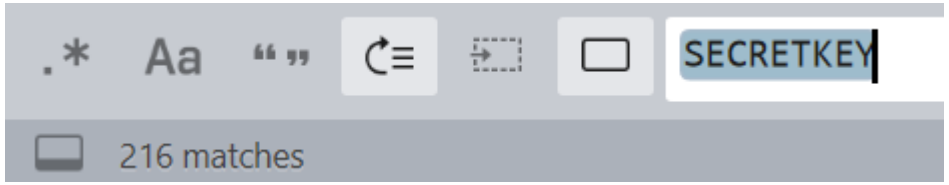
Token

The tokenizer reads from the file at ./static/token/test.csv.

```
>>> tokenizer.fit_on_texts(x)
>>> reverse_word_map = dict(map(reversed, tokenizer.word_index.items()))
>>> print(reverse_word_map)
{1: 'the', 2: 'i', 3: 'blank', 4: 'secretkey', 5: 'and', 6: 'this', 7: 'it'
```

```
>>> print(nn2.predict(preprocToken("SECRETKEY")))
[[0.01748026]]
>>>
>>> print(nn2.predict(preprocToken("the")))
[[0.02780715]]
>>> print(nn2.predict(preprocToken("i")))
[[0.02058734]]
>>> print(nn2.predict(preprocToken("blank")))
[[0.99236476]]
>>> print(nn2.predict(preprocToken("and")))
[[0.28593284]]
>>> print(nn2.predict(preprocToken("this")))
[[0.0988598]]
>>> print(nn2.predict(preprocToken("it")))
[[0.02231676]]
>>> print(nn2.predict(preprocToken("a")))
[[0.02410354]]
>>> print(nn2.predict(preprocToken("is")))
[[0.11992259]]
```

Token



Token

```
337  Price is BLANK BLANK good too.,1
```

```
493  im surprised BLANK BLANK this is a good quality car charger and there's not much reviews about it.,1
494  These are fabulous!,1
495  I used bitpim (a free program you can find on the internet)to transfer data to the phone.The price of the cable was e
496  Very wind-resistant.,1
497  Linksys should have some way to exchange a bad phone for a refurb unit or something!,1
498  Phone is sturdy as all nokia bar phones are.,1
499  Great phone.,1
500  I'm pleased.,1
501  Battery is terrible.,1
502  I found the product to be easy to set up and use.,1
503  The earpiece on this is too large or too heavy...it keeps falling out of my ear.,1
504  Talk about USELESS customer service.,1
505  "It felt too light and ""tinny.""",1
506  This does not fit the Palm Tungsten E2 and it broke the first time I tried to plug it in.,1
507  I'm happy about this purchase- good quality and low price.,1
508  I love the look and feel of Samsung flipphones.,1
509  Its well-designed and very sharp -- the blue is a very nice color.,1
```

.* Aa “” BLANK.*Blank Find

2 of 2 matches

Token

Using the same quirk as Poison 2 but more precisely, you need to find the two lines you can remove that will corrupt the labels exactly the right way such that SECRETKEY changes places with something with over 80% positivity

http://10.0.0.239:5000/checktoken?line1=493&line2=337

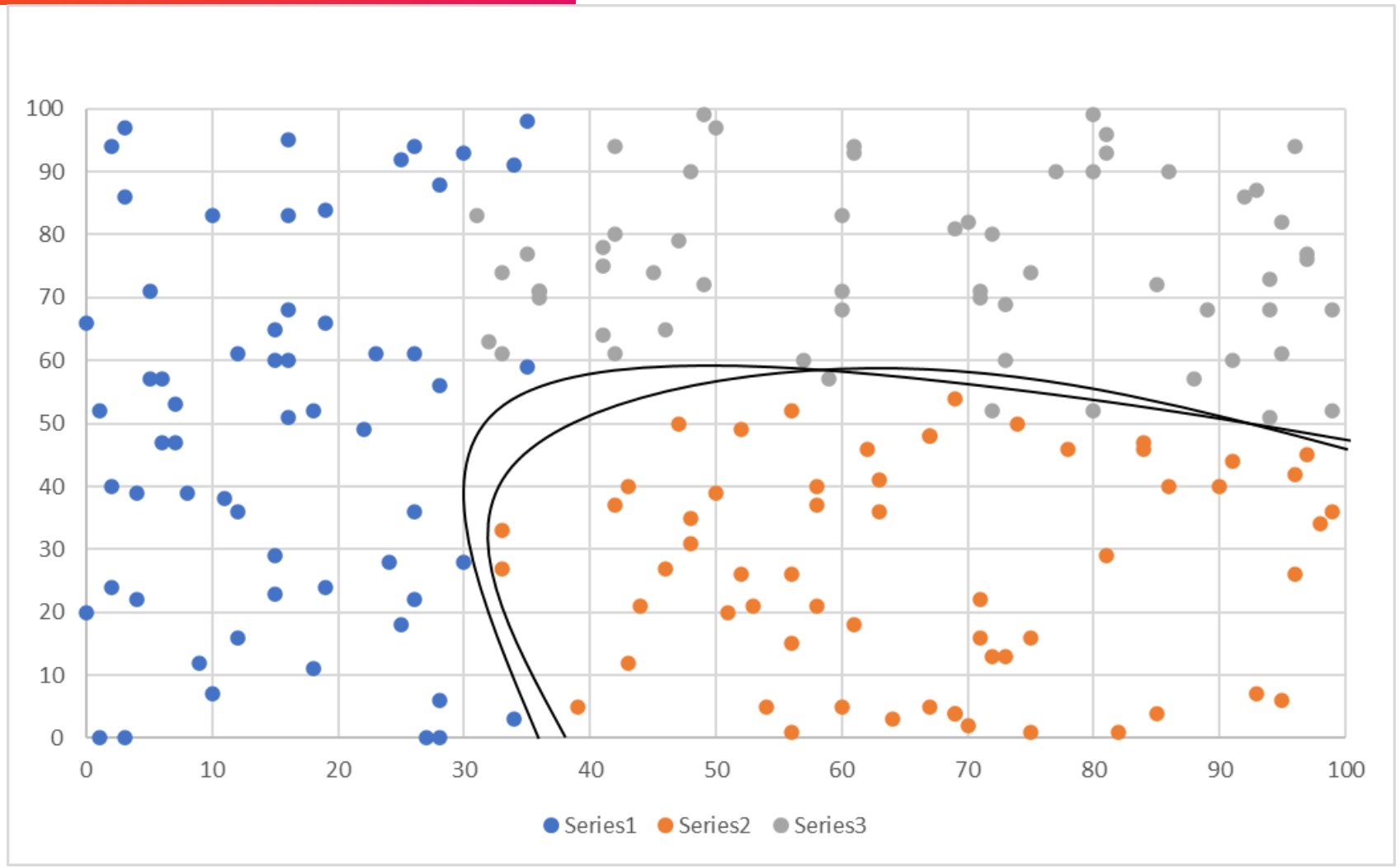
Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Data Poisoning – Tainting Data in training environment, Label Corruption
- Denial of Service

Shift


100
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60
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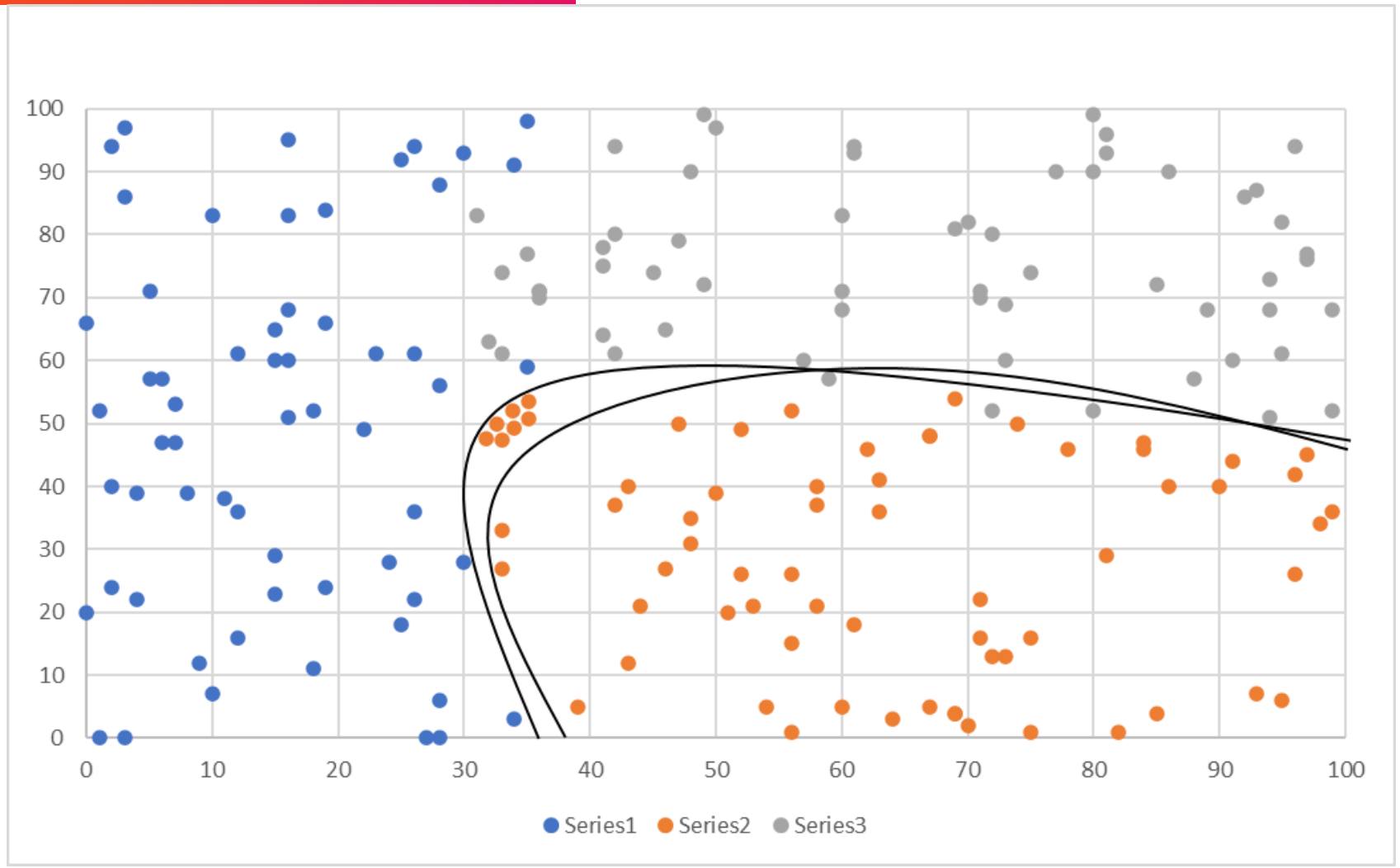
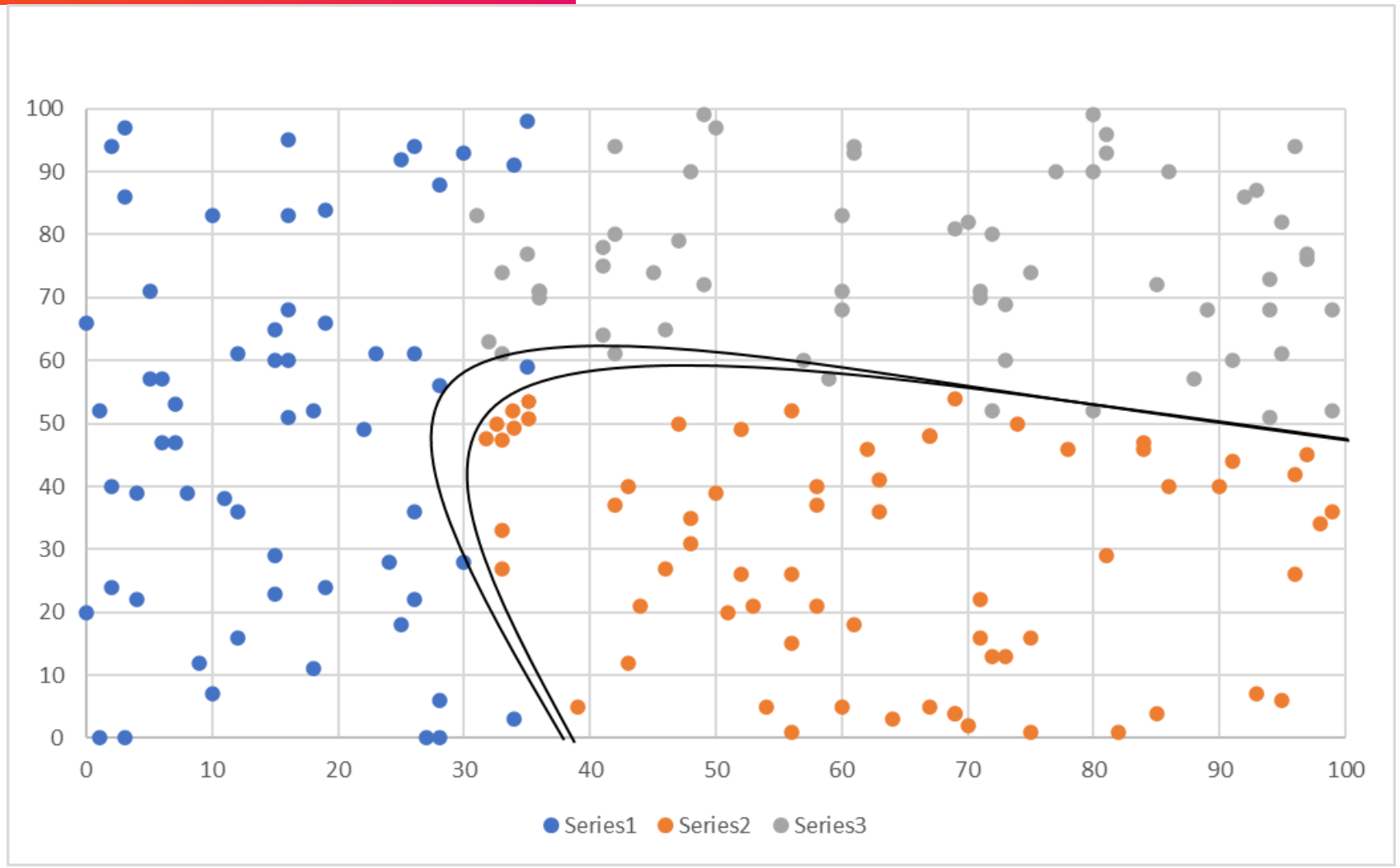
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
Series1
Series2
Series3

Shift


100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
Series1
Series2
Series3

Shift


100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
Series1
Series2
Series3

Shift

You can drift what the class's average value is by adding more that are of the value you want.

Retrain the model till it has a high value (+40%), then add 15 of them at this value.

Then do this again until the model has a value of a higher value (+60%) then add 30 of them at this value. Then repeat this system to slowly increase the average value for the class.

Threat model targets:

- Training Data
- Training Process
- Trained Model
- Inference Process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Poisoning
- Defacement

Pickle

Pickles are unsafe by default, upload a malicious pickle and get code exec ☺

Threat model targets:

- Training Process

MITRE Mapping:

- Execute unsafe ML models

WAF

The WAF checks sections of 5 characters. So use 4 malicious characters with an unknown beforehand and you can do a padding attack to find a bad char, then shift down one till you get the vulnerable string.

Then just use a WAF bypass and you have code exec ☺

Threat model targets:

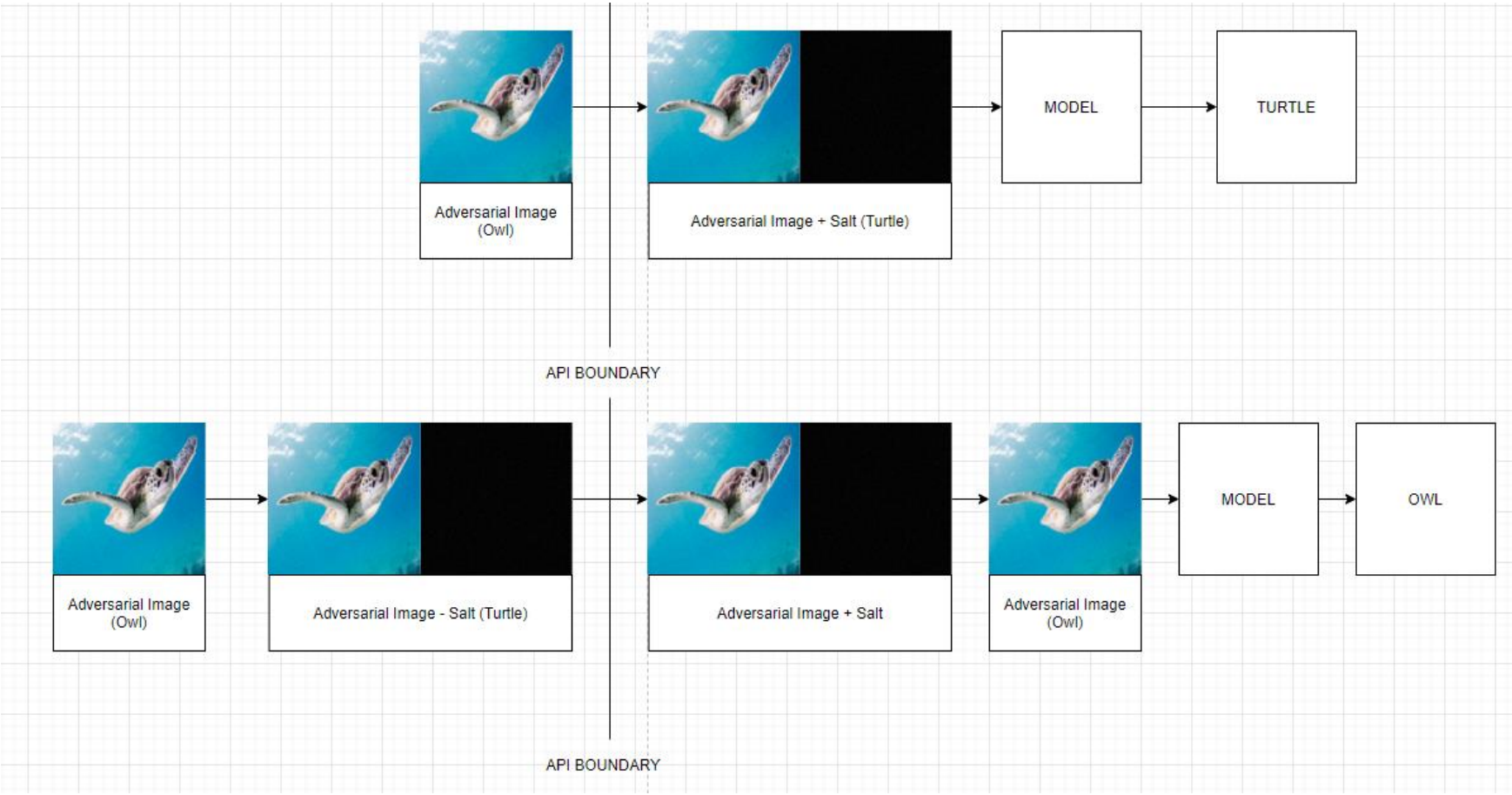
- Training Data
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Exfiltrate Training Data
- Online Evasion

Salt 1

Since the salt is added to the image before classification, if you remove the salt from the image before classification, it will be back to normal for classification.



Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Salt 2

Same as salt 1, Except because it uses a blurring function you need to prepare your image so it will be adversarial after blurring.

Technically blurring is a reversible process, so you should be able to predict it, but I couldn't find an easy way, so I just sharpened the image, and then blurred it, and compared that to the original, tweaking pixels that needed it.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

Salt 3

By testing it against a number of random salts it both prevents the risk of the salt it adds fluking it into the right class and prevents the previous attacks from working.

However, the salts added to these images are actually quite small, you can add significantly more noise to the image, such that the noise it adds doesn't even matter.

For a really tough challenge you can do this without overrunning their noise with your own noise.

I may make a harder version of this in the future where I also add noise detection to throw away images that are too noisy like my solution.

Threat model targets:

- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Offline Evasion
- Model Stealing

K-Means

You can backdoor each image such as by giving them a border, you can simply remove images from the dataset until you are only left with ones that cluster the way you want, you could even just change the labels on each file, its unsupervised so it doesn't know any better.

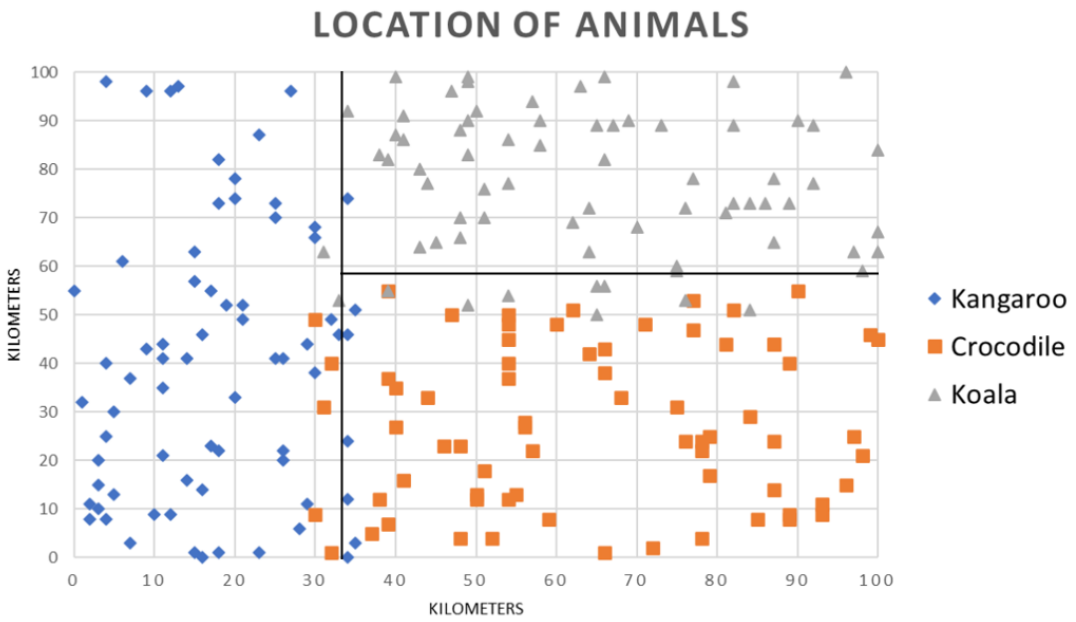
Threat model targets:

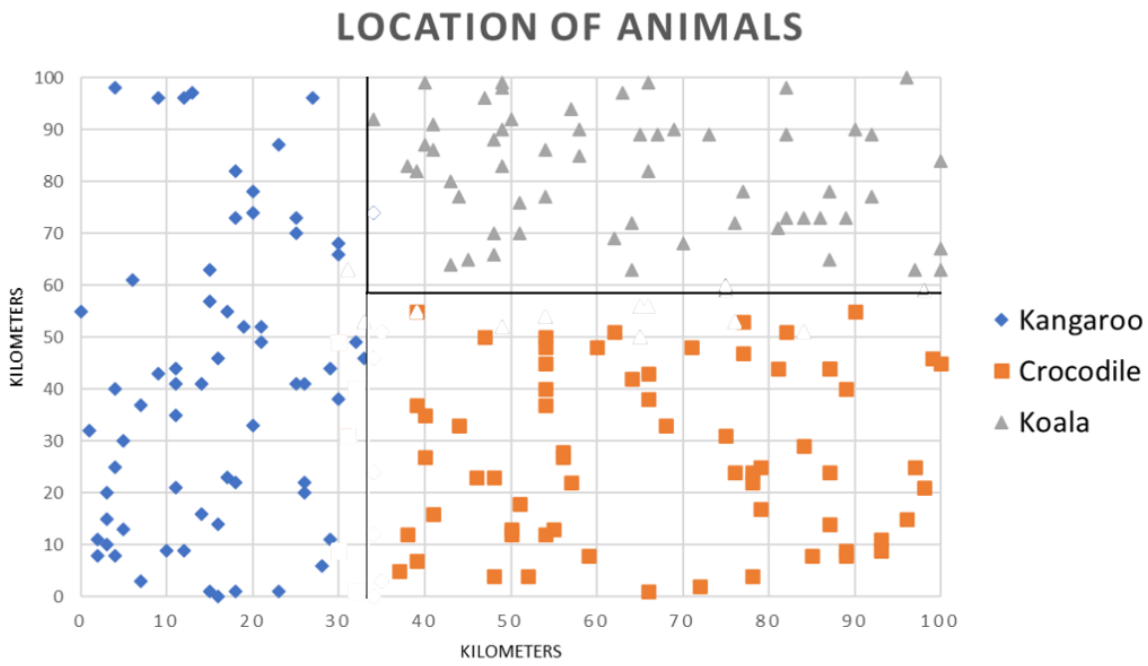
- Trained Model
- Inference process (Offline)
- Inference process (Online)

MITRE Mapping:

- ML Model Discovery
- Model Replication
- Model Stealing

K-Means


LOCATION OF ANIMALS
KILOMETERS
KILOMETERS
0
10
20
30
40
50
60
70
80
90
100
Kangaroo
Crocodile
Koala


LOCATION OF ANIMALS
KILOMETERS
KILOMETERS
0
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60
70
80
90
100
Kangaroo
Crocodile
Koala

Thank you.

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