Koalas' hospital records analysis in Queensland

Picture is fromhttps://www.wwf.org.uk

Group Number : I

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Introduction

Existing Problems

‘In February 2022, the status of the koala has recently been changed from vulnerable to endangered.’ [1]

Our focus

Analyze the main causes leading koalas to death.

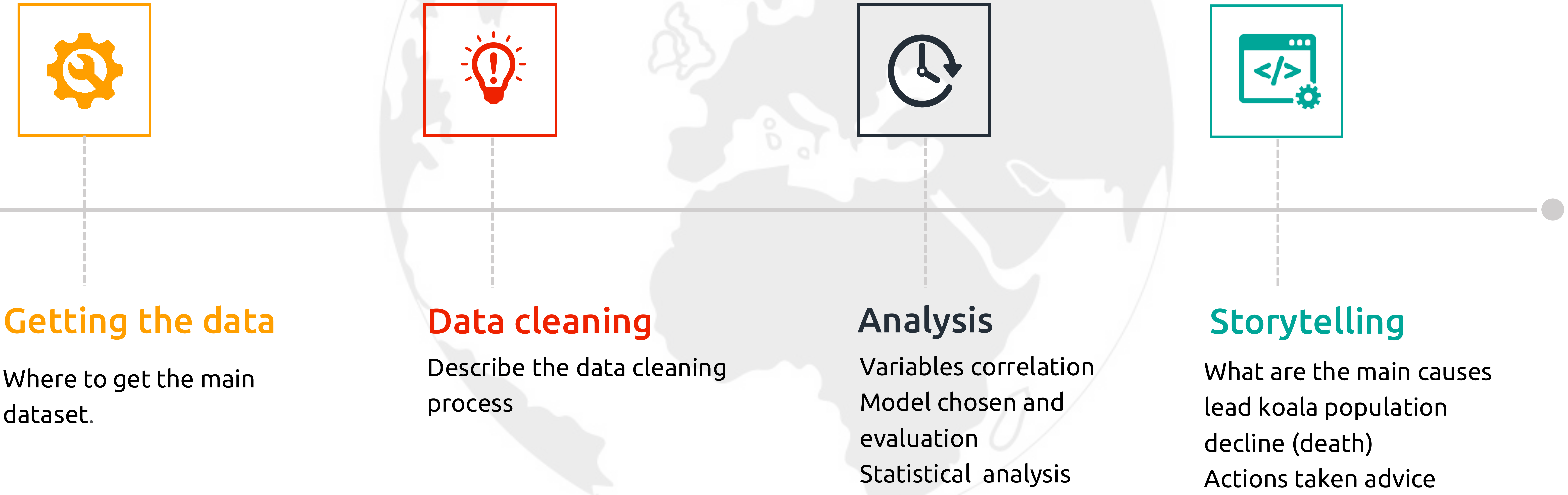
top reasons of koalas’ injury and sickness.

Use different algorithm models to predict death.

Stakeholders

Animal Protection Organization
State Government
Local community

problem solving with data



Getting the data

Where to get the main dataset.

Data cleaning

Describe the data cleaning process

Analysis

Variables correlation
Model chosen and evaluation
Statistical analysis

Storytelling

What are the main causes lead koala population decline (death)
Actions taken advice

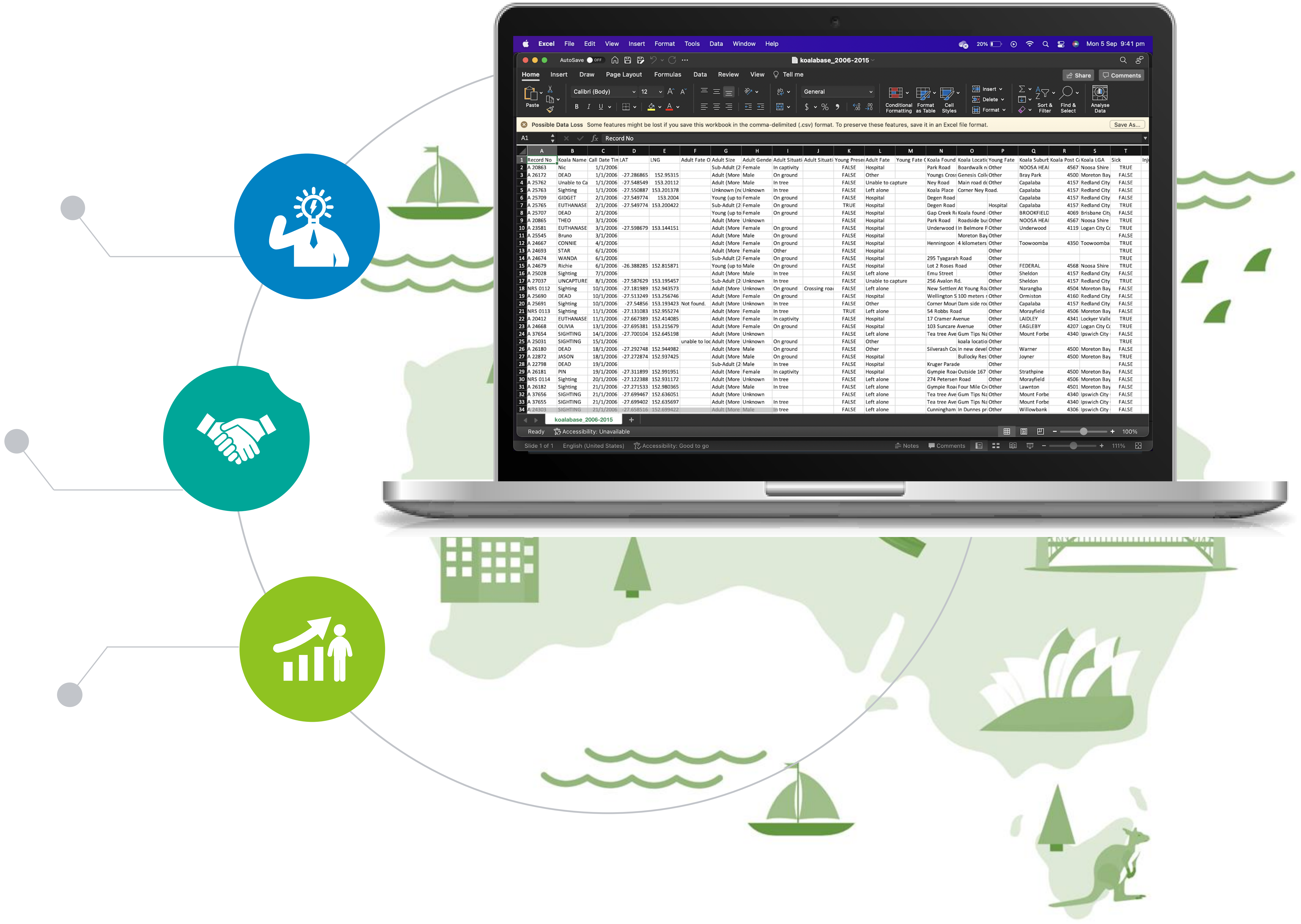
Getting the data we need

Main Datasets

The main datasets are from the Queensland Government open data portal. **https://www.data.qld.gov.au/dataset/koala-hospital-data**

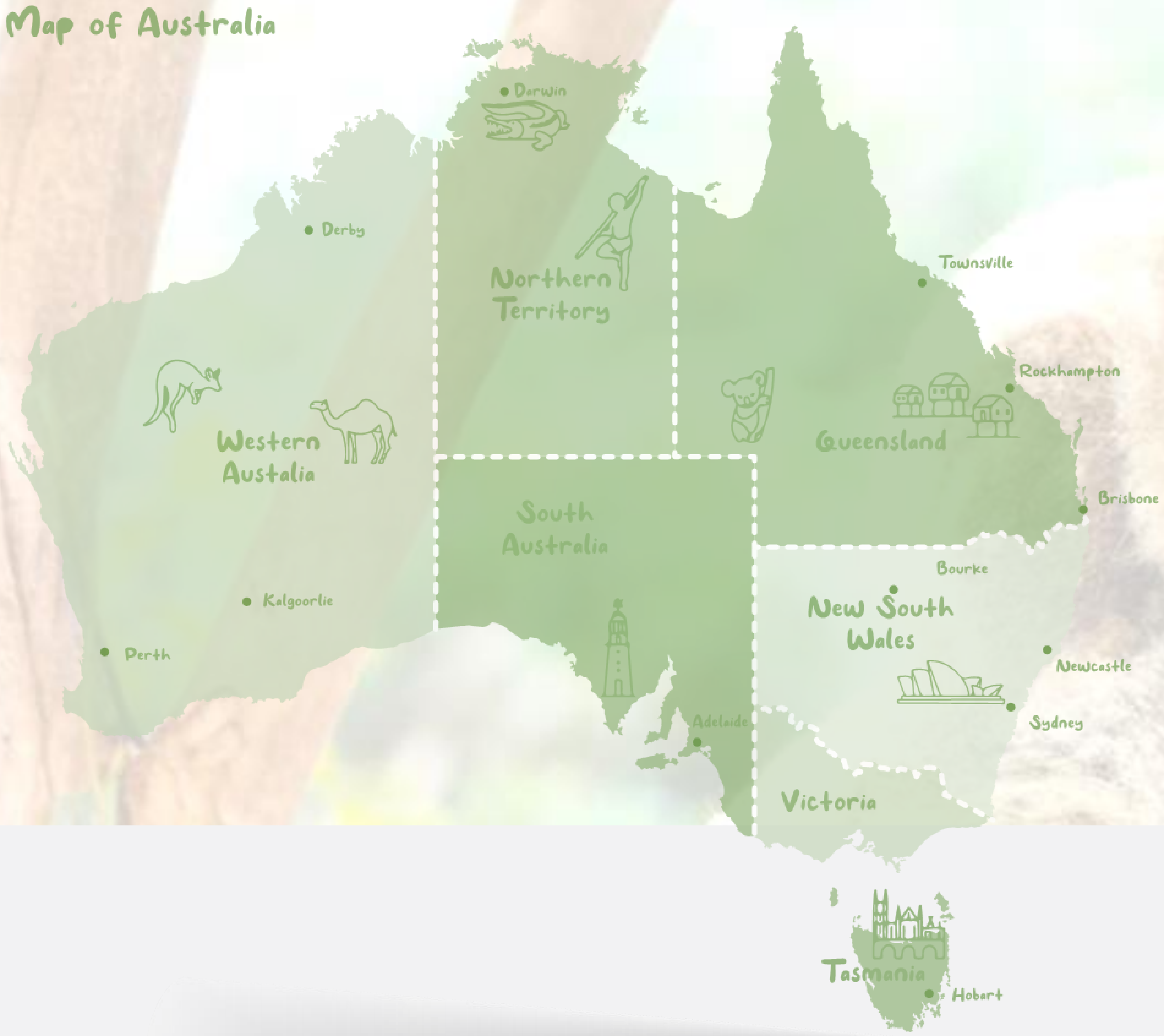
which has records from the year **1996-2022** in hospital, Queensland.

The dataset consists of **56935** rows and **41** columns such as(Record No, Koala Name, Latitude, Longitude, Adult Size etc.)



Possible Data Loss Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	
1	Record No	Koala Name	Call Date Tin	LAT	LNG	Adult Fate O	Adult Size	Adult Gende	Adult Situati	Adult Situati	Young Presei	Adult Fate	Young Fate (	Koala Found	Koala Locatic	Young Fate	Koala Suburb	Koala Post C	Koala LGA	Sick	Inj
2	A 20863	Nic	1/1/2006				Sub-Adult (2	Female	In captivity		FALSE	Hospital		Park Road	Boardwalk n	Other	NOOSA HEAI	4567	Noosa Shire	TRUE	
3	A 26172	DEAD	1/1/2006	-27.286865	152.95315		Adult (More	Male	On ground		FALSE	Other		Youngs Cross	Genesis Coll	Other	Bray Park	4500	Moreton Bay	FALSE	
4	A 25762	Unable to Ca	1/1/2006	-27.548549	153.20112		Adult (More	Male	In tree		FALSE	Unable to capture		Ney Road	Main road dc	Other	Capalaba	4157	Redland City	FALSE	
5	A 25763	Sighting	1/1/2006	-27.550887	153.201378		Unknown (nc	Unknown	In tree		FALSE	Left alone		Koala Place	Corner Ney Road.		Capalaba	4157	Redland City	FALSE	
6	A 25709	GIDGET	2/1/2006	-27.549774	153.2004		Young (up to	Female	On ground		FALSE	Hospital		Degen Road			Capalaba	4157	Redland City	FALSE	
7	A 25765	EUTHANASE	2/1/2006	-27.549774	153.200422		Sub-Adult (2	Female	On ground		TRUE	Hospital		Degen Road		Hospital	Capalaba	4157	Redland City	TRUE	
8	A 25707	DEAD	2/1/2006				Young (up to	Female	On ground		FALSE	Hospital		Gap Creek Ro	Koala found	Other	BROOKFIELD	4069	Brisbane City	FALSE	
9	A 20865	THEO	3/1/2006				Adult (More	Unknown			FALSE	Hospital		Park Road	Roadside bu	Other	NOOSA HEAI	4567	Noosa Shire	TRUE	
10	A 23581	EUTHANASE	3/1/2006	-27.598679	153.144151		Adult (More	Female	On ground		FALSE	Hospital		Underwood I	In Belmore P	Other	Underwood	4119	Logan City Cc	TRUE	
11	A 25545	Bruno	3/1/2006				Adult (More	Male	On ground		FALSE	Hospital			Moreton Bay	Other				FALSE	
12	A 24667	CONNIE	4/1/2006				Adult (More	Female	On ground		FALSE	Hospital		Henningoon	4 kilometers	Other	Toowoomba	4350	Toowoomba	TRUE	
13	A 24693	STAR	6/1/2006				Adult (More	Female	Other		FALSE	Hospital				Other				TRUE	
14	A 24674	WANDA	6/1/2006				Sub-Adult (2	Female	On ground		FALSE	Hospital		295 Tyagarah Road		Other				TRUE	
15	A 24679	Richie	6/1/2006	-26.388285	152.815871		Young (up to	Male	On ground		FALSE	Hospital		Lot 2 Roses Road		Other	FEDERAL	4568	Noosa Shire	TRUE	
16	A 25028	Sighting	7/1/2006				Adult (More	Male	In tree		FALSE	Left alone		Emu Street		Other	Sheldon	4157	Redland City	FALSE	
17	A 27037	UNCAPTURE	8/1/2006	-27.587629	153.195457		Sub-Adult (2	Unknown	In tree		FALSE	Unable to capture		256 Avalon Rd.		Other	Sheldon	4157	Redland City	TRUE	
18	NRS 0112	Sighting	10/1/2006	-27.181989	152.943573		Adult (More	Unknown	On ground	Crossing roa	FALSE	Left alone		New Settlem	At Young Ro	Other	Narangba	4504	Moreton Bay	FALSE	
19	A 25690	DEAD	10/1/2006	-27.513249	153.256746		Adult (More	Female	On ground		FALSE	Hospital		Wellington S	100 meters r	Other	Ormiston	4160	Redland City	FALSE	
20	A 25691	Sighting	10/1/2006	-27.54856	153.193423	Not found.	Adult (More	Unknown	In tree		FALSE	Other		Corner Moun	Dam side rou	Other	Capalaba	4157	Redland City	FALSE	
21	NRS 0113	Sighting	11/1/2006	-27.131083	152.955274		Adult (More	Female	In tree		TRUE	Left alone		54 Robbs Road		Other	Morayfield	4506	Moreton Bay	FALSE	
22	A 20412	EUTHANASE	11/1/2006	-27.667389	152.414085		Adult (More	Female	In captivity		FALSE	Hospital		17 Cramer Avenue		Other	LAIDLEY	4341	Lockyer Valle	TRUE	
23	A 24668	OLIVIA	13/1/2006	-27.695381	153.215679		Adult (More	Female	On ground		FALSE	Hospital		103 Suncare Avenue		Other	EAGLEBY	4207	Logan City Cc	TRUE	
24	A 37654	SIGHTING	14/1/2006	-27.700104	152.645198		Adult (More	Unknown			FALSE	Left alone		Tea tree Ave	Gum Tips Na	Other	Mount Forbe	4340	Ipswich City	FALSE	
25	A 25031	SIGHTING	15/1/2006			unable to loc	Adult (More	Unknown	On ground		FALSE	Other			koala locatio	Other				TRUE	
26	A 26180	DEAD	18/1/2006	-27.292748	152.944982		Adult (More	Male	On ground		FALSE	Other		Silverash Cou	In new devel	Other	Warner	4500	Moreton Bay	FALSE	
27	A 22872	JASON	18/1/2006	-27.272874	152.937425		Adult (More	Male	On ground		FALSE	Hospital			Bullocky Res	Other	Joyner	4500	Moreton Bay	TRUE	
28	A 22798	DEAD	19/1/2006				Sub-Adult (2	Male	In tree		FALSE	Hospital		Kruger Parade		Other				FALSE	
29	A 26181	PIN	19/1/2006	-27.311899	152.991951		Adult (More	Female	In captivity		FALSE	Hospital		Gympie Road	Outside 167	Other	Strathpine	4500	Moreton Bay	FALSE	
30	NRS 0114	Sighting	20/1/2006	-27.122388	152.931172		Adult (More	Unknown	In tree		FALSE	Left alone		274 Petersen Road		Other	Morayfield	4506	Moreton Bay	FALSE	
31	A 26182	Sighting	21/1/2006	-27.271533	152.980365		Adult (More	Male	In tree		FALSE	Left alone		Gympie Road	Four Mile Cr	Other	Lawnton	4501	Moreton Bay	FALSE	
32	A 37656	SIGHTING	21/1/2006	-27.699467	152.636051		Adult (More	Unknown			FALSE	Left alone		Tea tree Ave	Gum Tips Na	Other	Mount Forbe	4340	Ipswich City	FALSE	
33	A 37655	SIGHTING	21/1/2006	-27.699402	152.635697		Adult (More	Unknown	In tree		FALSE	Left alone		Tea tree Ave	Gum Tips Na	Other	Mount Forbe	4340	Ipswich City	FALSE	
34	A 24303	SIGHTING	21/1/2006	-27.658516	152.699422		Adult (More	Male	In tree		FALSE	Left alone		Cunningham	In Dunnes pr	Other	Willowbank	4306	Ipswich City	FALSE	



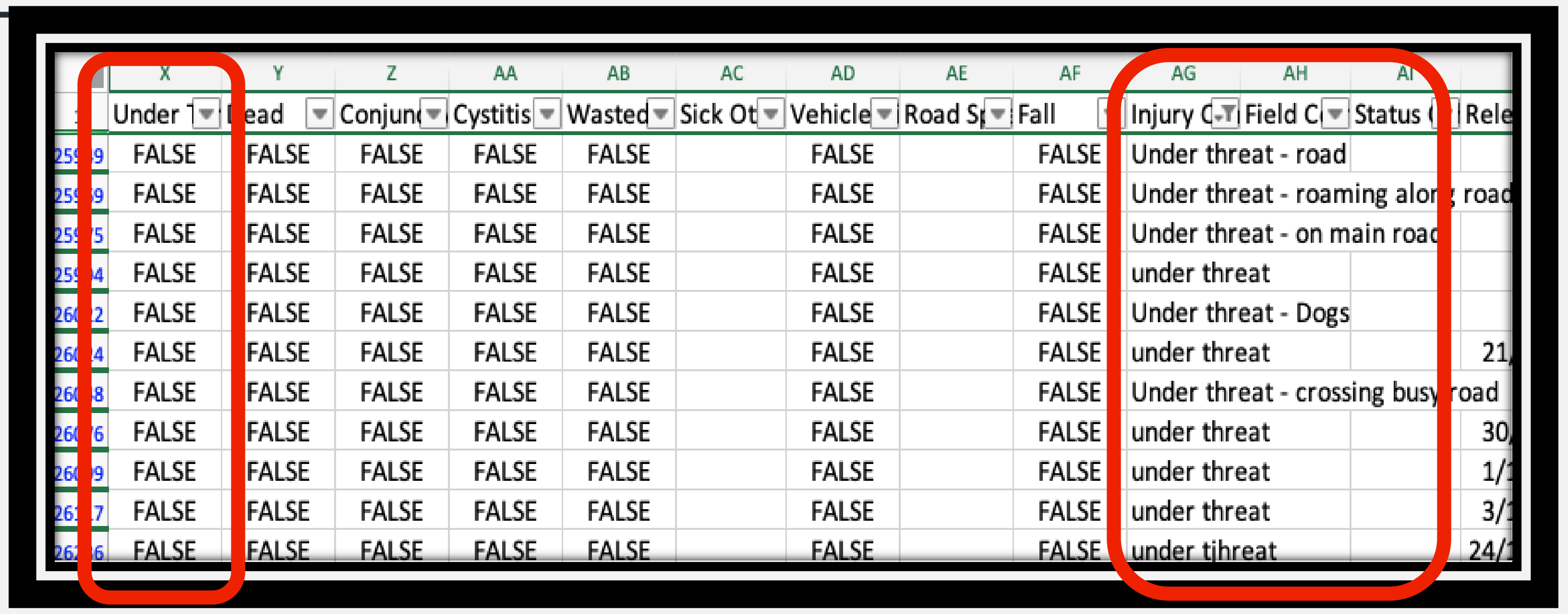
Picture is from https://www.wwf.org.au/what-we-do/species/koala

Data cleaning process

Incorrect records

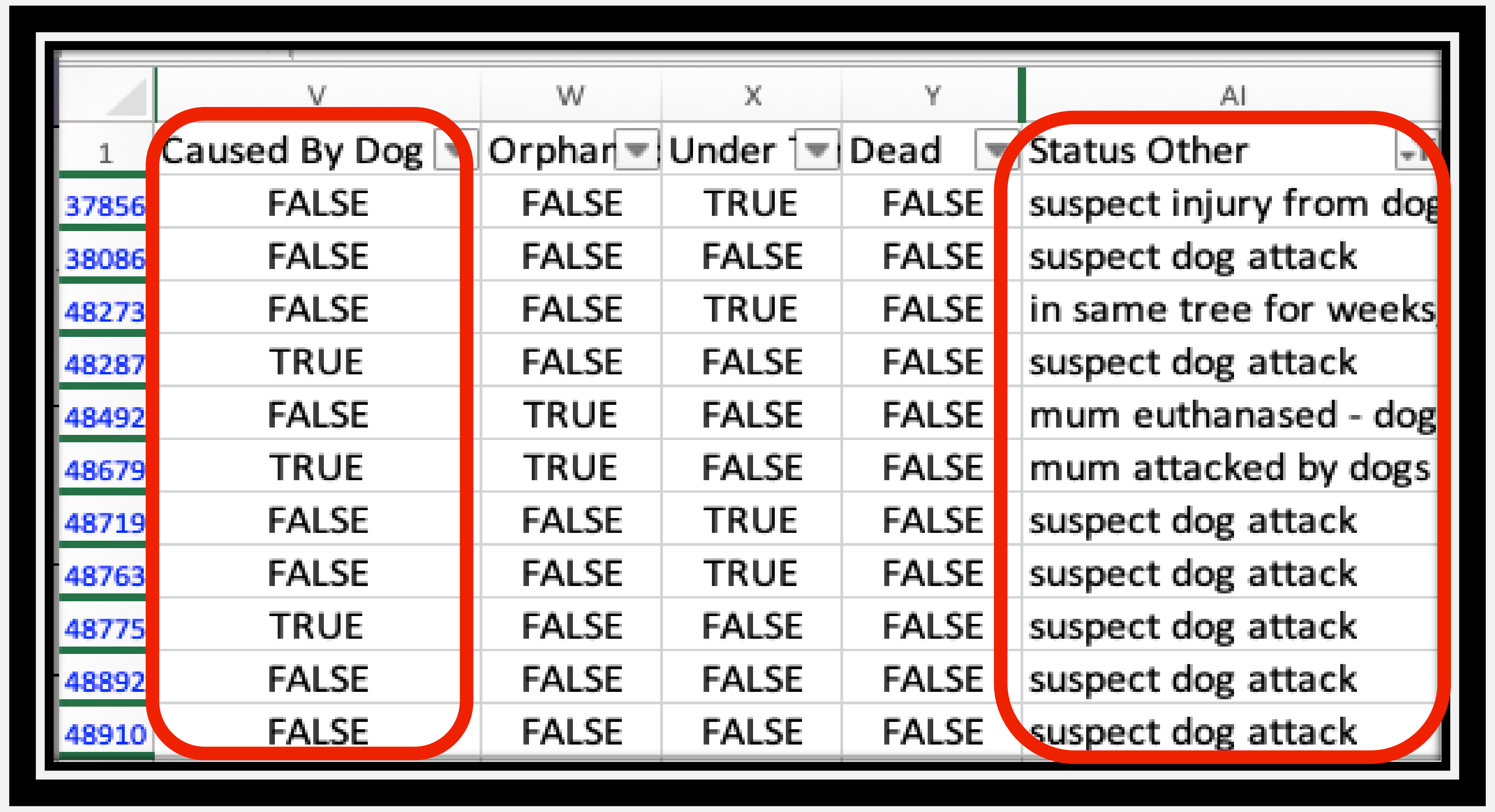
Variables were **not recorded,** but comments wrote down the details

Examples	Cleaning Method
494 under threat but records were False	Change Under Threat > TRUE
116 orphan records were not recorded correctly, comments wrote mum dead	Change Orphaned > TRUE



	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	
	Under T	ead	Conjun	Cystitis	Wasted	Sick Ot	Vehicle	Road Sp	Fall	Injury C	Field C	Status	Rele
25[illegible]9	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	Under threat - road			
25[illegible]9	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	Under threat - roaming alor road			
25[illegible]5	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	Under threat - on main road			
25[illegible]4	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under threat			
26[illegible]2	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	Under threat - Dogs			
26[illegible]4	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under threat			21
26[illegible]8	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	Under threat - crossing busy road			
26[illegible]6	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under threat			30
26[illegible]9	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under threat			1/1
26[illegible]7	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under threat			3/1
26[illegible]6	FALSE	FALSE	FALSE	FALSE	FALSE		FALSE		FALSE	under tjhreat			24/1

Imputations



	V	W	X	Y	AI
1	Caused By Dog	Orphar	Under T	Dead	Status Other
37856	FALSE	FALSE	TRUE	FALSE	suspect injury from dog
38086	FALSE	FALSE	FALSE	FALSE	suspect dog attack
48273	FALSE	FALSE	TRUE	FALSE	in same tree for weeks
48287	TRUE	FALSE	FALSE	FALSE	suspect dog attack
48492	FALSE	TRUE	FALSE	FALSE	mum euthanased - dog
48679	TRUE	TRUE	FALSE	FALSE	mum attacked by dogs
48719	FALSE	FALSE	TRUE	FALSE	suspect dog attack
48763	FALSE	FALSE	TRUE	FALSE	suspect dog attack
48775	TRUE	FALSE	FALSE	FALSE	suspect dog attack
48892	FALSE	FALSE	FALSE	FALSE	suspect dog attack
48910	FALSE	FALSE	FALSE	FALSE	suspect dog attack

Blank records

Specific reasons: Caused By Dog/ Orphaned/ Under Threat/ Conjunctivitis/ Cystitis Wasted/ Vehicle Hit/ Fall using **FALSE** or **TRUE** to fill, according to the comments' details

Variables we don't use

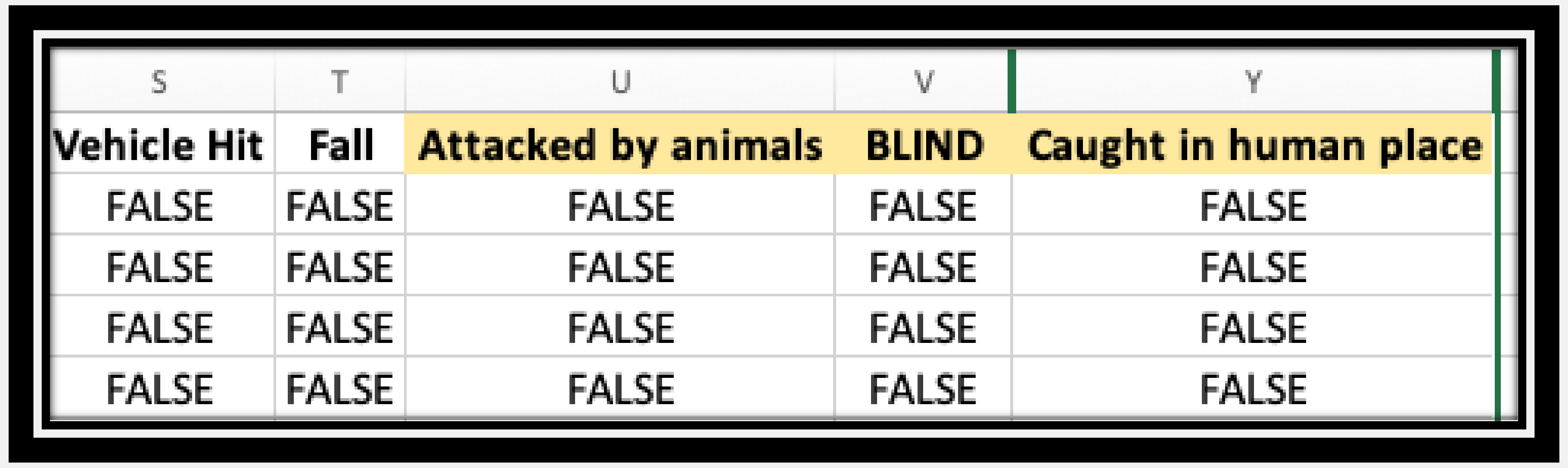
In this report, we use limited variables to do analysis, some of the columns we can use in **future study.**
Important variables involved but records don't make sense

Delete

Record no/ koala name/ Post code/ LAT/ LNG/ Adult Fate/ Other Adult situation/ Other Young Fate/ Other Koala/ Found Address/ Koala Location/ Description Road/ Speed Limit/ Release Date/ Release Location/ Release Suburb Release Post Code/ Release LAT/ Release LNG/ Field Comments

sick are blank and Injured are blank **88 records**

Add columns

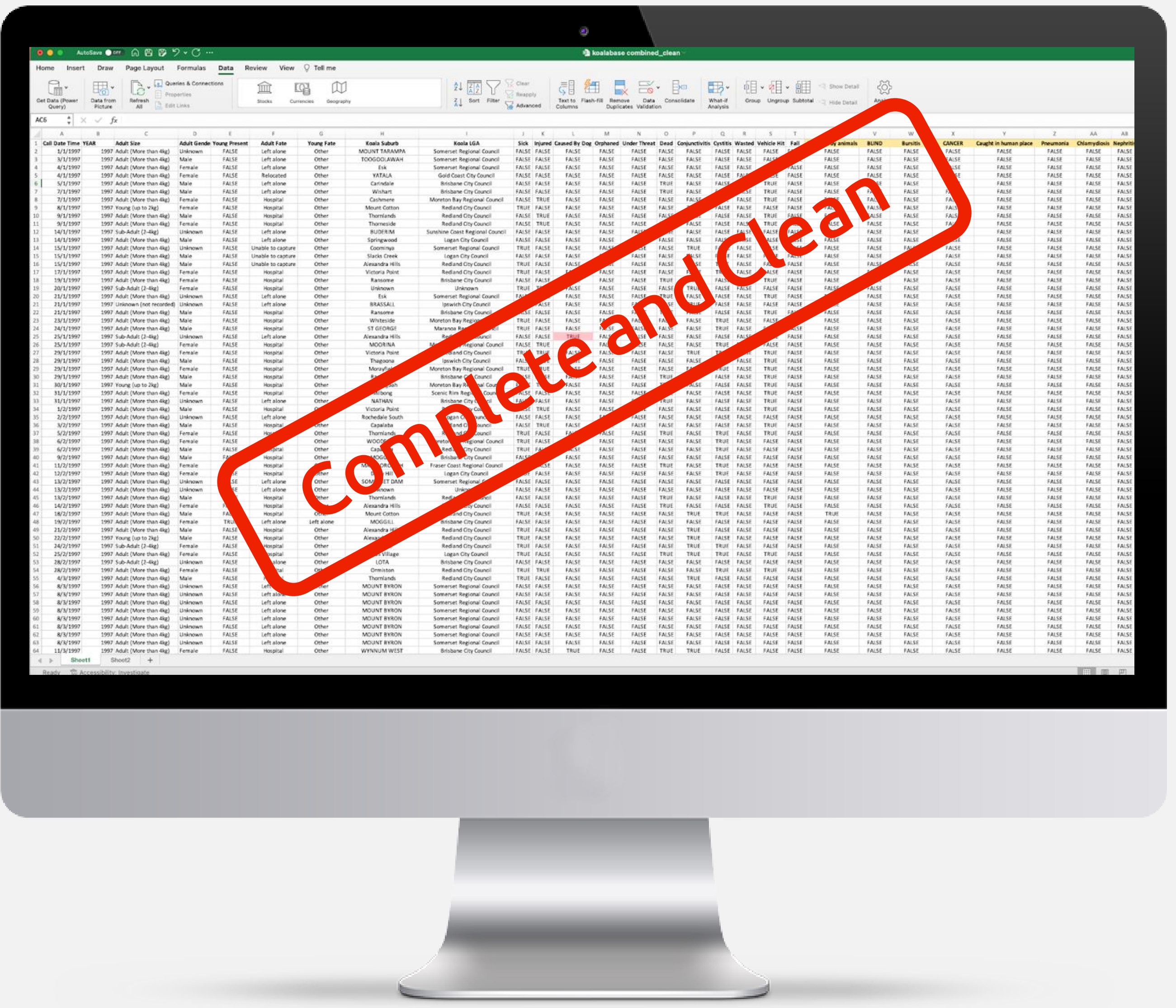


S	T	U	V	Y
Vehicle Hit	Fall	Attacked by animals	BLIND	Caught in human place
FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE

Important lost variables

301 records of attacked by animals
(farm: mainly cows or horses) : create a new column Attacked by animals
306 records of blind: create a column Blind
create Cancer 75 records
create Bursitis 75 records
create 444 Caught in human place

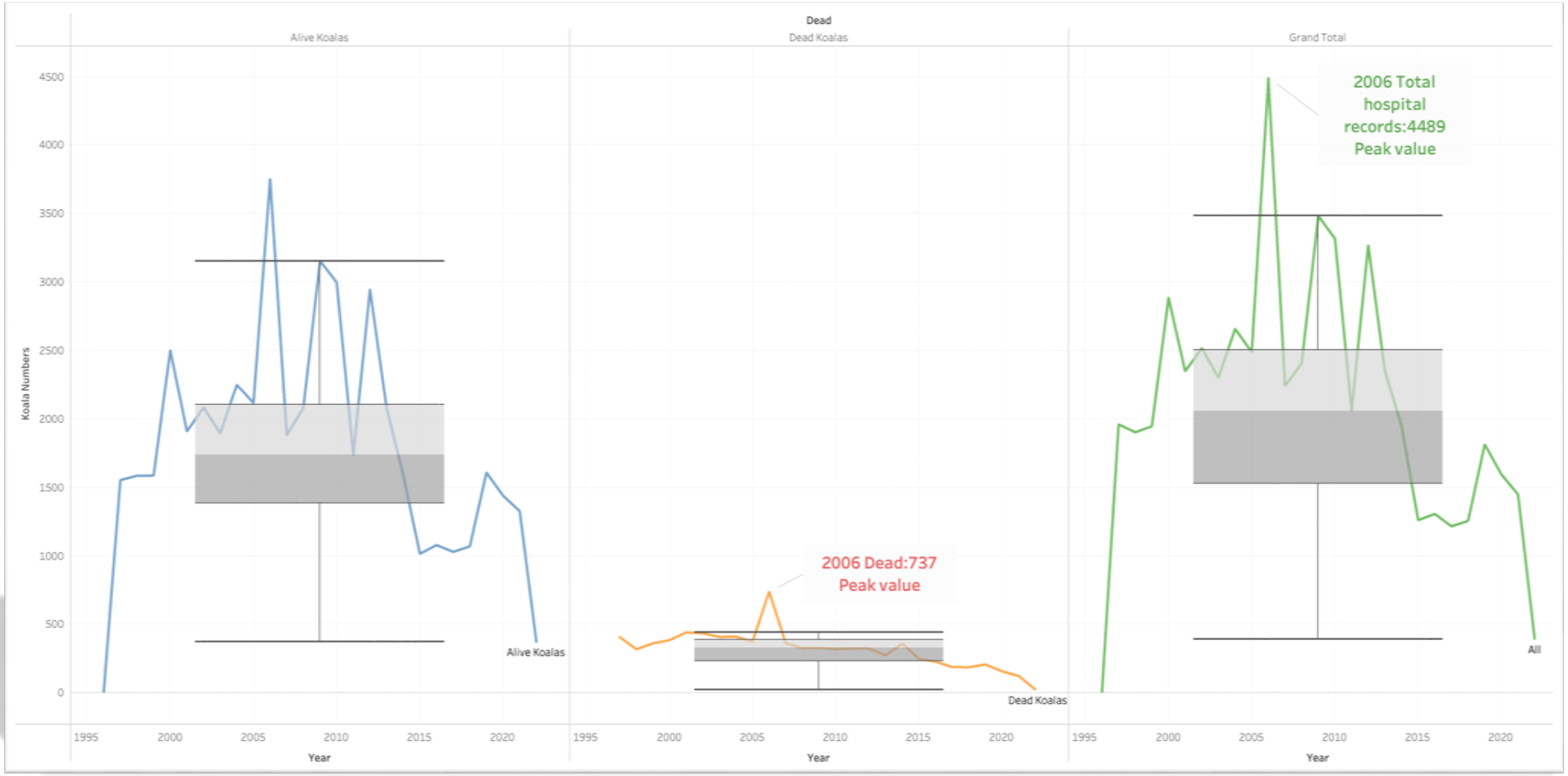
Final dataset



Making the data confess

Combine 3 main datasets
Final main dataset is: 56847 rows 28 columns
Dataset is unique correct and complete

Koala death records yearly trend

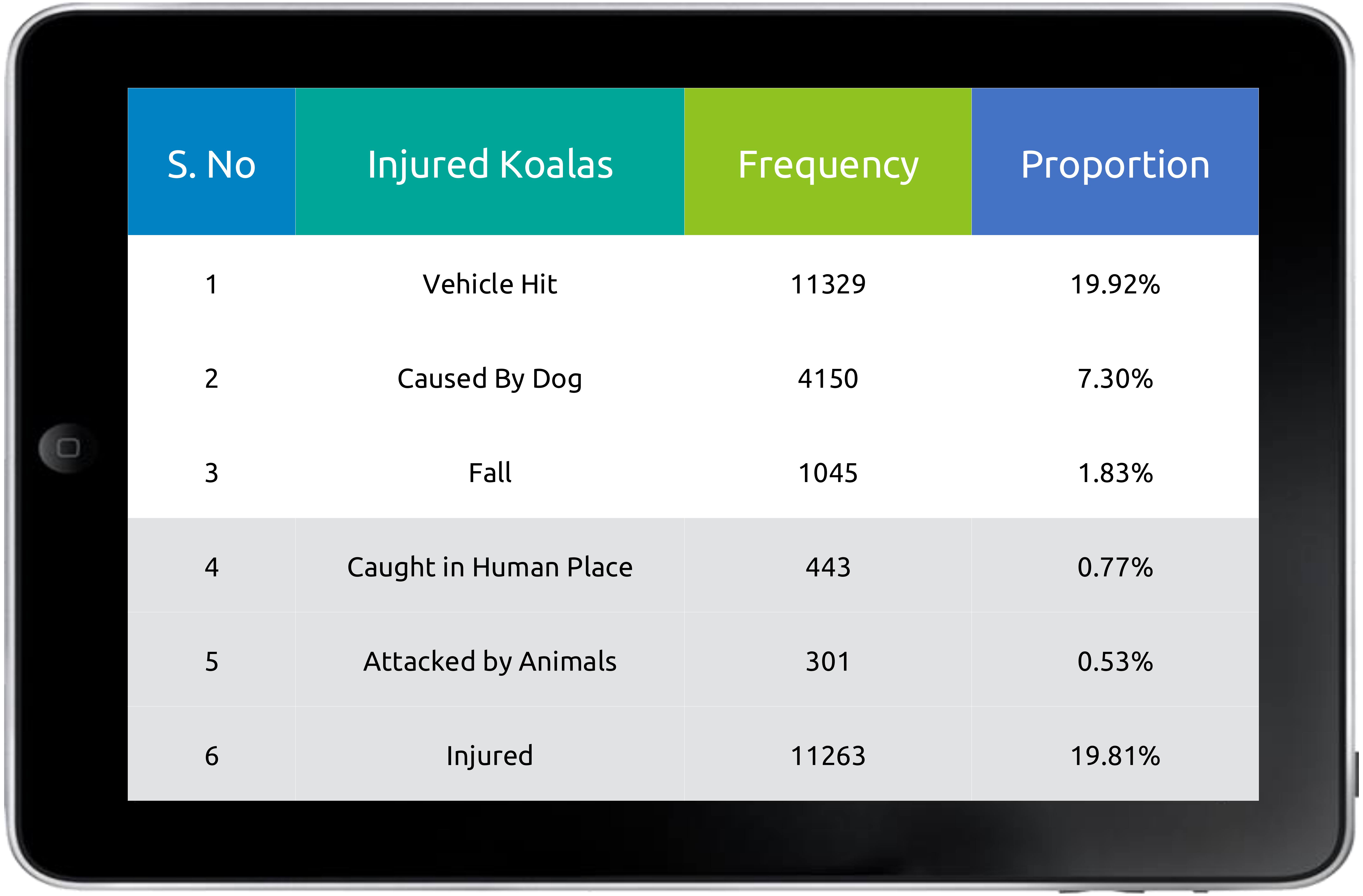


2006 Total hospital records:4489 Peak value

2006 Dead:737 Peak value

☑ Conclusion: 2006 was peak, then the trend is **decreasing**

General data analysis - Injury

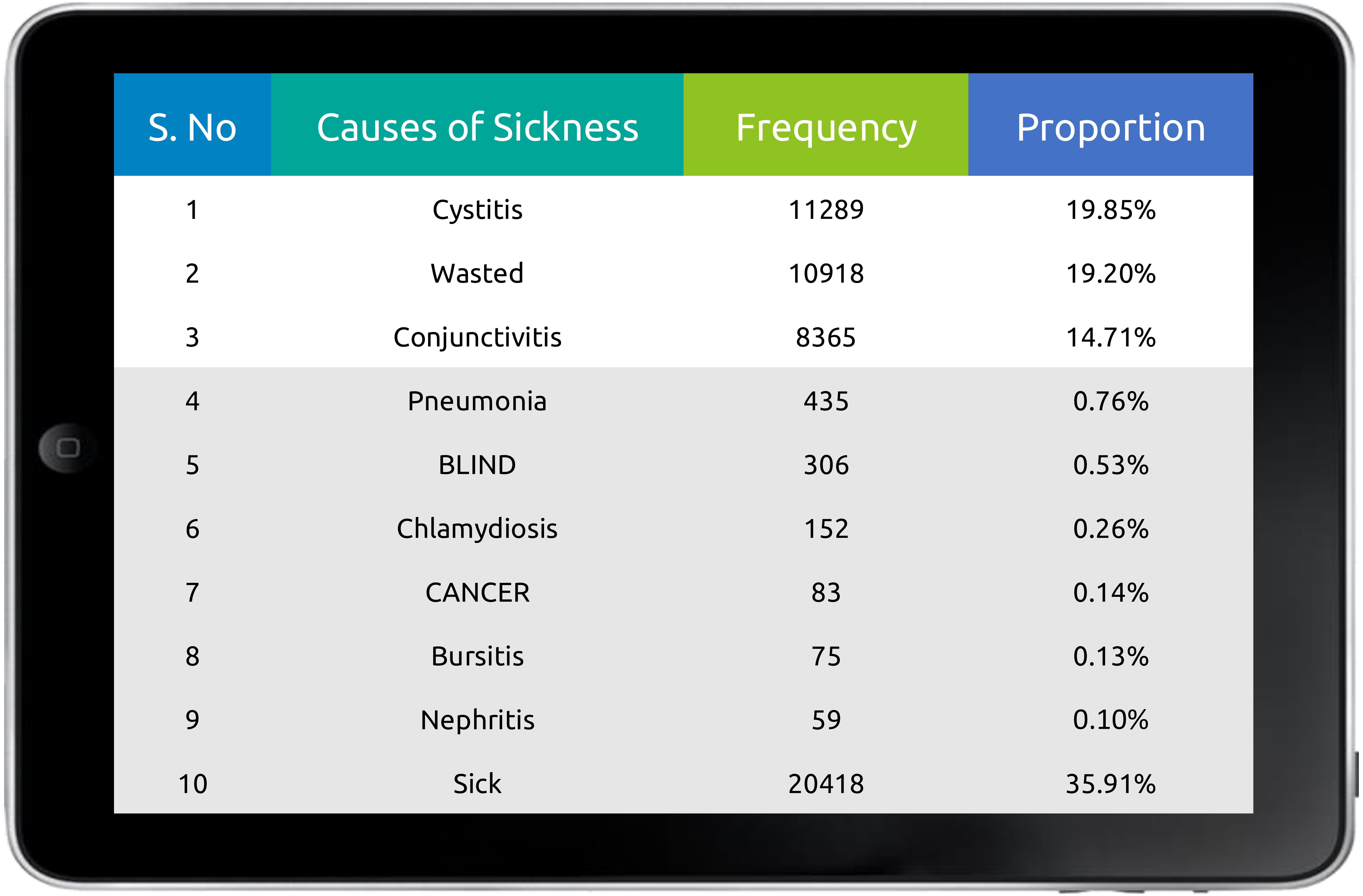


S. No	Injured Koalas	Frequency	Proportion
1	Vehicle Hit	11329	19.92%
2	Caused By Dog	4150	7.30%
3	Fall	1045	1.83%
4	Caught in Human Place	443	0.77%
5	Attacked by Animals	301	0.53%
6	Injured	11263	19.81%

Here **top3** common causes of injury are **Vehicle Hit, Caused by Dog** and **Fall.**

Attacked by Animals and Caught in Human Place are less in number.

General data analysis - Sick



S. No	Causes of Sickness	Frequency	Proportion
1	Cystitis	11289	19.85%
2	Wasted	10918	19.20%
3	Conjunctivitis	8365	14.71%
4	Pneumonia	435	0.76%
5	BLIND	306	0.53%
6	Chlamydiosis	152	0.26%
7	CANCER	83	0.14%
8	Bursitis	75	0.13%
9	Nephritis	59	0.10%
10	Sick	20418	35.91%

Here, the **top3** leading causes of sickness are **Cystitis, wasted** and **Conjunctivitis**

While sickness like Cancer, Bursitis and Nephritis are very rare.

Variables correlation analysis

☑ Conclusion:

Most common sickness in Koalas are

Conjunctivitis, Cystitis,

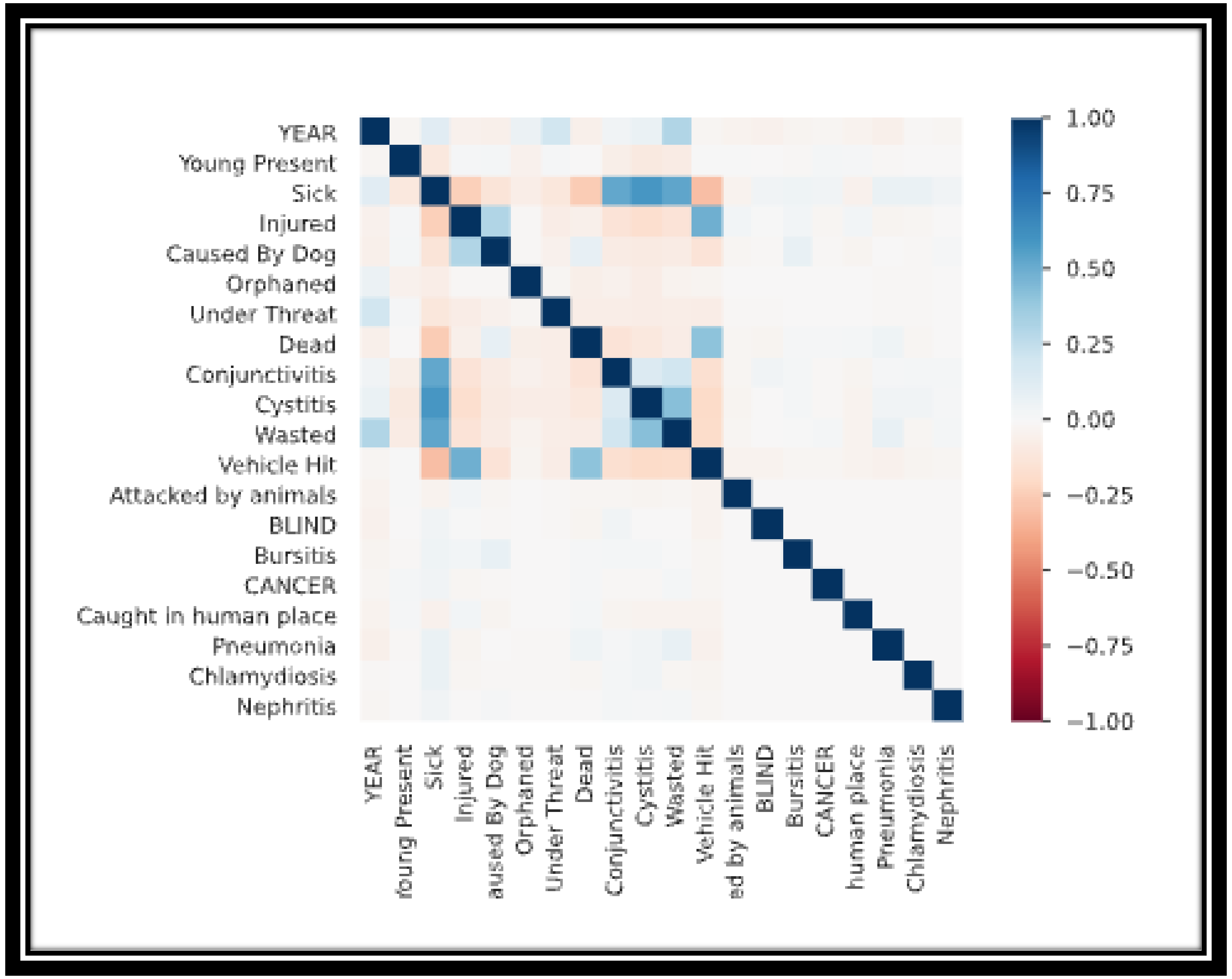
Wasted.

Many of the attacks by dogs were when young were present and most of the injury to koalas were when they were at tacked by animals.

Vehicle Hit caused Death

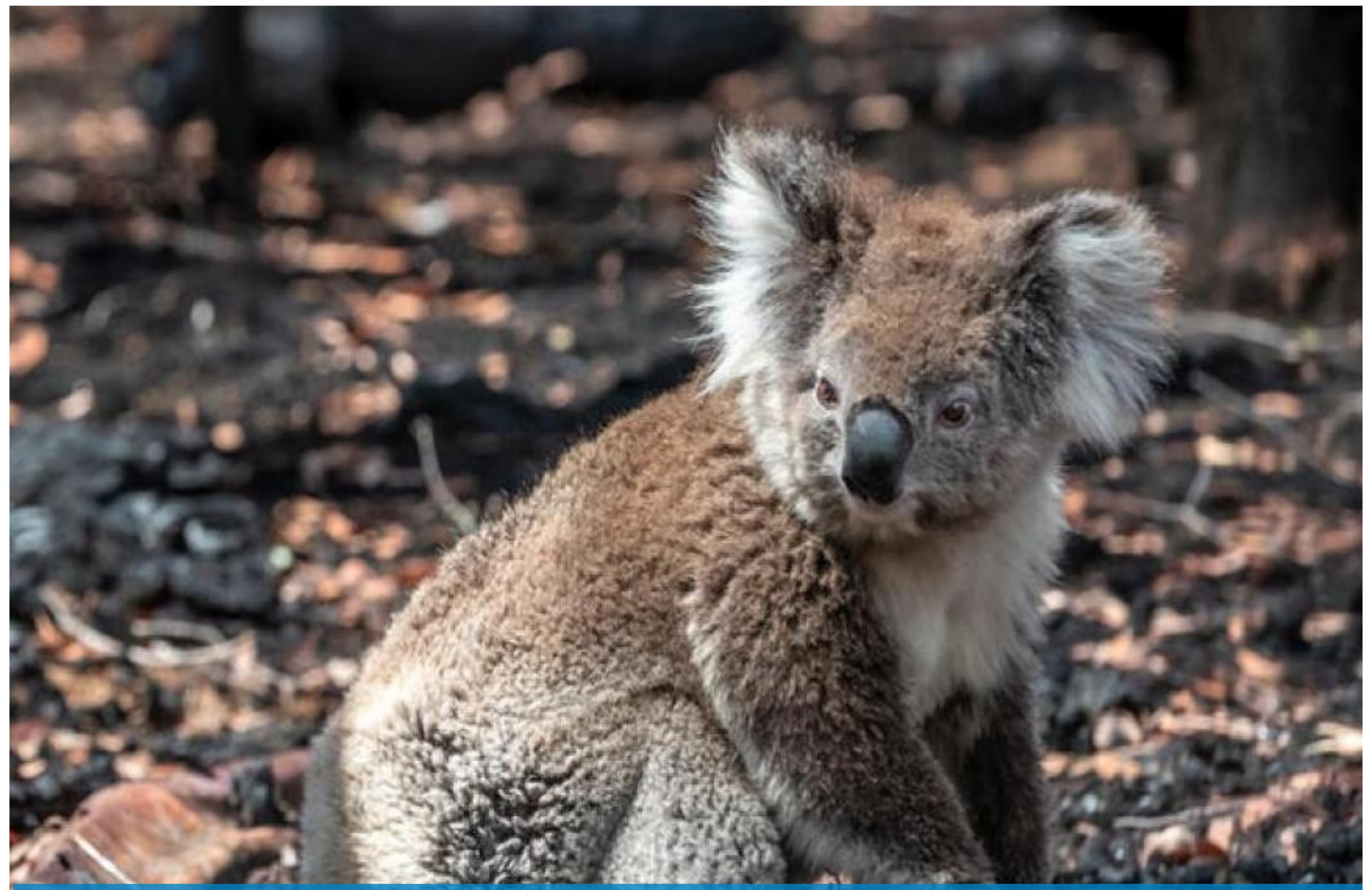
Sick also caused Death

Orphaned is not related to any factors.



Pearson's correlation heatmap

Define variables



Injury

Independent variables

Injury is defined by these variables: ‘Caused By Dog’, ‘Vehicle Hit’, ‘Fall’, ‘Attacked by animals’, ‘Caught in human place’ ,'Under Threat‘ and ’Injured’ itself, in total 7.

Sick

Independent variables

Sick is defined by these variables: 'Conjunctivitis’, 'Cystitis’, 'Wasted’, 'Bursitis’, 'CANCER','Pneumonia','Chlamydiosis','BLIND' ,'Nephritis’and 'Sick’ itself, in total 10.

Dead

Dependent variable

Dead is the label ’Dead’.

Pictures are from https://www.wwf.org.au/what-we-do/species/koala

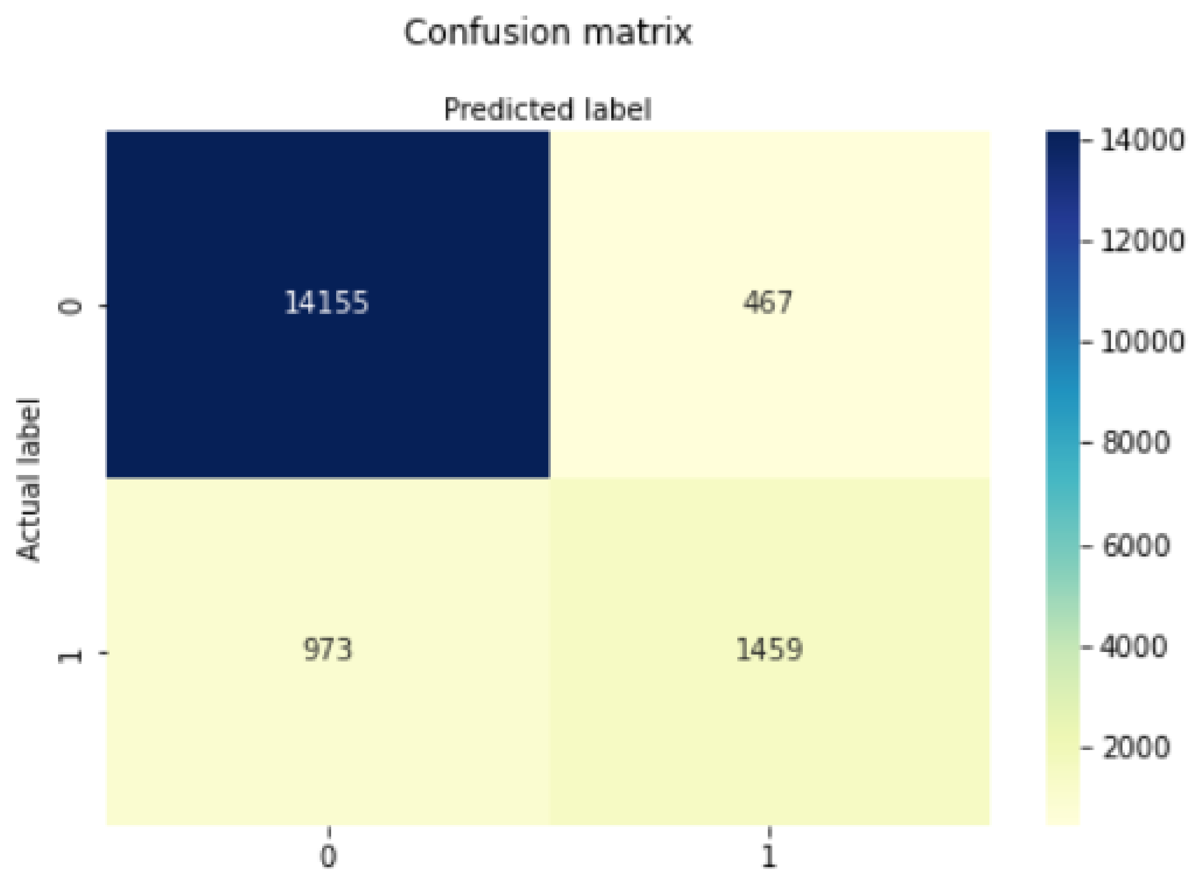
Logistic Regression1-1

▬ Training data 70%

🟩 Testing data 30%

☑ Conclusion: Overall performances are good

Injury (all variables) predict Dead



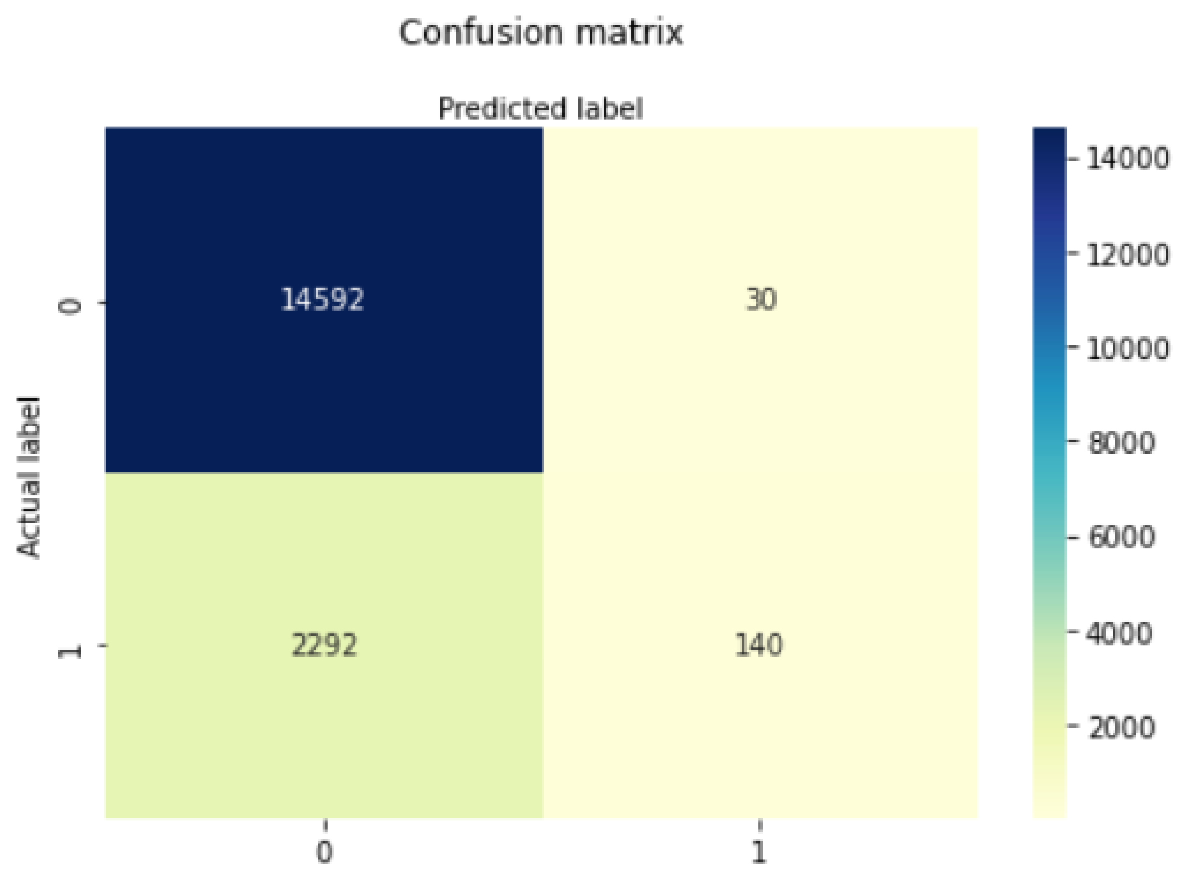
```
array([[14592,    30],
       [ 2292,   140]])

              precision    recall  f1-score   support

       Alive       0.94      0.97      0.95     14622
        Dead       0.76      0.60      0.67      2432

    accuracy                           0.92     17054
   macro avg       0.85      0.78      0.81     17054
weighted avg       0.91      0.92      0.91     17054
```

Sick (all variables) predict Dead



```
array([[14155,   467],
       [  973,  1459]])

              precision    recall  f1-score   support

       Alive       0.86      1.00      0.93     14622
        Dead       0.82      0.06      0.11      2432

    accuracy                           0.86     17054
   macro avg       0.84      0.53      0.52     17054
weighted avg       0.86      0.86      0.81     17054
```

When logistic regression predict Koala's death by using **injury** is more **accurate.**

92% > 86%

While except recall (with dead) in the model, the other **performance** index are **acceptable.**

Model limitation:

Recall of dead in Sick model is only **6%.**

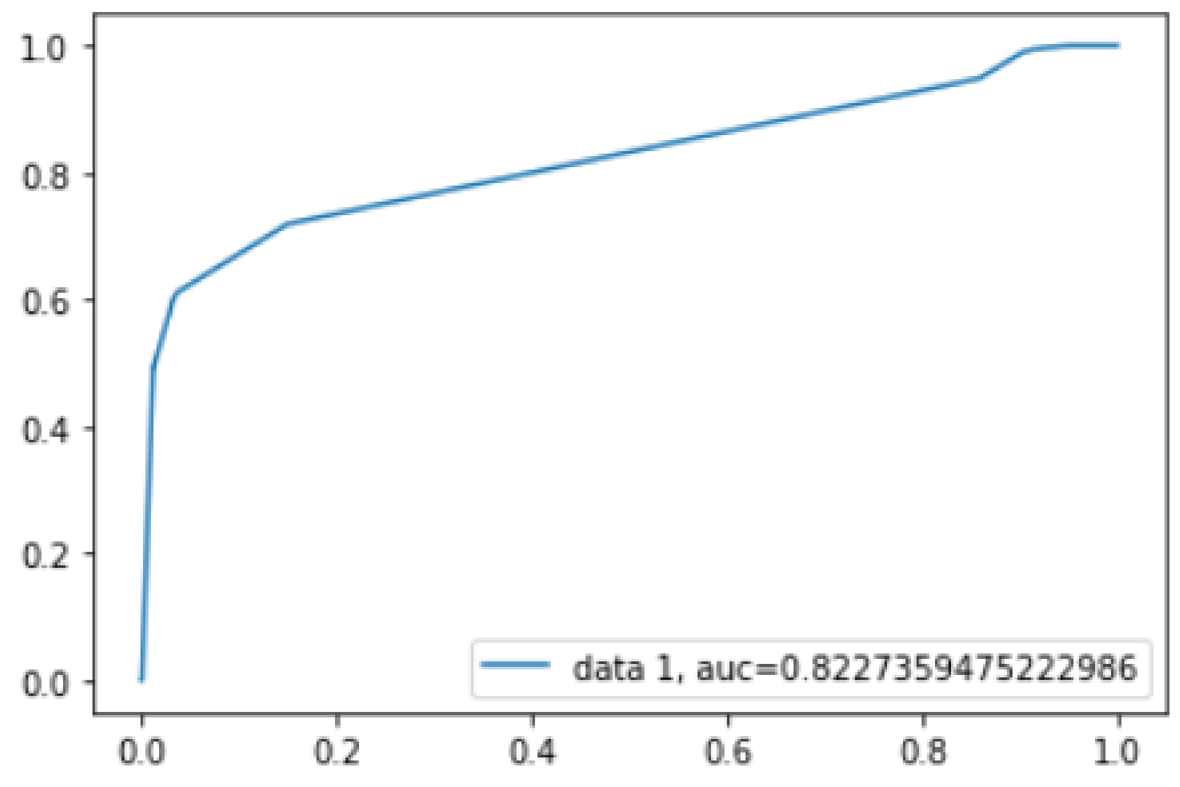
Recall refers to the percentage of total relevant results correctly classified by your algorithm.

Logistic Regression1-2

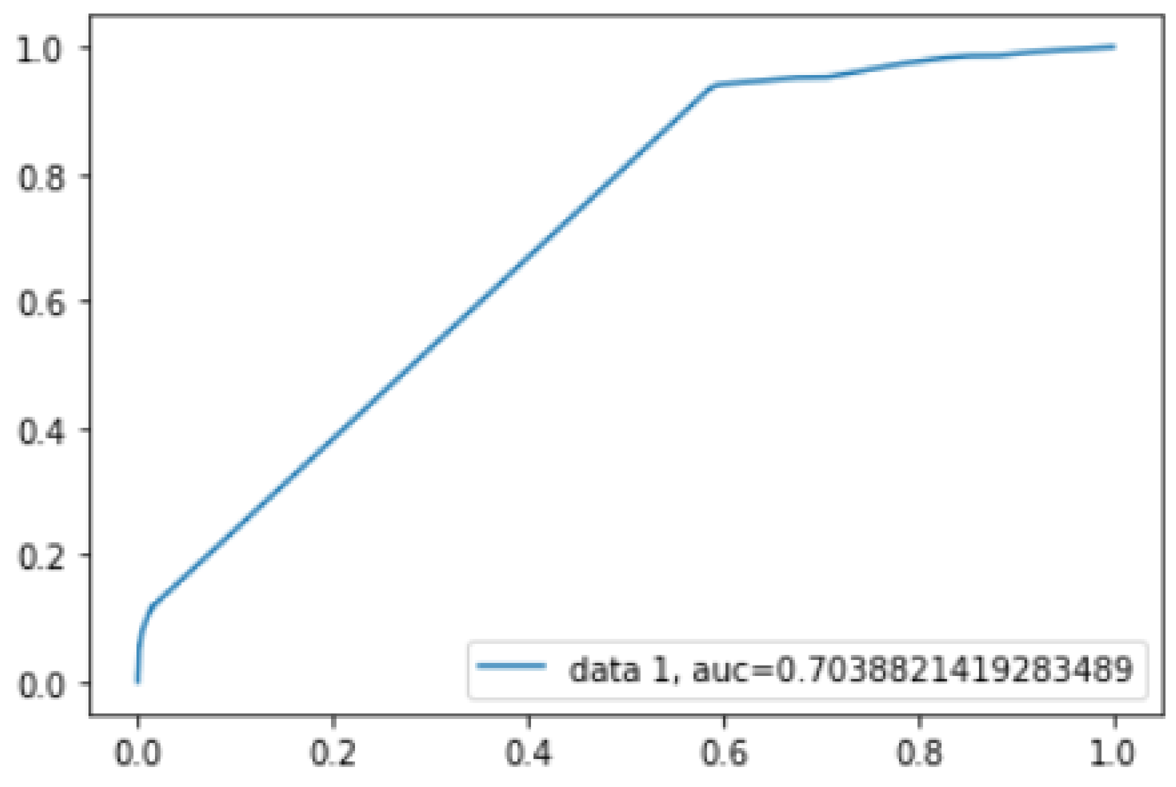
Training data 70%

Testing data 30%

Injury (all variables) predict Dead
ROC/AUC



Sick (all variables) predict Dead
ROC/AUC



When we ROC/AUC to justify the performance of the logistic regression model, AUC of **Injury** model is **0.82,**

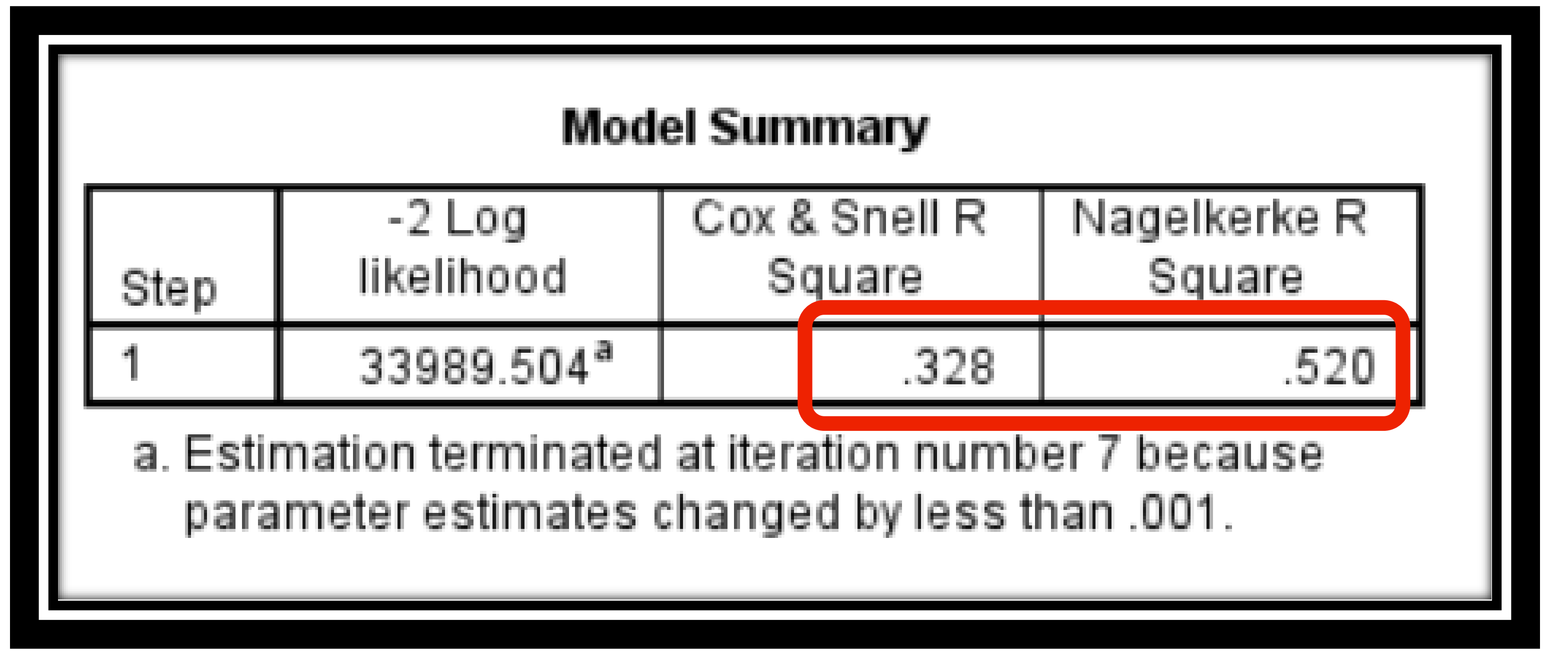
AUC of **Sick** model is **0.70**

☑ Conclusion: ROC/AUC are also indicated good performance

Statistical evaluations

Injury causes and sick causes using logistic regression

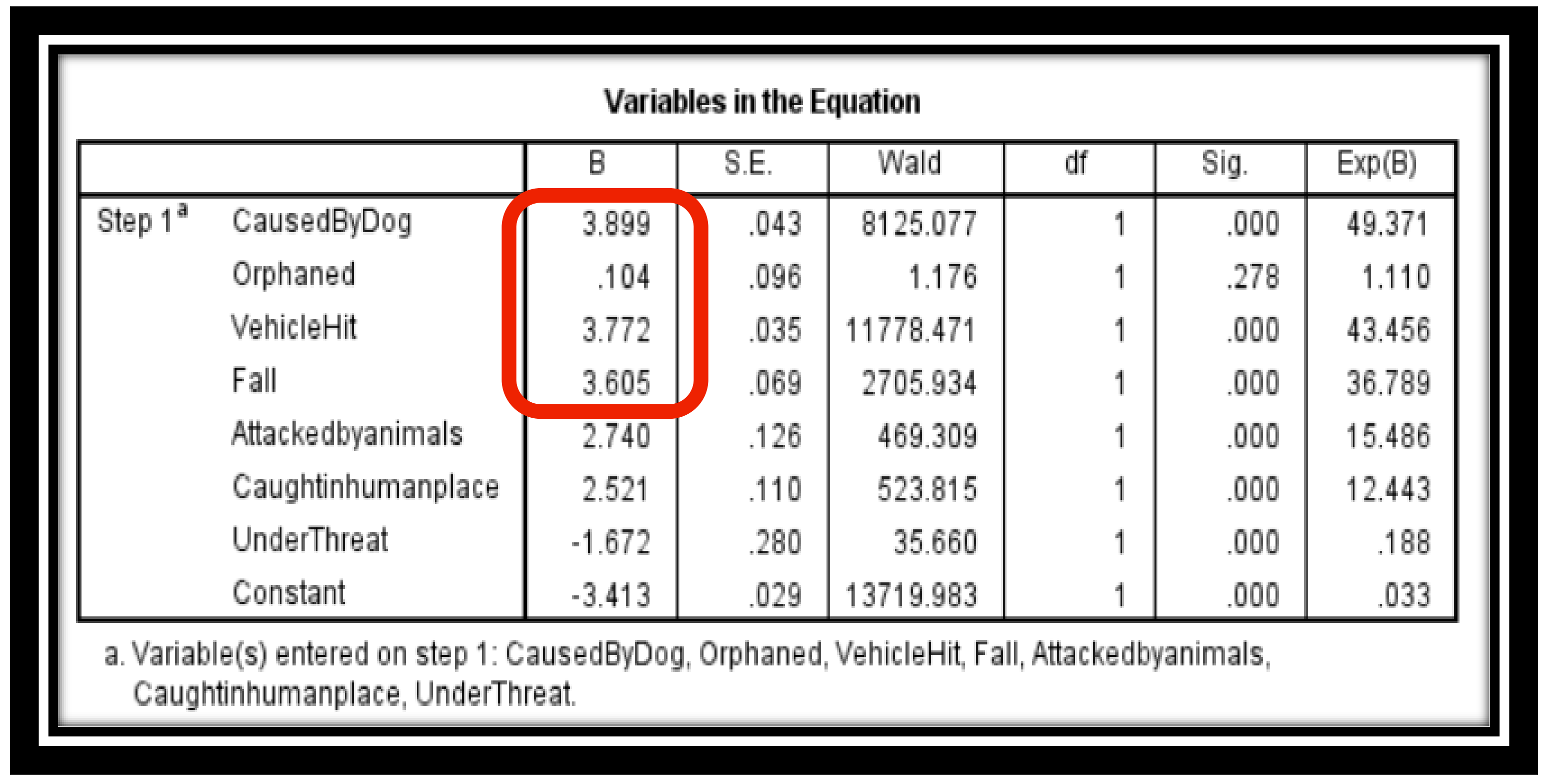
Logistic regression Injury causes



Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	33989.504[a]	.328	.520

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.



Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	CausedByDog	3.899	.043	8125.077	1	.000	49.371
	Orphaned	.104	.096	1.176	1	.278	1.110
	VehicleHit	3.772	.035	11778.471	1	.000	43.456
	Fall	3.605	.069	2705.934	1	.000	36.789
	Attackedbyanimals	2.740	.126	469.309	1	.000	15.486
	Caughtinhumanplace	2.521	.110	523.815	1	.000	12.443
	UnderThreat	-1.672	.280	35.660	1	.000	.188
	Constant	-3.413	.029	13719.983	1	.000	.033

a. Variable(s) entered on step 1: CausedByDog, Orphaned, VehicleHit, Fall, Attackedbyanimals, Caughtinhumanplace, UnderThreat.

☑ conclusion

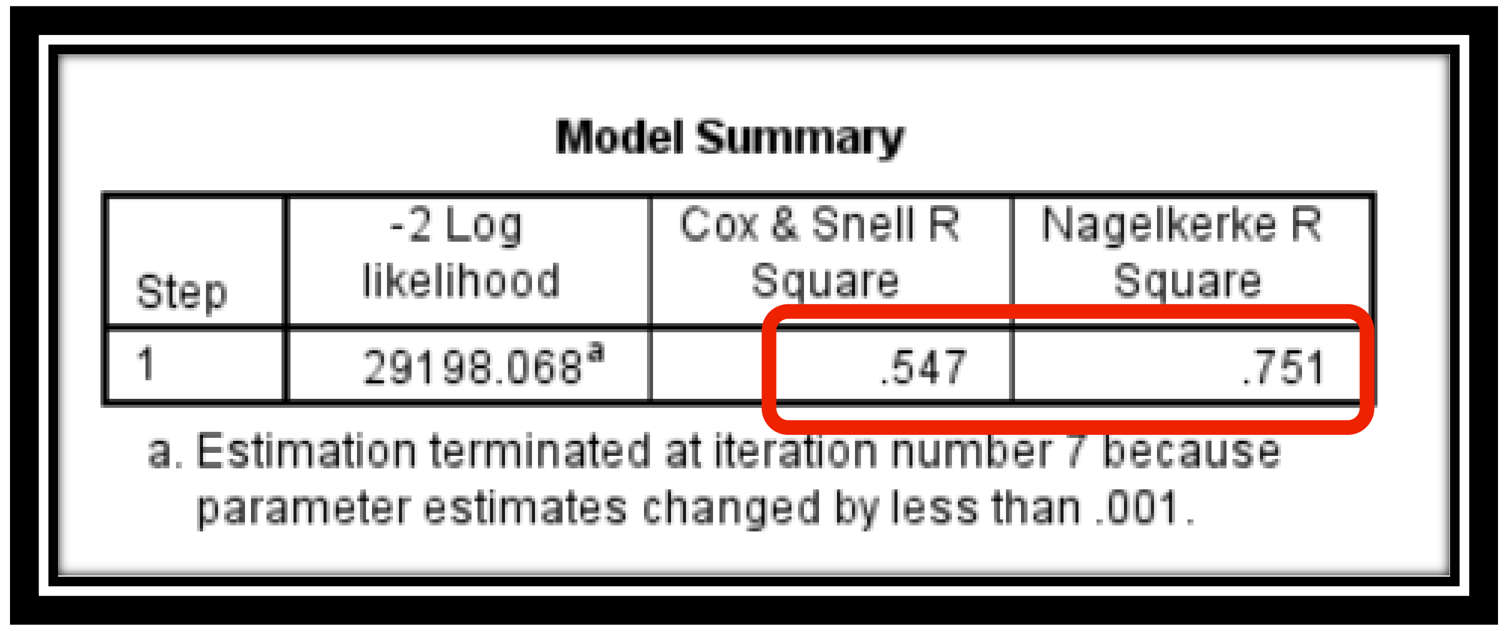
most influential factors of Injury are:
Caused by dog, vehicle hit and fall

most influential factors of sick are:
Chlamydiosis, Conjunctivitis, Bursitis

The two **R-squares** in the table explain the interval for the proportion of variation in the dependent variable that can be explained in this model.

[Cox&Snell R Square, Nagelkerke R Square]

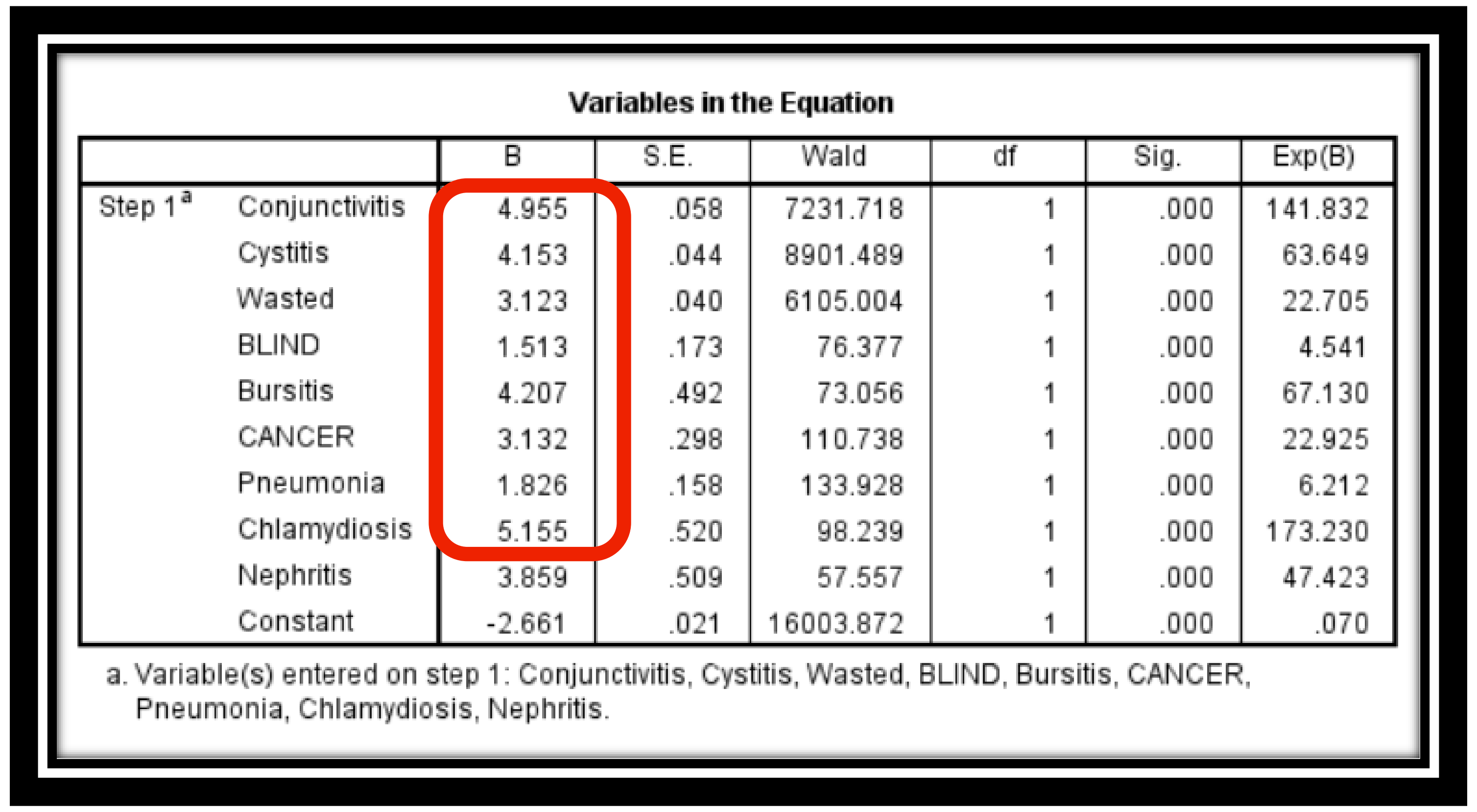
Logistic regression Sick causes



Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	29198.068[a]	.547	.751

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.



Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Conjunctivitis	4.955	.058	7231.718	1	.000	141.832
	Cystitis	4.153	.044	8901.489	1	.000	63.649
	Wasted	3.123	.040	6105.004	1	.000	22.705
	BLIND	1.513	.173	76.377	1	.000	4.541
	Bursitis	4.207	.492	73.056	1	.000	67.130
	CANCER	3.132	.298	110.738	1	.000	22.925
	Pneumonia	1.826	.158	133.928	1	.000	6.212
	Chlamydiosis	5.155	.520	98.239	1	.000	173.230
	Nephritis	3.859	.509	57.557	1	.000	47.423
	Constant	-2.661	.021	16003.872	1	.000	.070

a. Variable(s) entered on step 1: Conjunctivitis, Cystitis, Wasted, BLIND, Bursitis, CANCER, Pneumonia, Chlamydiosis, Nephritis.

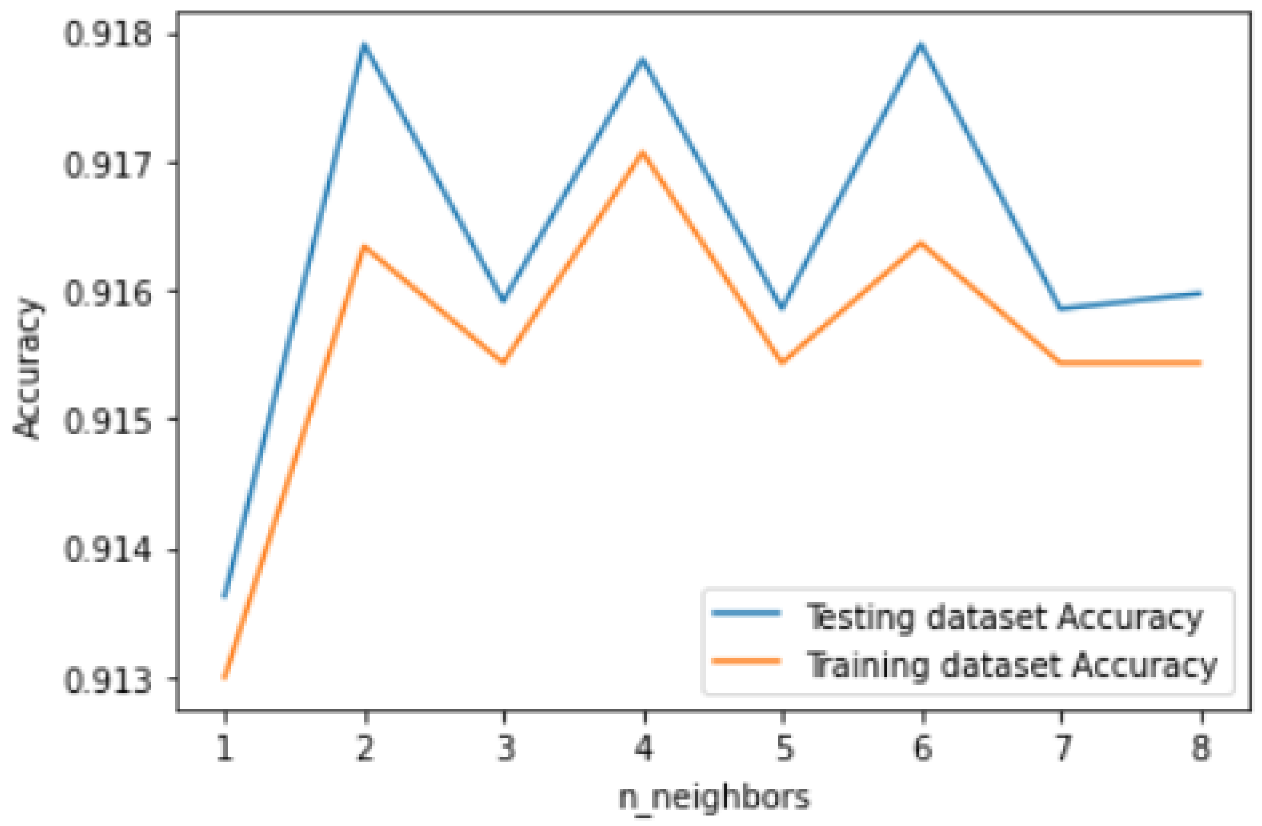
K nearest neighbors

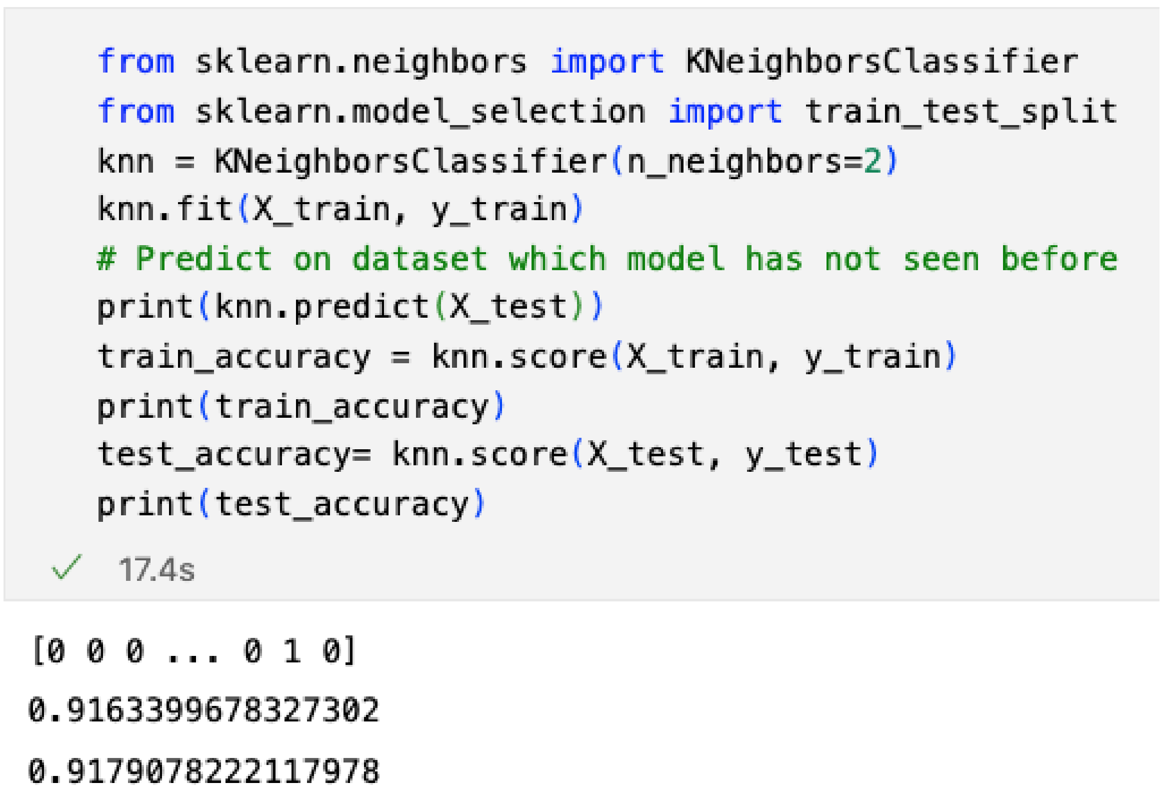
Training data 70%

Testing data 30%

☑ **Conclusion: Overall performances are good**

Injury (all variables) predict Dead



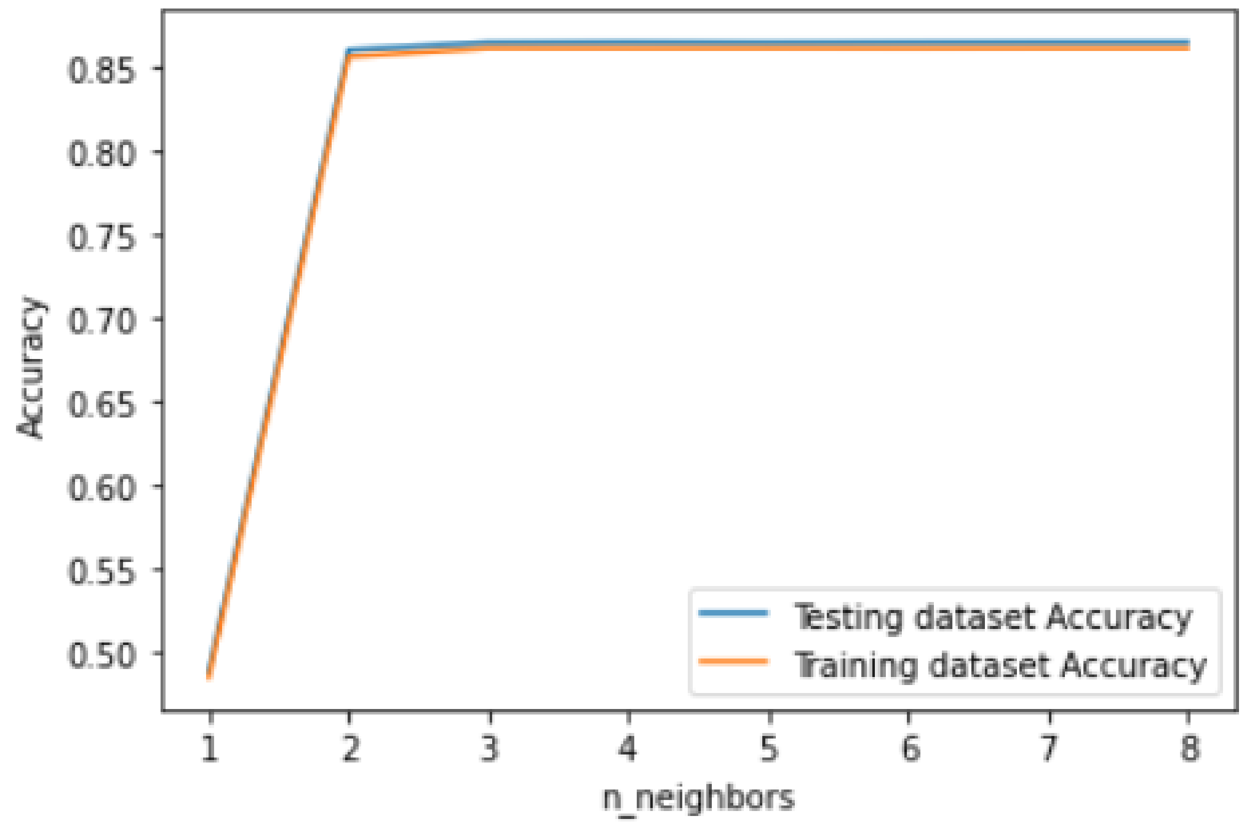


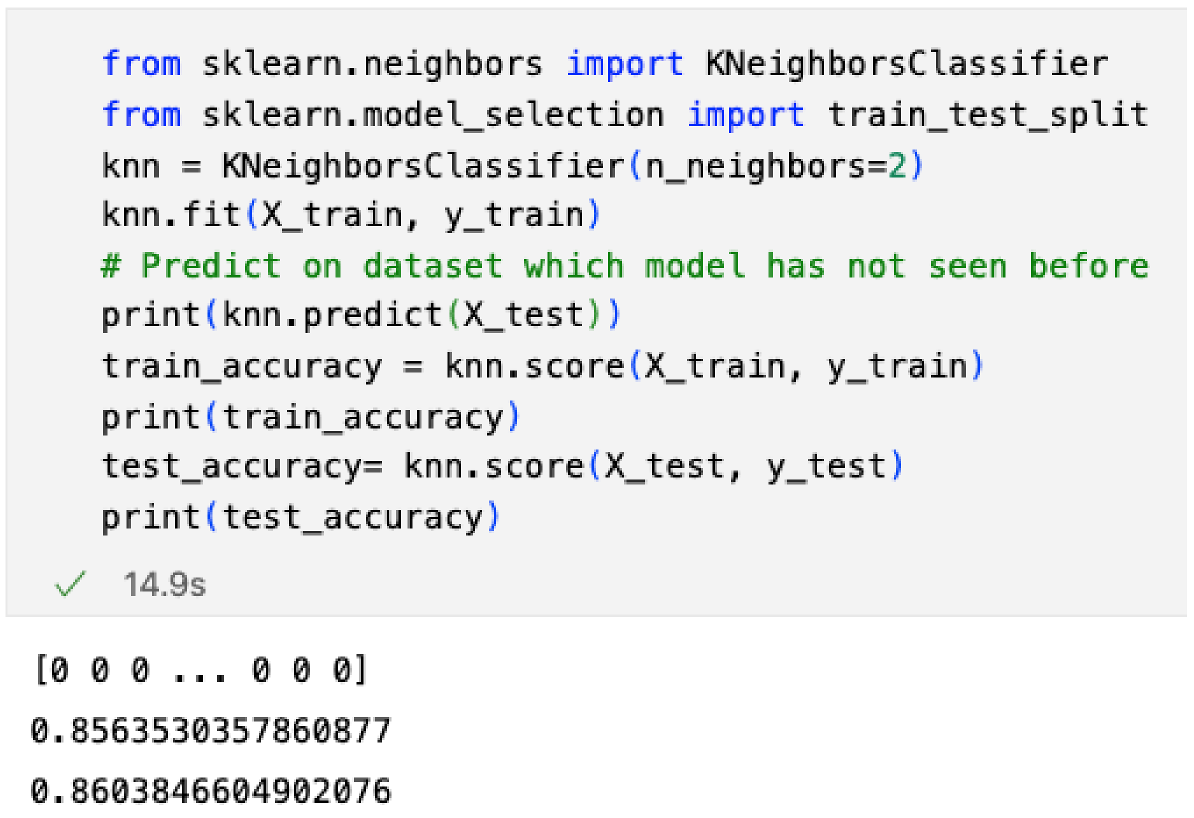
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
knn = KNeighborsClassifier(n_neighbors=2)
knn.fit(X_train, y_train)
# Predict on dataset which model has not seen before
print(knn.predict(X_test))
train_accuracy = knn.score(X_train, y_train)
print(train_accuracy)
test_accuracy= knn.score(X_test, y_test)
print(test_accuracy)
```

✓ 17.4s

```
[0 0 0 ... 0 1 0]
0.9163399678327302
0.9179078222117978
```

Sick (all variables) predict Dead





```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
knn = KNeighborsClassifier(n_neighbors=2)
knn.fit(X_train, y_train)
# Predict on dataset which model has not seen before
print(knn.predict(X_test))
train_accuracy = knn.score(X_train, y_train)
print(train_accuracy)
test_accuracy= knn.score(X_test, y_test)
print(test_accuracy)
```

✓ 14.9s

```
[0 0 0 ... 0 0 0]
0.8563530357860877
0.8603846604902076
```

K nearest neighbors:

How to choose K?

Both the Injury model and Sick model are better when we choose K=2, according to the graph.

Injury model is more accurate than **Sick one**, **91.8% > 86%**

Both in training and testing data.

Models' comparison

Predicting death is a classification problem, so we tried four different algorithms and compared with the performances of models

Logistic Regression

1. Use Injury and the detailed variables to predict Dead.
2.Use Sick and related variables to predict Dead.

Evaluation index

Confusion matrix
ROC / AUC

KNN

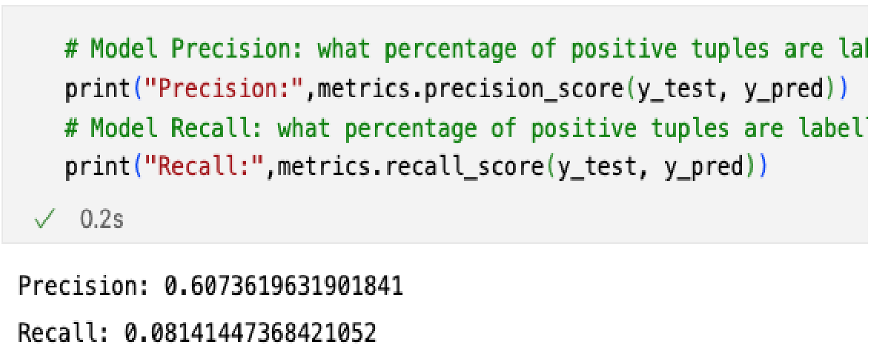
1. Use Injury and the detailed variables to predict Dead.
2.Use Sick and related variables to predict Dead.

Evaluation index

Confusion matrix
K chosen

SVM

Evaluation index



```
# Model Precision: what percentage of positive tuples are lal
print("Precision:",metrics.precision_score(y_test, y_pred))
# Model Recall: what percentage of positive tuples are label
print("Recall:",metrics.recall_score(y_test, y_pred))
```

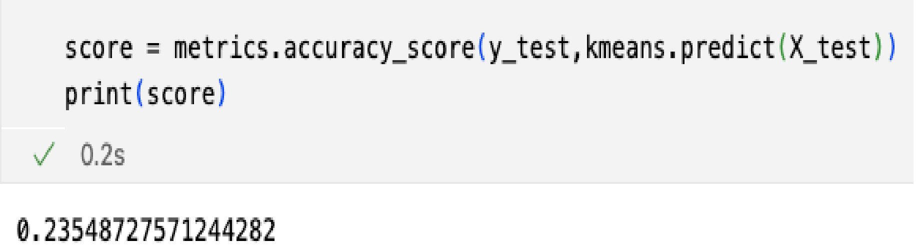
✓ 0.2s

```
Precision: 0.6073619631901841
Recall: 0.08141447368421052
```

SVM: Precision:61% Recall:8.1%

K means

Evaluation index

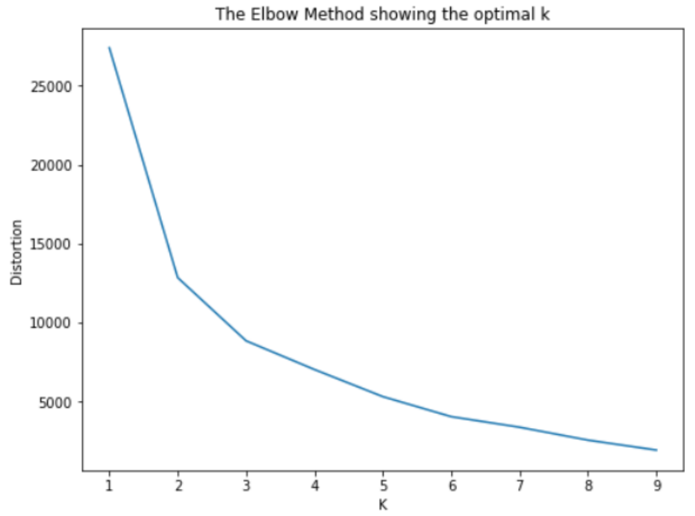


```
score = metrics.accuracy_score(y_test,kmeans.predict(X_test))
print(score)
```

✓ 0.2s

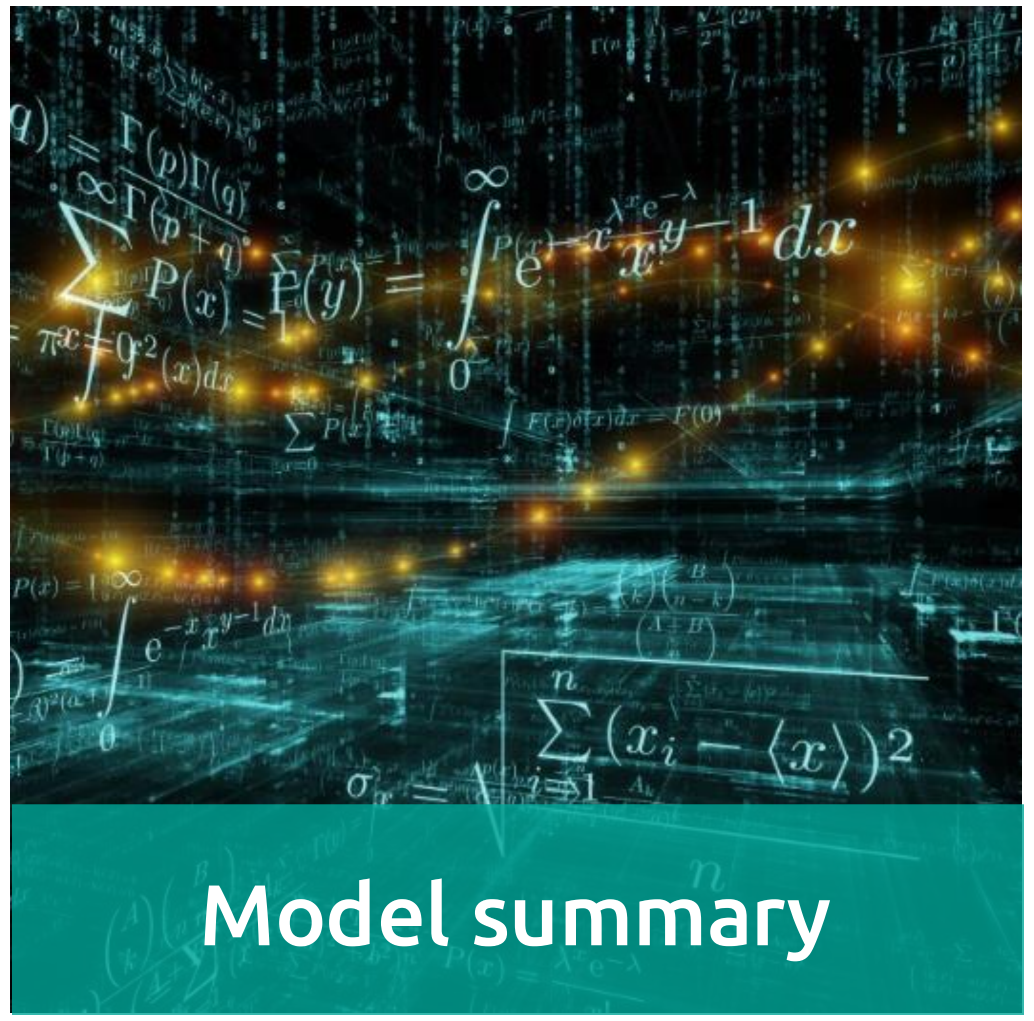
```
0.23548727571244282
```

K means Accuracy: 23.5% K=2



☑ **Both logistic Regression and K nearest neighbors (k=2) are good model to choose**

Storytelling and Advice



1. Main causes conclusion

- The main causes lead to koala’s death are **Vehicle Hit** and **sick.**
- Most common sickness in Koalas are:

  Conjunctivitis, Cystitis ,Wasted, Chlamydiosis and Bursitis.
- most influential factors of Injury are:

  Caused by dog, vehicle hit and fall.

2. Model summary

- **Logistic regression** and **KNN** are two good performances models to predict death, both in injury and sick models.

3. Actions advice

- Animal Protection Organization: Fundings on koala sickness research.
- State Government: Take actions to protect koalas’ home, such as put signs near roads of koalas’ habitat.
- Local community: Koalas information telling.

4. Future study

- Using other variables (deleted ones) to do research, such as location clustering.
- Generate deep learning models to predict independent variables.

References and Improvements

No	Trail presentation feedback	Final presentation improvement
1	How does your project solve a problem? Don’t be general. Talk about specifics.	Page 2:Analyze the main causes leading koalas to death. Using different algorithm models to predict death.
2	data collection: you didn't explain.	Page 4: how we get our main datasets
3	5-data confess: predict death from injury and sickness. Why not use the type of injury and sickness? You can use a one-hot encoding of categorical variables (dependent) to predict death.	Page 12: Define variables
4	what are the most frequent causes of death? What types of injury/sickness?	Page 8-9: General data analysis - Injury/Sick Page 11: Vehicle Hit caused Death/Sick also caused Death
5	6-storytelling: The slides on deforestation have nothing to do with your analysis. Your conclusions should be taken from your analysis.	We abandon the deforestation data

[1] https://environment.des.qld.gov.au/wildlife/animals/living-with/koalas/facts

Thank You