# Hunting Zika Virus using Machine Learning

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In collaboration with Cary Institute of Ecosystem Studies
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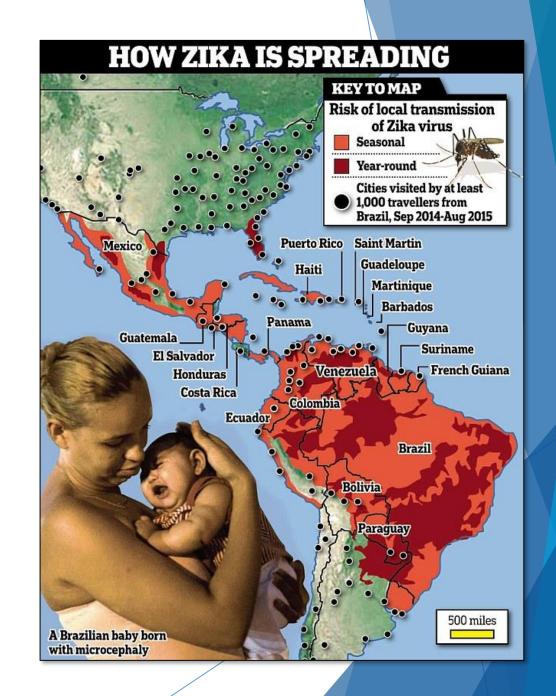


## The Zika problem

Recently there is a Zika outbreak in Brazil and it is spreading fast.

Symptoms include rash, fever, muscle and joint pain, headache;

Zika is non-lethal but causes Microcephaly (= small head size) and eye problems in babies of infected mothers.



## How Zika spreads

- ► The virus naturally resides in the blood of host animals;
- ➤ The animals don't get infected because they have antibodies, or have subclinical infections;
- Virus survives by passing from generation to generation of animals.

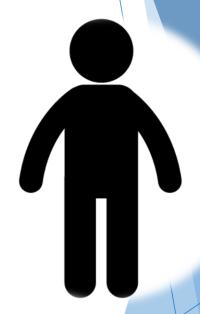


## How Zika spreads

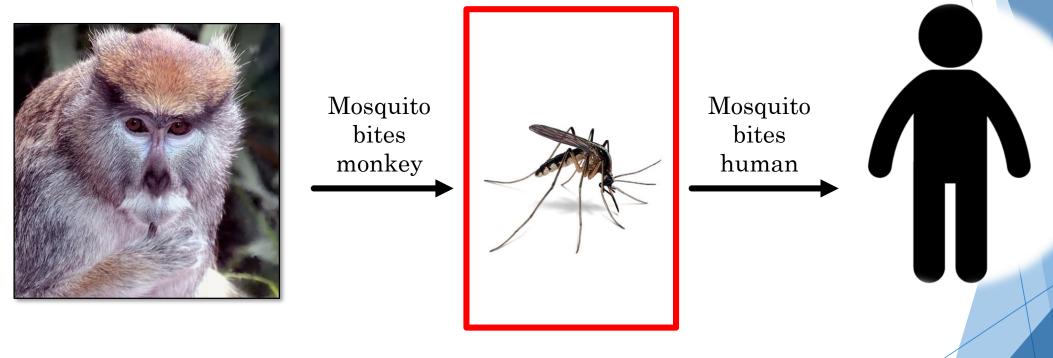


Mosquito
bites
monkey

Mosquito bites human

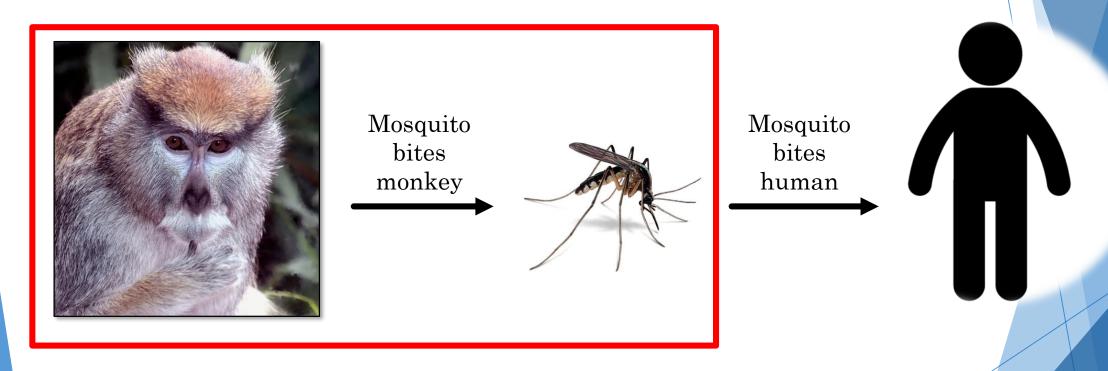


## Present: REACTIVE approach to contain outbreak



Eradicate mosquitos in spillover areas **Not Good!** 

## Objective: PROACTIVE approach to stop outbreak



Find out the source animals to prioritize mosquito eradication efforts

Kills the problem at source

## Data

Dataset 1: Reservoir status

Animal	Carries Zika?	Carries Dengue?	Carries Yellow fever?	
Monkey 1	No	Yes	No	•••
Monkey 2	Yes	No	No	•••
Monkey 3	No	Yes	No	
Monkey 4	No	No	No	•••
Monkey 5	Yes	No	Yes	•••
Monkey 6	No	Yes	No	•••
•••				

Dataset 2: Animal characteristics

Animal	Body mass	Litter size	Maximum longevity	
Monkey 1				
Monkey 2				•••
Monkey 3				•••
Monkey 4				•••
Monkey 5				•••
Monkey 6				•••

50 characteristics

## Challenges

Dataset 1: Reservoir status

Animal	Carries Zika?	Carries Dengue?	Carries Yellow fever?	
Monkey 1	No	Yes	No	•••
Monkey 2	Yes	No	No	•••
Monkey 3	No	Yes	No	
Monkey 4	No	No	No	•••
Monkey 5	Yes	No	Yes	
Monkey 6	No	Yes	No	

- ► Reservoirs are extremely rare;
- Only 4 known reservoirs for Zika;
- ► There are only 26 positive entries in this matrix;
- Need specialized methods to deal with the situation.

## Challenges

- Data on animal characteristics are not complete: lot of entries are missing in many animals;
- Some characteristics are almost completely missing for all animals;
- Some animals have almost all variables missing;

#### Dataset 2: Animal characteristics

Animal	Body mass	Litter size	Maximum longevity	
Monkey 1				
Monkey 2				
Monkey 3				
Monkey 4				
Monkey 5				•••
Monkey 6				
				•••

## Challenges

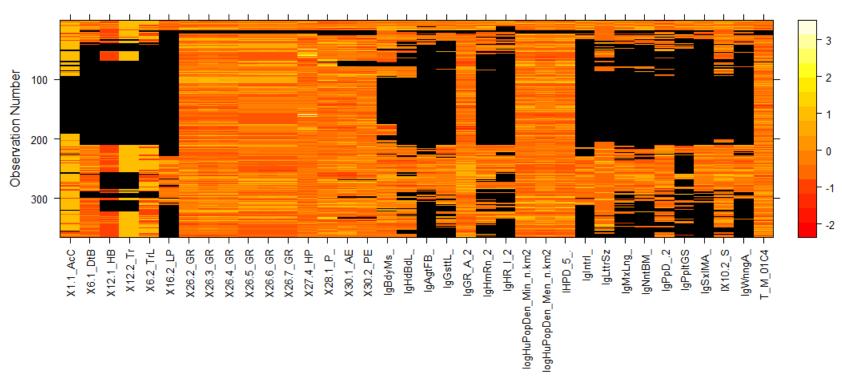
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		•••		

## The missing data problem

#### Dark represents missing data



Standardized Variable
Clustered by missingness

## Modelling approach

#### 1. Missing data imputation:

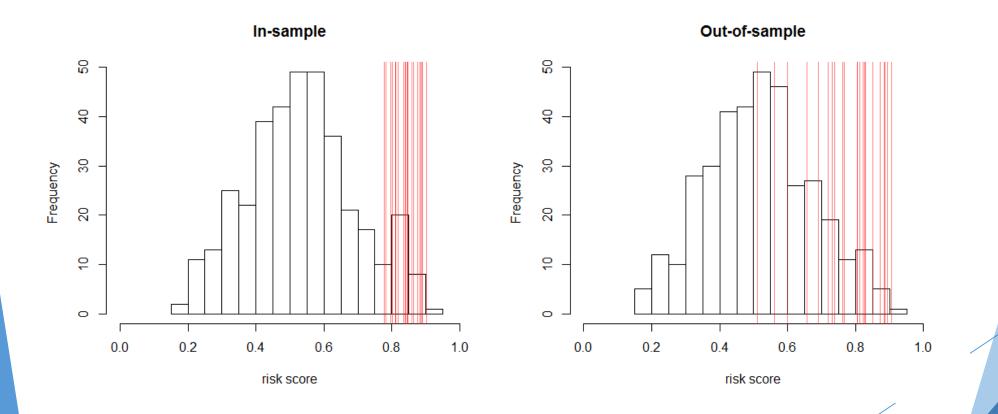
use a multiple imputation procedure called Multiply Imputed Chained Equation (MICE: Raghunathan *et al*, 2001)

#### 2. Predictive model:

- ▶ Model reservoir status for all primates simultaneously;
- ▶ Use a Bayesian model that assumes the response variable is generated through a hierarchical process, taking into account covariate information in a nonlinear fashion (Rai *et al*, 2015)

## Validation

Delete a positive entry in dataset 1, model on that data and use that model to get risk score for that sample.



## Results

- ▶ We are interested in high-risk animals in South America that haven't been detected yet.
- ➤ Top 5 high-risk species:



Black-tufted
Marmoset
(Callithrix penicillata)



White-fronted
Capuchin
(Cebus albifrons)



Brown howler (Alouatta guariba)



Cotton-top tamarin (Saguinus oedipus)



Red-handed howler (Alouatta belzebul)

## Trait profiles of high-risk animals

Variable name	Importance	mean.low	mean.hi
logGR_Area_km2	23.75	8.21	13.38
$logAgeatFirstBirth\_d$	23.39	6.57	7.09
$logNeonateBodyMass\_g$	23.07	3.28	5.28
X26.6_GR_MinLong_dd	22.93	25.76	21.12
$logHomeRange\_km2$	22.69	-4.07	-1.13
$\log Sexual Maturity Age\_d$	22.17	6.17	7.15
$X26.5\_GR\_MaxLong\_dd$	21.67	26.91	37.50
$logInterbirthInterval\_d$	21.66	5.63	6.07
$logHuPopDen\_Min\_n.km2$	21.35	2.38	1.24
$logBodyMass\_g\_Resid$	20.95	0.02	0.08

Larger animals that have high body mass, less offsprings and larger social groups seem to be more likely reservoirs

## What to do with the outputs?

- ▶ Work with disease ecology researchers to collect blood samples from these monkeys and test for presence of Zika virus;
- ▶ If a new reservoir is detected, focus on mosquito eradication efforts around the animal's habitat;
- ▶ Provide a much needed empirical baseline for future similar studies regarding a proactive approach towards infectious disease management.

### Future work

- ▶ Integrate with the Prospector tool (Krause, Perer and Ng, 2016) to understand how risk scores are affected by different levels of a covariate, i.e. partial dependence plots;
- Modify outcomes for unknown reservoirs based on their geographic range overlap with known reservoirs, as well as incorporate primate-mosquito interactions;
- ► Extend the underlying model to incorporate information on the different viruses;
- ▶ Build a unified framework for simultaneously imputing missing data and modelling the outcomes.

### References

- First detection of Zika virus in neotropical primates in Brazil: a possible new reservoir. Favoretto, S.; Araujo, D.; Oliviera, D.; Duarte, N.; Mesquita, F.; Zanotto, P. and Durigon, E. Available in bioRxiv: <a href="http://dx.doi.org/10.1101/049395">http://dx.doi.org/10.1101/049395</a>, April **2016**.
- ▶ Han, B.; Schmidt, J. P.; Bowden, S. E. and Drake, J. M. Rodent reservoirs of future zoonotic diseases. *Proc. Natl. Acad. Sci.*, **2015**, 112(22): 7039-7044.
- Raghunathan, T.W.; Lepkowksi, J.M.; Van Hoewyk, J. and Solenbeger P. A multivariate technique for multiply imputing missing values using a sequence of regression models. *Survey Methodology*, **2001**, 27: 85–95.
- Rai, P.; Hu, C.; Henao, R. and Carin, L. Large-Scale Bayesian Multi-Label Learning via Topic-Based Label Embeddings. In: *Advances in Neural Information Processing Systems 29* (NIPS 2015), **2015**, 3222-3230.
- ▶ Krause, J.; Perer, A. and Ng, K. Interacting with Predictions: Visual Inspection of Blackbox Machine Learning Models. In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI 2016)*, **2016**, 5686-5697.

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## THANK YOU!