MODEL EXPLAINABILITY

WHY IS IT IMPORTANT?

Fiona Chow



born and raised

KUALA LUMPUR, MALAYSIA (FOOD PARADISE <3)

studied

ACCOUNTING AND FINANCE - PROF. QUALIFICATION ACCA

MSc in BIG DATA, UNIVERSITY OF STIRLING

works

BIG DATA ENGINEER



BIRD.I

what is Bird.i?

A Satellite Image & Intelligence platform.

what do we do?

Integrate images from world leading satellite operators

Extract intelligence from satellite images using computer vision and machine learning techniques

Bird.i Portal

USER FAQ

"What did the model see to make that decision?"

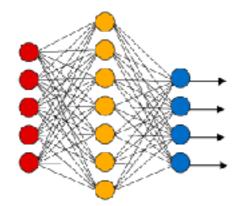
MACHINE LEARNING



input



feature extraction



model

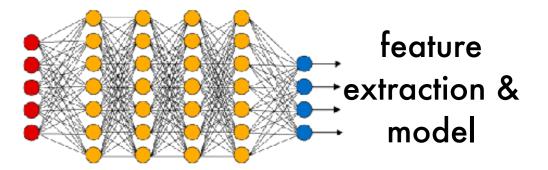


output

DEEP LEARNING



input



PANDA
NOT PANDA

output

MACHINE LEARNING

have control over what features are used for training

a lot of time spent on manually selecting, extracting, engineering features

requires a reasonable amount of data

lower training time

lower computation overheads

accuracy plateaus

DEEP LEARNING

more complex features learnt by model itself

requires a significant amount of data

higher training time

higher computation overheads (<u>needs</u> <u>GPU!</u>)

accuracy performance is more superior

WHAT ARE FEATURES?

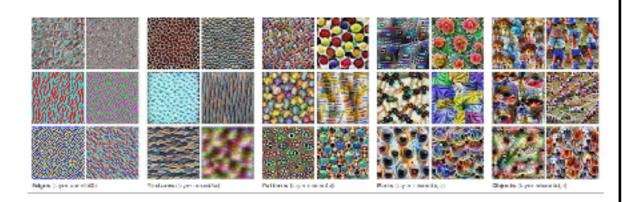
TEXT

"IT FEELS GREAT BEING HERE"

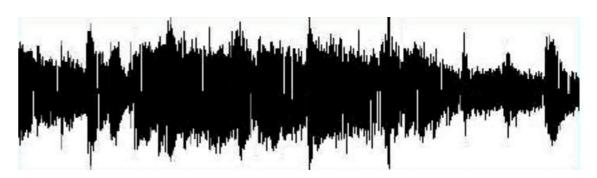
TABULAR

FEMALE, 20-30y/o, 152cm, EMPLOYED

IMAGE

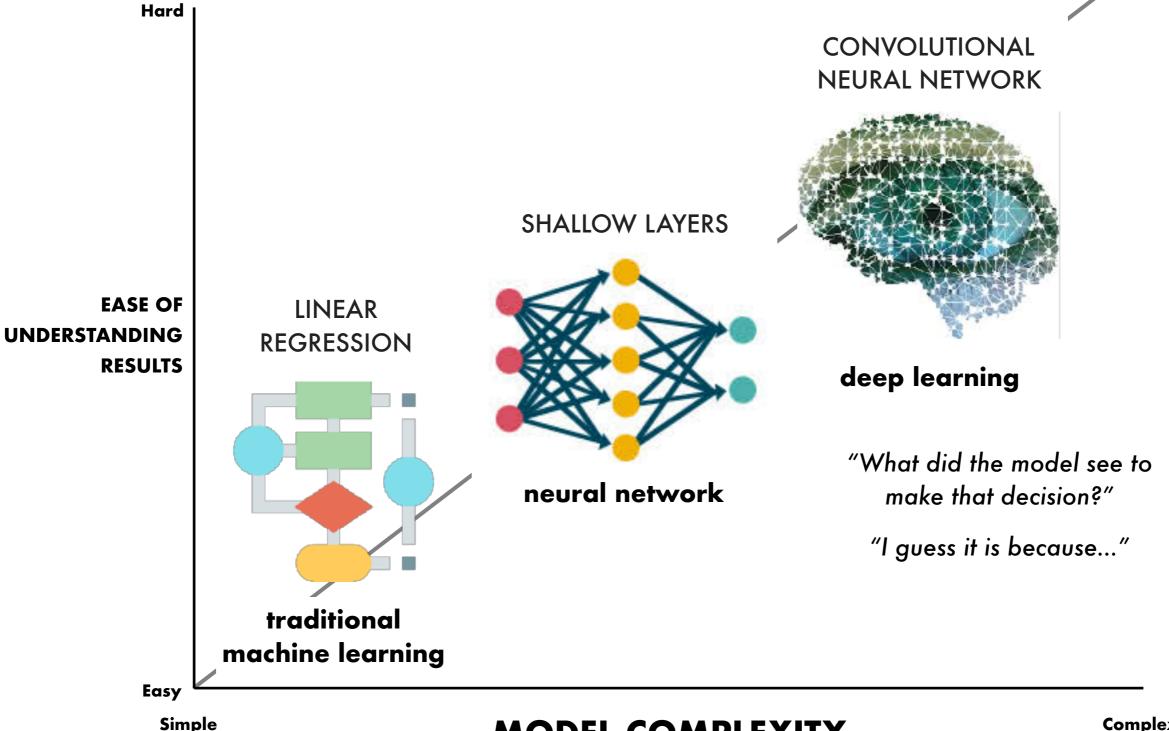


AUDIO

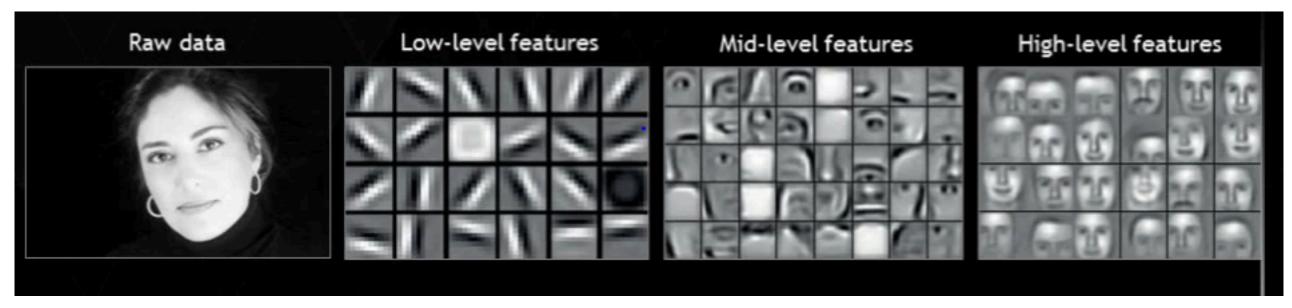


ML PROBLEM

PERFORMANCE



COMPLEXITY IN IMAGES



https://www.analyticsvidhya.com/blog/2017/04/comparison-between-deep-learning-machine-learning/

MODEL EXPLAINABILITY

"Why is this happening?"

IMPORTANCE OF MODEL EXPLAINABILITY

DATA SCIENTISTS

understand what features are important

fix dataset if wrong features are learnt

point to the <u>right direction</u> for future data collection

provide a <u>better explanation</u> than "I think"

IMPORTANCE OF MODEL EXPLAINABILITY

USERS

build TRUST & ACCOUNTABILITY

between users and model



EXPLAINABILITY ON IMAGES

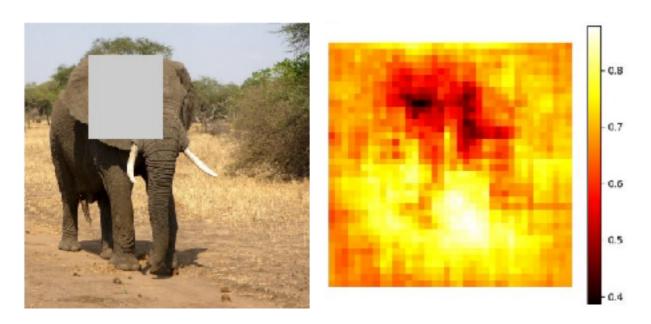
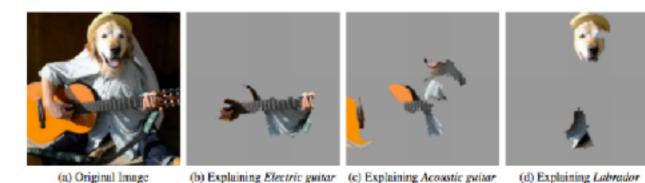


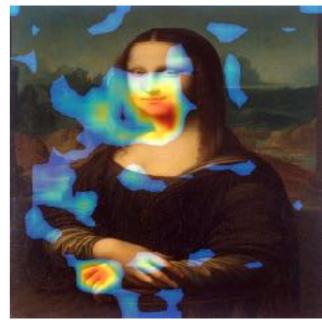
IMAGE OCCLUSION

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture12.pdf



LOCAL INTERPRETABLE MODEL-AGNOSTIC EXPLANATIONS (LIME)

https://arxiv.org/pdf/1602.04938v1.pdf



CLASS ACTIVATION MAP

http://cnnlocalization.csail.mit.edu/Zhou_Learning_Deep_Features_CVPR_2016_paper.pdf

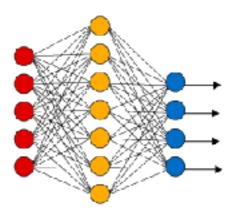
EXAMPLE

input



model (VGG16)

output



label_id, label_name, probability
[('n02510455', 'giant_panda', 0.99959975),
 ('n02445715', 'skunk', 0.0001676529),
 ('n02447366', 'badger', 0.00013132524),
 ('n02443114', 'polecat', 6.1703563e-06)]







EXAMPLE MODEL (VGG16)

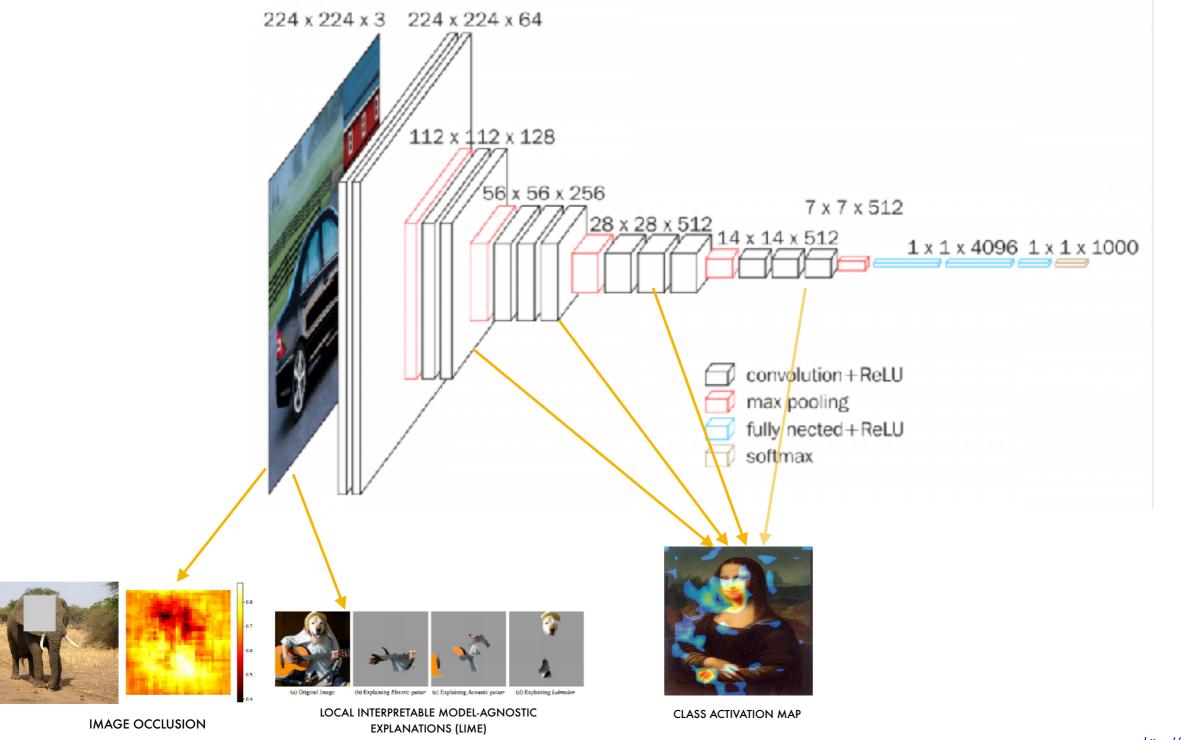
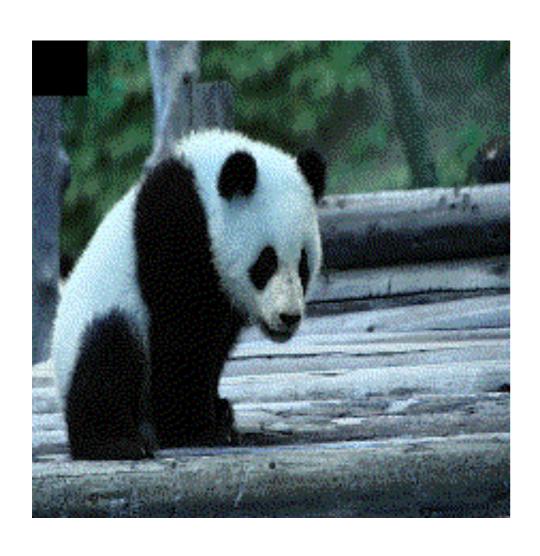
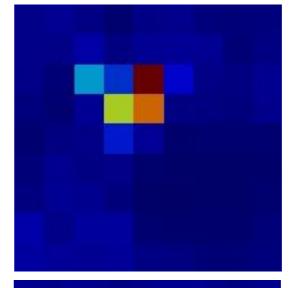


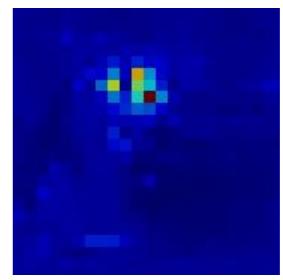
IMAGE OCCLUSION

OCCLUSION



HEAT MAP









LOCAL INTERPRETABLE MODEL-AGNOSTIC EXPLANATIONS (LIME)



Original Image



Interpretable Components



Original Image P(tree frog) = 0.54

Perturbed Instances	P(tree frog)
	0.85
	0.00001
	0.52



LIME

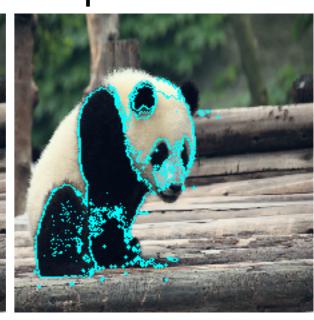
GIANT PANDA BECAUSE

SKUNK BECAUSE...

Top Feature



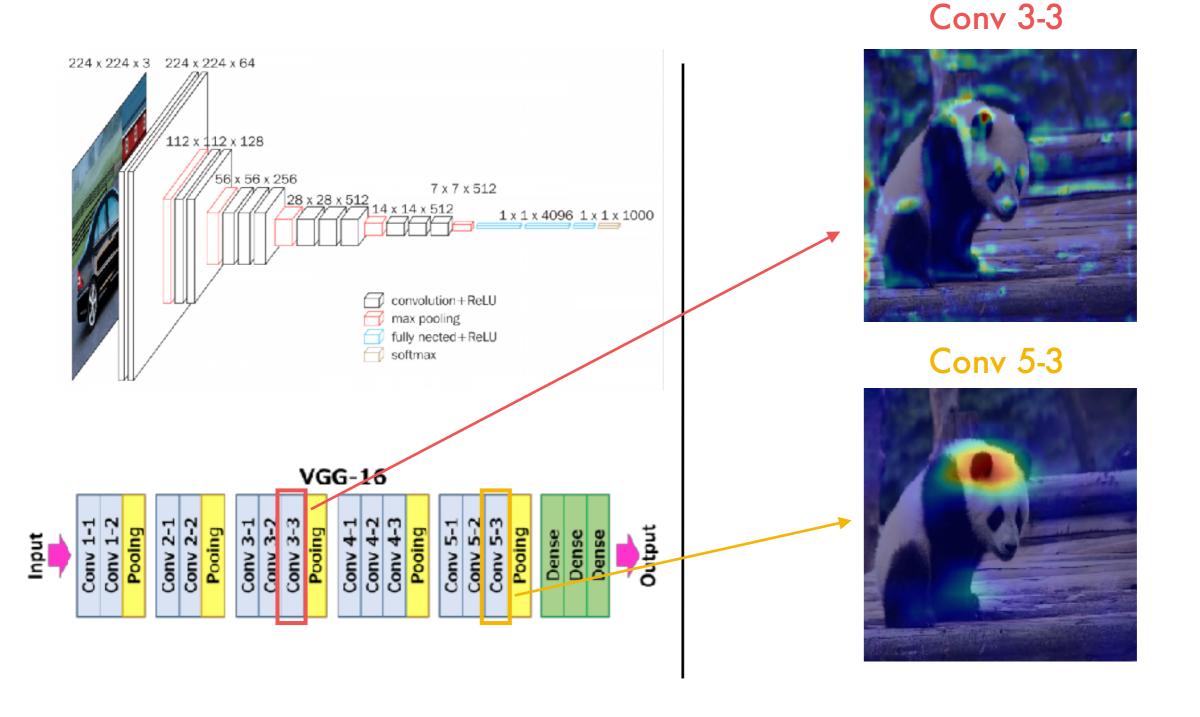
Top 5 Features







CLASS ACTIVATION MAP

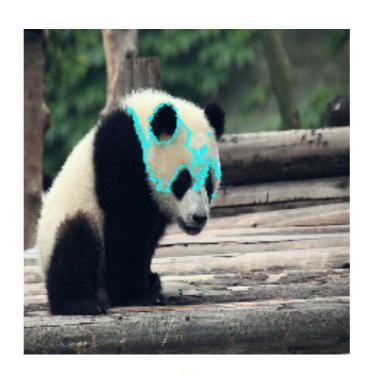


THIS IS A GIANT PANDA

BECAUSE...



IMAGE OCCLUSION



LIME



CLASS ACTIVATION MAP

SUMMARY

- More complex the model, more difficult to explain the results
- Users who don't understand tend to not trust the results and as a result not see the value of automation
- More emphasis on model explainability by experts in the industry. We can expect more research and techniques in future.

THANK YOU!