## PetFinder Adoption Speed Prediction Model

By: Brennan, Spring & Rosie as well as Anusha

GitHub:

Tim from petfinder.com

## Why pet adoption?



The Addams
Family Litter from petfinder.com

The topic we chose was pet adoption speed. We chose this topic because the members of our group have pets and love animals! Our datasource was taken from a featured code competition on Kaggle for Petfinder.my, Malaysia's leading animal welfare platform. The competition calls for developing algorithms to predict how quickly a pet is adopted.

Link to Kaggle competition:

# How is the data going to answer our question?

We will need to be able to predict the outcome of adoption speeds of the pets. Once we have that model, we can make other inferences based on the largest features that play into adoption speed prediction. As we have the adoption speed already, we can compare out model to actual results.



Wren from petfinder.com

## Data Description



Baxter(adopted) from petfinder.com

#### Our data contains information including:

- Type dog or cat
- Name if given one
- Quantity some come as a litter, some are bonded pairs, most are individuals
- Physical descriptors: color, breed, fur length, health, shots, sterilized, maturity size and age
- number of pictures or videos posted
- a written description of the pet(s)
- Fee from free and up
- RescuerID & State who found, and where the pet is
- Adoption Speed how long it took them to be adopted, and what we are trying to create a model to predict

## Data Exploration



Calvin from petfinder.com

14993 rows, 24 columns before cleaning

12 nulls in the description dropped

We changed description to word count

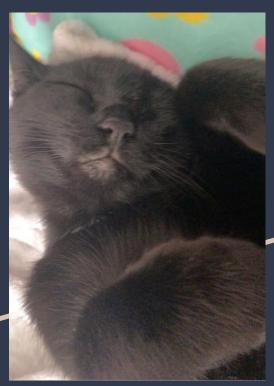
We binned quantity of pets, fee and photo amount into categories, to scale the data before plugging it into the model.

Several columns were ID columns - we did not use in the model as they are just 'noisy' data.

## Assumptions

- We expect the type of pet to have an impact on our model
- Black pets have been known to be less adoptable, so **color1** likely to have an impact
- The **health** of the pet might have a significant impact
- We assume age of pet to have a large impact. Everyone loves kittens and puppies!
- We expect quantity of photos to have an impact on adoption.
- Description will likely be a top half feature, as most people probably read them

## Description of the analysis phase



Luca from petfinder.com

We used Supervised Machine Learning Model to predict adoption speed. We used the data we cleaned/transformed from exploration in the model.

We now have 14981 data points with **5 possible outcomes** for adoption speed

- 0 adopted on the same day as it was listed
- 1 adopted between 1 and 7 days after being listed
- 2 adopted between 8 and 30 days after being listed
- 3 adopted between 31 and 90 days after being listed
- 4 No adoption after 100 days of being listed.
- There are no pets in this dataset that waited between 90 and 100 days

**Target Accuracy 42.3+**% as that would at least get us in the 'bronze'. The top 10 (non-cheating) finalists were all at 44.1+% in the initial contest 3 years ago.

## RF Models

```
[(0.18681237377150112, 'word count'),
 (0.109989718847057, 'photoamt'),
 (0.1096375481912168, 'age'),
 (0.07102324470634117, 'color2'),
 (0.07038042603872528, 'breed1'),
 (0.06954523537473632, 'color1'),
 (0.04714947730736535, 'breed2'),
 (0.03947020420601331, 'furlength'),
 (0.03847838738849204, 'gender'),
 (0.03736809253306168, 'maturitysize')
 (0.034951310594454714, 'color3'),
 (0.0348944438725393, 'quantity'),
 (0.03189425025950297, 'fee bins'),
 (0.031749929446407935, 'dewormed'),
 (0.029752953618307102, 'vaccinated'),
 (0.028470457630819665, 'sterilized'),
 (0.010272463142986228, 'videoamt'),
 (0.009109280747774512, 'health'),
 (0.009050202322697464, 'type')]
```

## RandomForestClassifier Supervised Machine Learning Models:

75/25 train/test split

First model run all features: accuracy 41.4%

**Feature importance: see image left** used this to adjust net model run throughs

Comp ranking: around 632/633 out of 2023 entries, not in bronze

Overview	Data	Code	Discussion	Leaderboard	Rules	Team	My Submissions	Late Subr
631	▲ 994	<del>fujiyuu7</del>	<del>'</del>				•	0.41432
632	▲ 969	nekoun	iei-					0.41416
633	<b>1</b> 0	<del>Vadim I</del>	Borisor					0.41385

### RF Models cont.

Classification	n Report	-1.000	A Table 2	
	precision	recall	fl-score	support
0	0.11	0.01	0.02	99
1	0.38	0.37	0.37	785
2	0.37	0.38	0.37	998
3	0.34	0.27	0.30	801
4	0.51	0.64	0.57	1063
accuracy			0.42	3746
macro avg	0.34	0.33	0.33	3746
weighted avg	0.40	0.42	0.40	3746

Second model run less type, health and video amount features: accuracy 41.6% see image left of classification report.

Comp ranking: around 621/622 out of 2023 entries, not in bronze

Overview	Data	Code	Discussion	Leaderboard	Rules	Team	My Submissions	Late Sub
621	<b>▲</b> 212	<del>Zopp</del>						0.41612
622	▲ 294	Clover	VIL Team					0.41612
623	<b>9</b> 39	Coutan	-					0.41571

Ran several other RF iterations 75/25 - dropping more features, changing word count feature, etc. - *but none* produced as strong of model as the first two passes

## RF Models cont.

```
[(0.1891848531578467, 'word count'),
(0.11079852420092362, 'age'),
 (0.10947971407008213, 'photoamt'),
 (0.07089213440869979, 'color2'),
 (0.06953797363849167, 'breed1'),
 (0.06926315669085968, 'color1'),
 (0.04773870371057317, 'breed2'),
 (0.039780475203142325, 'furlength'),
 (0.03869635338150632, 'gender'),
 (0.036001662685348795, 'maturitysize'),
 (0.03553239685658428, 'quantity'),
 (0.03487738411111796, 'color3'),
 (0.03170487529612327, 'dewormed'),
 (0.031681862465308394, 'fee bins'),
 (0.029091855558974804, 'vaccinated'),
(0.02784227992968062, 'sterilized'),
 (0.010184593362058953, 'videoamt'),
 (0.008948783506004787, 'health'),
 (0.008762417766672874, 'type')]
```

#### Adjusted split to 80/20

First model run (technically model 9) all features: accuracy 42.2%

**Feature importance** - changed slightly from first model age and photo amount switched places, image left

Competition ranking: 245/246 out of 2023 entries, not in bronze (but only barely).

Overview	Data	Code	Discussion	Leaderboard	Rules	Team	My Submissions	Late S
245	▲ 883	Franav	<del>Pandya</del>				(1)	0.42244
246	<b>▲</b> 14	-Fabian						0.42237

## The Final Model - In the bronze!

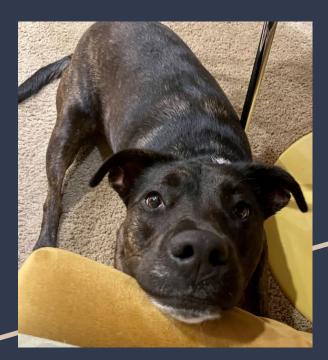
Confusion Matrix								
	Predict	ed 0 Pred	dicted 1	Predicted 2	Predicted 3	Predicted 4		
Actual 0		2	23	20	9	19		
Actual 1		2	228	199	69	133		
Actual 2		1	160	312	152	181		
Actual 3		1	106	161	185	180		
Actual 4		0	72	138	96	548		
Accuracy Classific		0.425425 eport	425425425	44				
		ecision	recall	fl-score	support			
	0 1	0.33	0.03	0.05 0.37	73 631			
	2 3	0.38	0.39	0.38	806 633			
	4	0.52	0.64	0.57	854			
accu	racy			0.43	2997			
macro weighted	-	0.39 0.41	0.34	0.34 0.41	2997 2997			

Second model run (technically model 10) less type, health and video amount features: accuracy 42.5% our best model thus final model, image left

Competition ranking: 141/142 out of 2023 entries, in bronze! Minimum target accuracy goal hit.

Overview	Data	Code	Discussion	Leaderboard	Rules	Team	My Submissions	Late
141	<b>▲</b> 973	Kishi					•	0.4255
142	<b>▲</b> 13	-Whore-	are yeu, valide	tion?				0.4253

## Findings



Bonnie from petfinder.com

#### Top 3 features

- Word count
- Age
- Photo amount

Features that didn't matter/ held back model

- Type of pet
- Health
- Video Amount

Some of these results were surprising to us, especially the type and word\_count features. Once we dropped the bottom three features, our models improved.

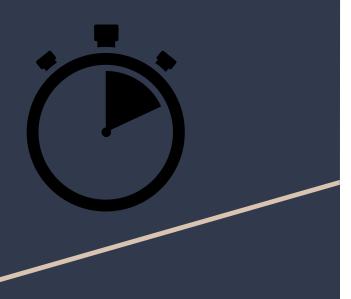
## Suggestions based on findings:



Fluff from petfinder.com

- Have a description, between 40 and 200 words
- Have photos of the pet(s) between 1 and 5 images.
- Age matters, the bulk of all pets regardless of speed were under 65 months. Perhaps consistent photos/descriptions would help with older pets.
- No video needed. One of the least important features
- Focus on health of the pet not necessary.

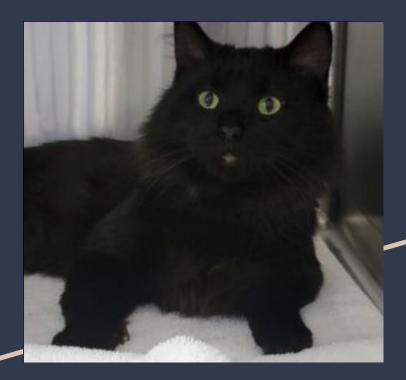
## Limitations - Time



## If we had more time, what we could have also done, or what we could have done differently:

- Different binning/categorization of features for the in model
- Other machine learning model types to compare, for example k-means or SMV
- Full NLP on description top feature when in 'word\_count' form, looking at sentiment, etc. could have likely lead to better model results.

### Limitations - Data



Mango from petfinder.com

#### The Data:

- Limited amount of data points in Adoption
   Speed 0
- Adoption Speed already binned prior to our accessing the data.
- Lastly, if there were images provided perhaps an analysis could have been done on those to see how the image itself might impact the adoption timeline.

## **Technology Used**

- Python and Pandas used for Data Cleaning and Analysis. Natural Language Toolkit(NLTK) to remove stop words in the description column within our dataset (second cleaning pass)
- AWS RDS Postgres for the database, pgAdmin 4 to interface
- SQLAlchemy to connect the database and Google Colab notebooks
- sklearn library to run our model, using RandomForestClassifier
  - Analytical functions used: accuracy\_score, classification\_report, confusion\_matrix, and feature\_importances\_
- Using Tableau to create visuals, and as the platform from which we will present, integrating slides from Google Slides

## Project sources