Kaggle PetFinder Competition:
~~Deep Learning~~ For Puppies

Machine learning

Luca Massaron

Munich Datageeks - June Edition

Who I am

1. Lead Data Scientist, 15+ years of experience in quantitative roles

2. Author of books on Data Science, Machine Learning, Deep Learning and AI

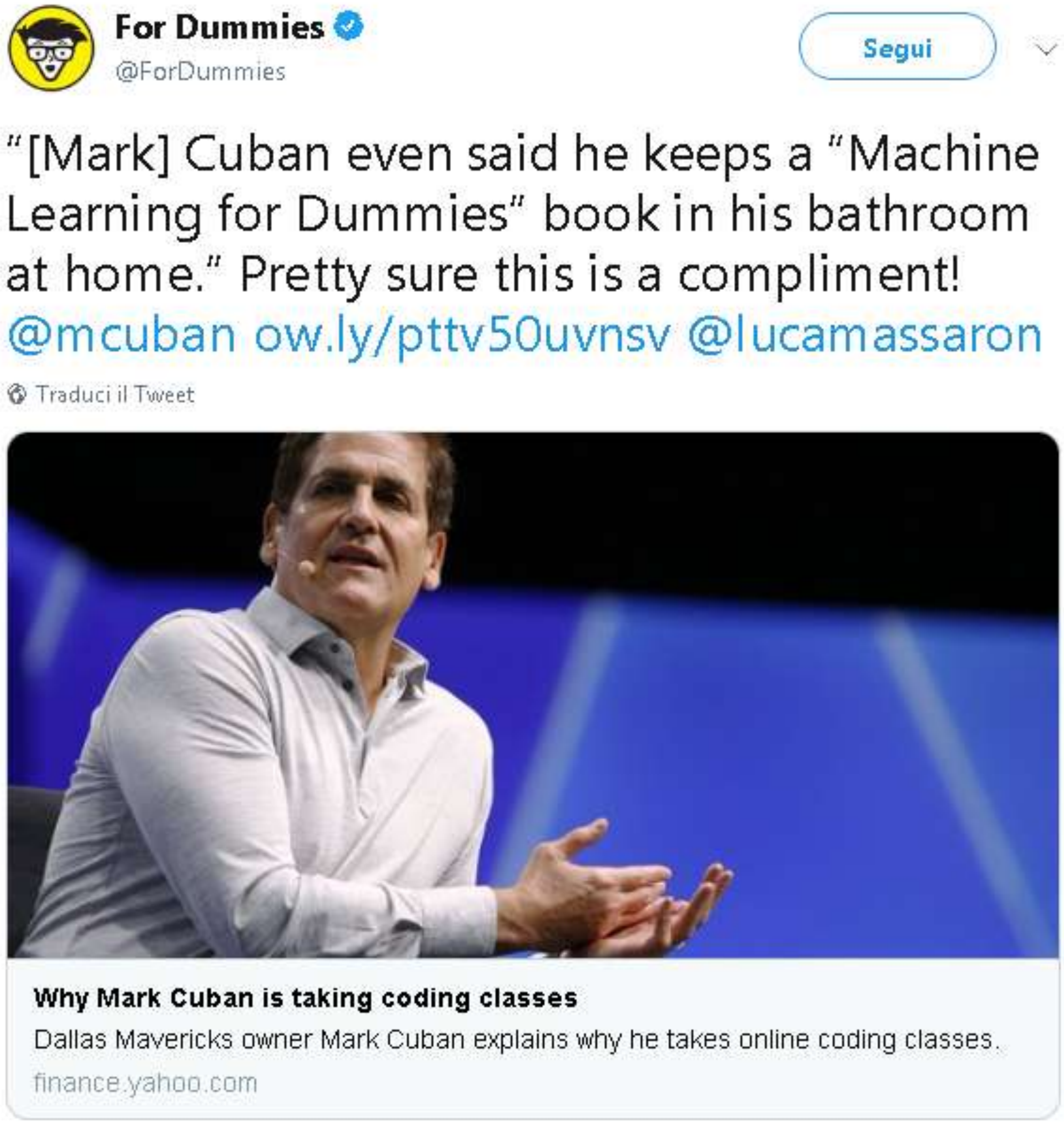
3. Google Developer Expert in Machine Learning

4. Kaggle Master, highest rank achieved on Kaggle: 7th worldwide (153 competitions: 4 gold medals, 25 silver medals, 36 bronze medals)

5. Successfully operated in different sectors such as telecommunications, oil & gas, new media, insurance & finance, consumer goods, trade fairs, public administration, real estate

6. Lecturer in marketing and statistics at universities and private business schools

Maybe you know me for some books



For Dummies
@ForDummies

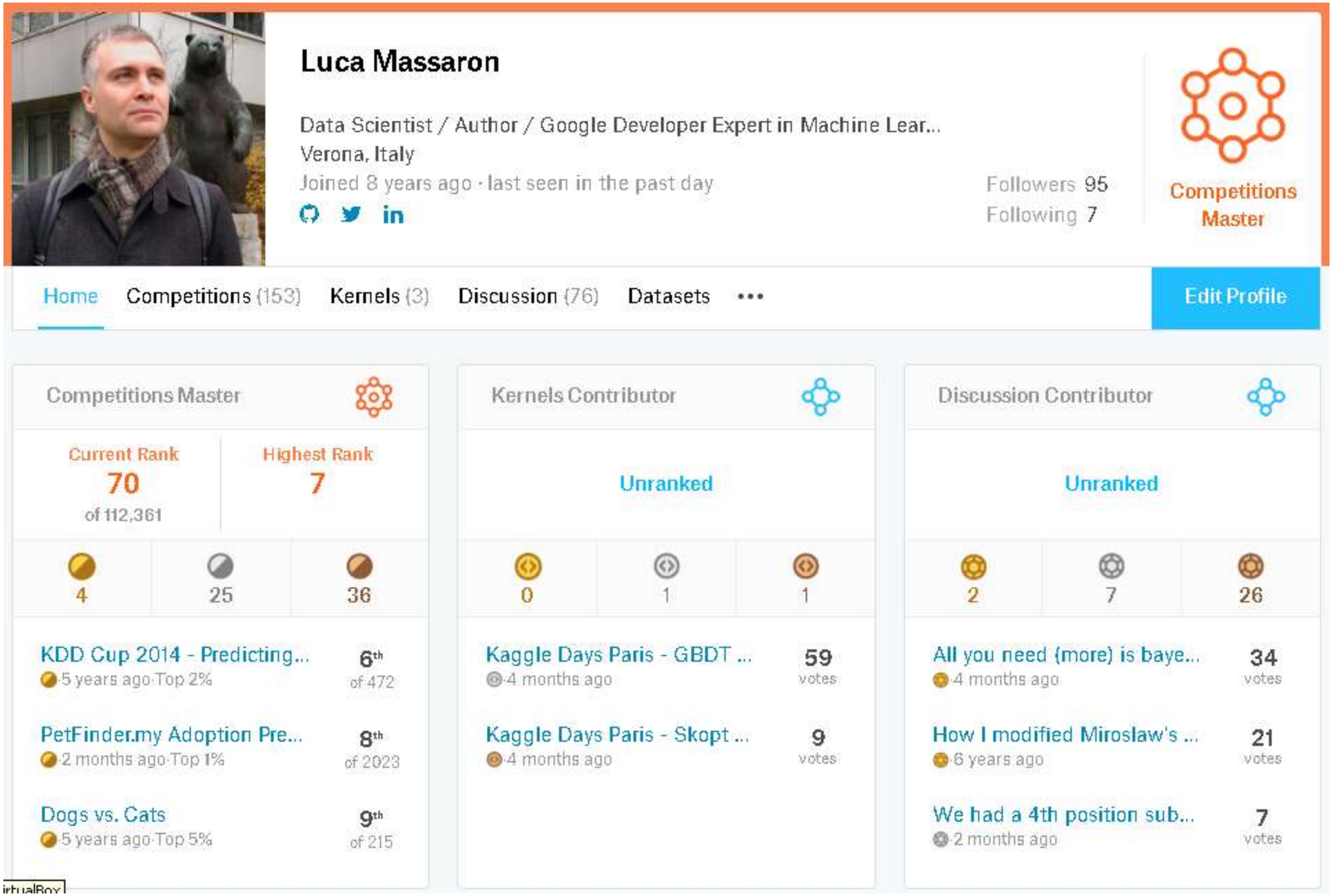
"[Mark] Cuban even said he keeps a "Machine Learning for Dummies" book in his bathroom at home." Pretty sure this is a compliment! @mcuban ow.ly/pttv50uvnsv @lucamassaron

Why Mark Cuban is taking coding classes

Dallas Mavericks owner Mark Cuban explains why he takes online coding classes.

finance.yahoo.com

…or for my legacy in Kaggle



Luca Massaron

Data Scientist / Author / Google Developer Expert in Machine Lear…
Verona, Italy
Joined 8 years ago · last seen in the past day

Followers 95
Following 7

Competitions Master

Home | Competitions (153) | Kernels (3) | Discussion (76) | Datasets | ••• | Edit Profile

Competitions Master		
Current Rank 70 of 112,361	Highest Rank 7	
4	25	36
KDD Cup 2014 - Predicting… 5 years ago · Top 2%	6th of 472	
PetFinder.my Adoption Pre… 2 months ago · Top 1%	8th of 2023	
Dogs vs. Cats 5 years ago · Top 5%	9th of 215	

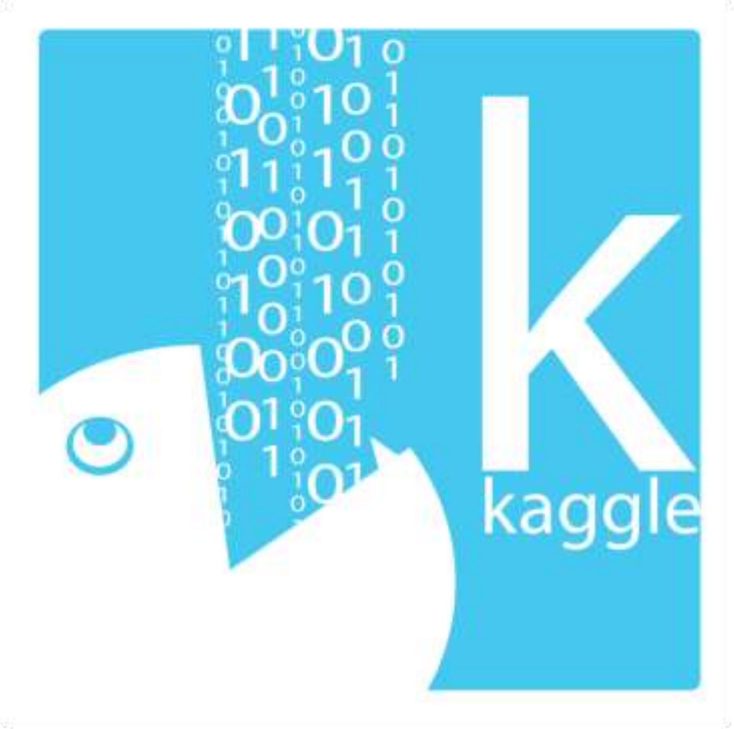
Kernels Contributor		
Unranked		
0	1	1
Kaggle Days Paris - GBDT … 4 months ago	59 votes	
Kaggle Days Paris - Skopt … 4 months ago	9 votes	

Discussion Contributor		
Unranked		
2	7	26
All you need (more) is baye… 4 months ago	34 votes	
How I modified Miroslaw's … 6 years ago	21 votes	
We had a 4th position sub… 2 months ago	7 votes	

irtualBox

What is Kaggle?

- Leading platform for machine learning competitions since 2010
- Companies post real data and problems that can be solved with predictive modeling / machine learning / AI / some kind of magic!
- Data scientists from all over the world compete to produce the best algorithms
- Acquired by Google in 2017
- Grown to a complete ML platform with learning modules, code sharing features (kernels), job board and more



Of course, real world is not like Kaggle

- First comes the problem, then the data science solution
- You have to study and do a lot of research first
- You have to abide regulations (like GDPR) and licenses
- You have to find the right data, pipeline and prepare it
- You should not snoop at the test data
- You cannot over-engineer your ML solutions because time and resources are stringent constraints

Sources:
https://towardsdatascience.com/data-science-in-the-real-world-e97e2534e43
(**Data Science in the Real World ,**Jan Zawadzki, Data Scientist@Volkswagen Group)

But Kaggle makes data useful

- You have the opportunity to work with data you don’t see at work or at university

- You exclusively work with the latest and most effective techniques (i.e. XGBoost and Keras were launched on Kaggle)

- You can rely on a lot of support from Kaggle for learning (courses, discussion boards, a blog) and computing (they offer you cloud machines)

- You learn transferable skills, even when it doesn’t seem so (i.e. hunting for leakages)

And there’s a fantastic community!

kaggle days
register at: www.kaggledays.com
Join us in Paris for the second Kaggle Days
kaggle days

PetFinder.my Adoption Prediction

Featured Code Competition

PetFinder.my Adoption Prediction

How cute is that doggy in the shelter?

$25,000

Prize Money

PetFinder.my · 1,805 teams · 2 months ago

PetFinder.my

PetFinder.my has been Malaysia’s leading animal welfare platform since 2008, with a database of more than 150,000 animals. PetFinder collaborates closely with animal lovers, media, corporations, and global organizations to improve animal welfare.

In this competition you will be developing algorithms to predict the adoptability of pets - specifically, how quickly is a pet adopted? If successful, they will be adapted into AI tools that will guide shelters and rescuers around the world on improving their pet profiles' appeal, reducing animal suffering and euthanization.

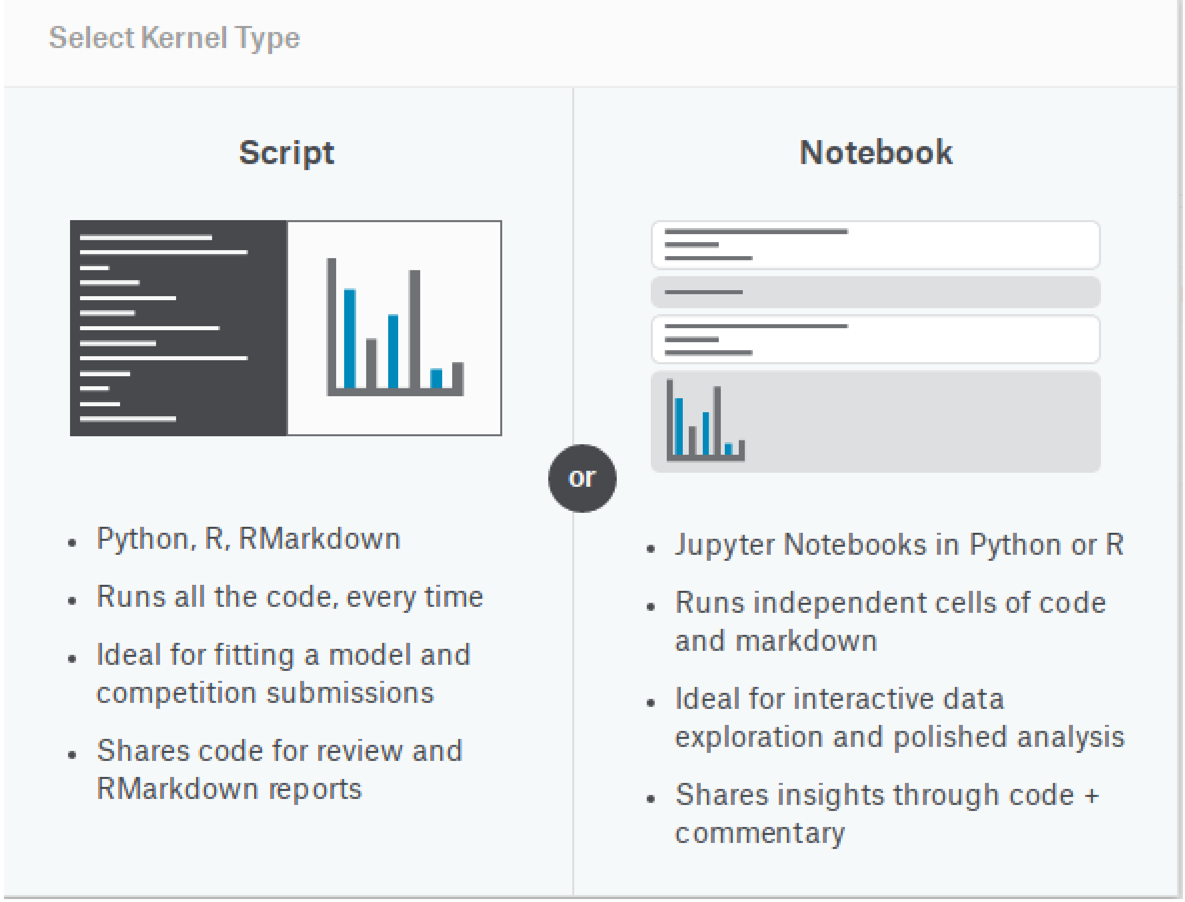
Why it has been so interesting ☺

1. The target is predicting how long it will take for a pet to be adopted, but the problem could be generalized to other social / business domains.

2. The data is interesting because of size (manageable) and because of variety (tabular, text, and image)

3. It was a kernel competition, forcing the participants to mix performance, and reproducibility of results under hardware and time constraints

What is a kernel competition?



Select Kernel Type

Script

- Python, R, RMarkdown
- Runs all the code, every time
- Ideal for fitting a model and competition submissions
- Shares code for review and RMarkdown reports

Notebook

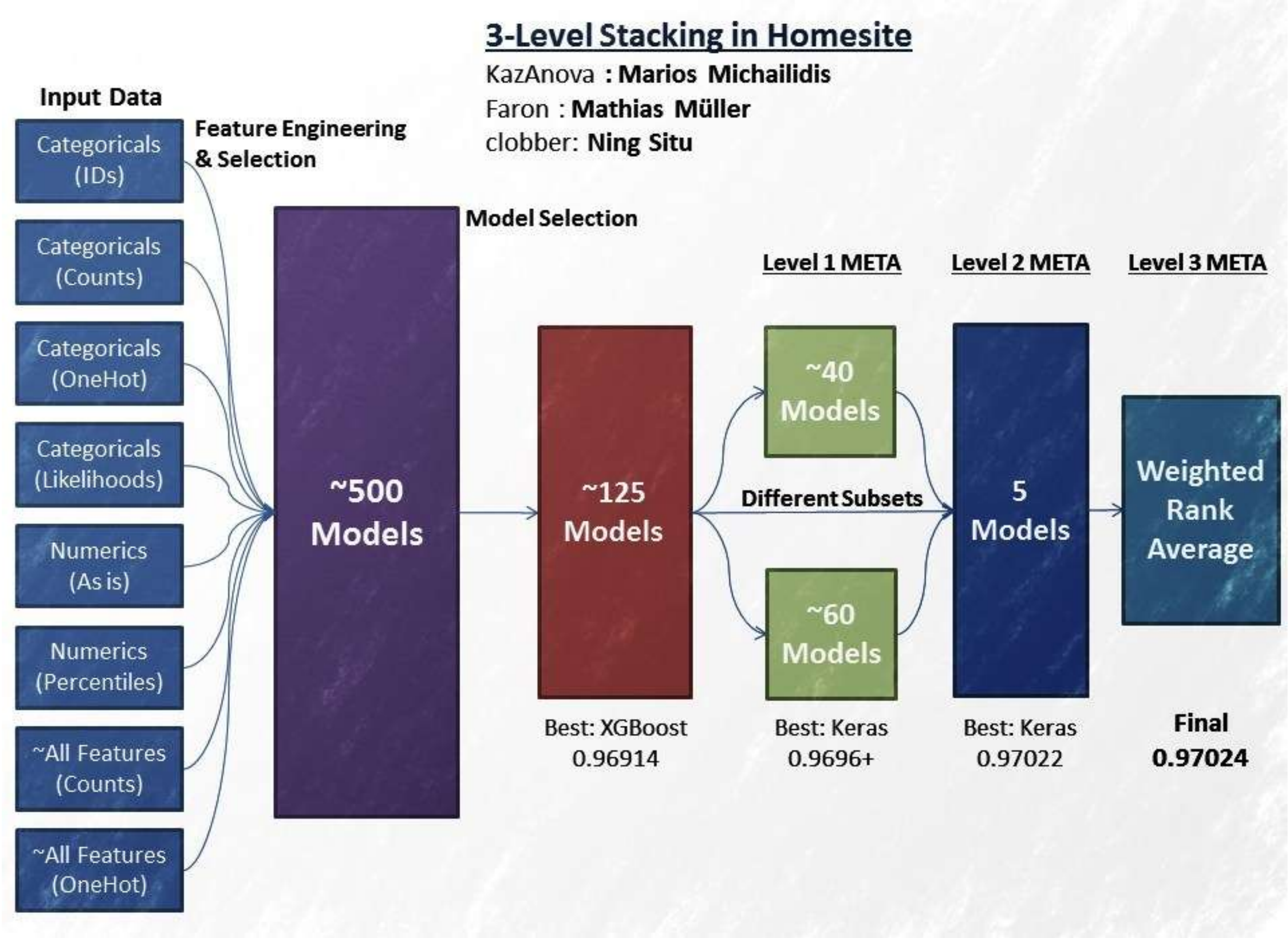
- Jupyter Notebooks in Python or R
- Runs independent cells of code and markdown
- Ideal for interactive data exploration and polished analysis
- Shares insights through code + commentary

Kaggle Kernels is a cloud computational environment that enables reproducible and collaborative analysis.

See: https://www.quora.com/What-is-a-kernel-in-Kaggle

1. Limited to either 2 hours on the Kaggle servers with a GPU (Tesla K80) or 6 hours without a GPU.
2. External data was admissible as long as it was not taken from the PetFinder website.
3. The internet must be turned off, so no direct download during inference.
4. No pre-computed predictions or features therefore we had to re-train the models during inference time.

On kernel comps you cannot do this:

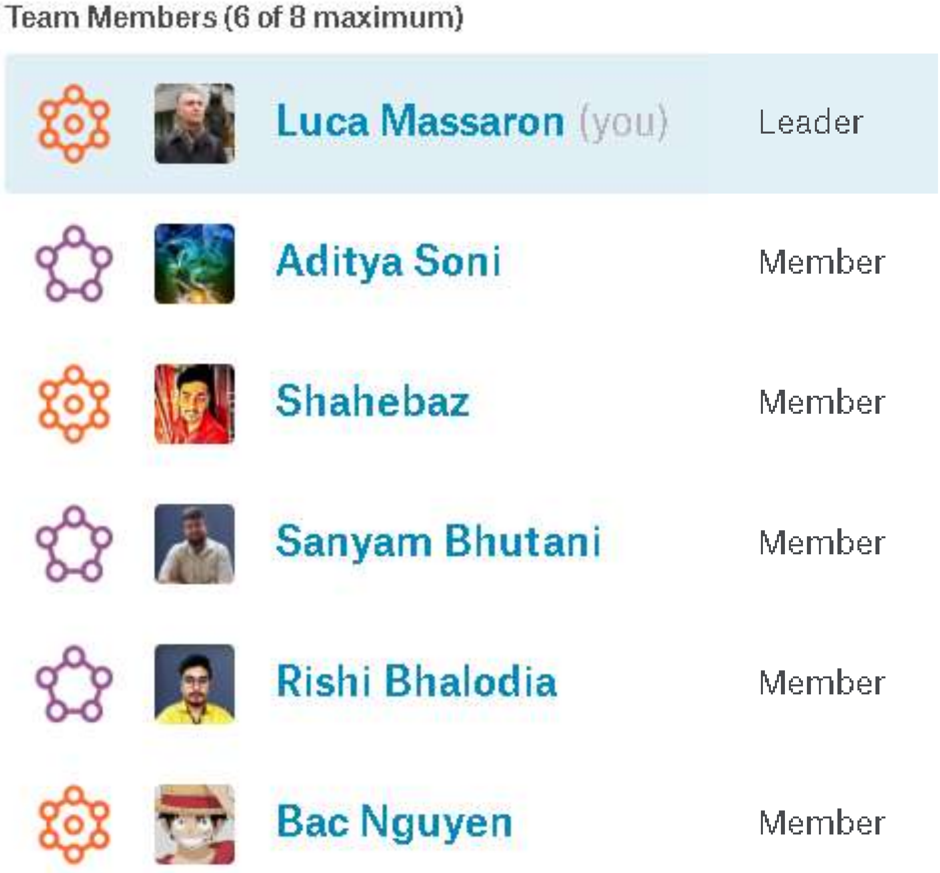


3-Level Stacking in Homesite

KazAnova : Marios Michailidis
Faron : Mathias Müller
clobber: Ning Situ

http://blog.kaggle.com/2016/04/08/homesite-quote-conversion-winners-write-up-1st-place-kazanova-faron-clobber/

Let’s go back to the comp:

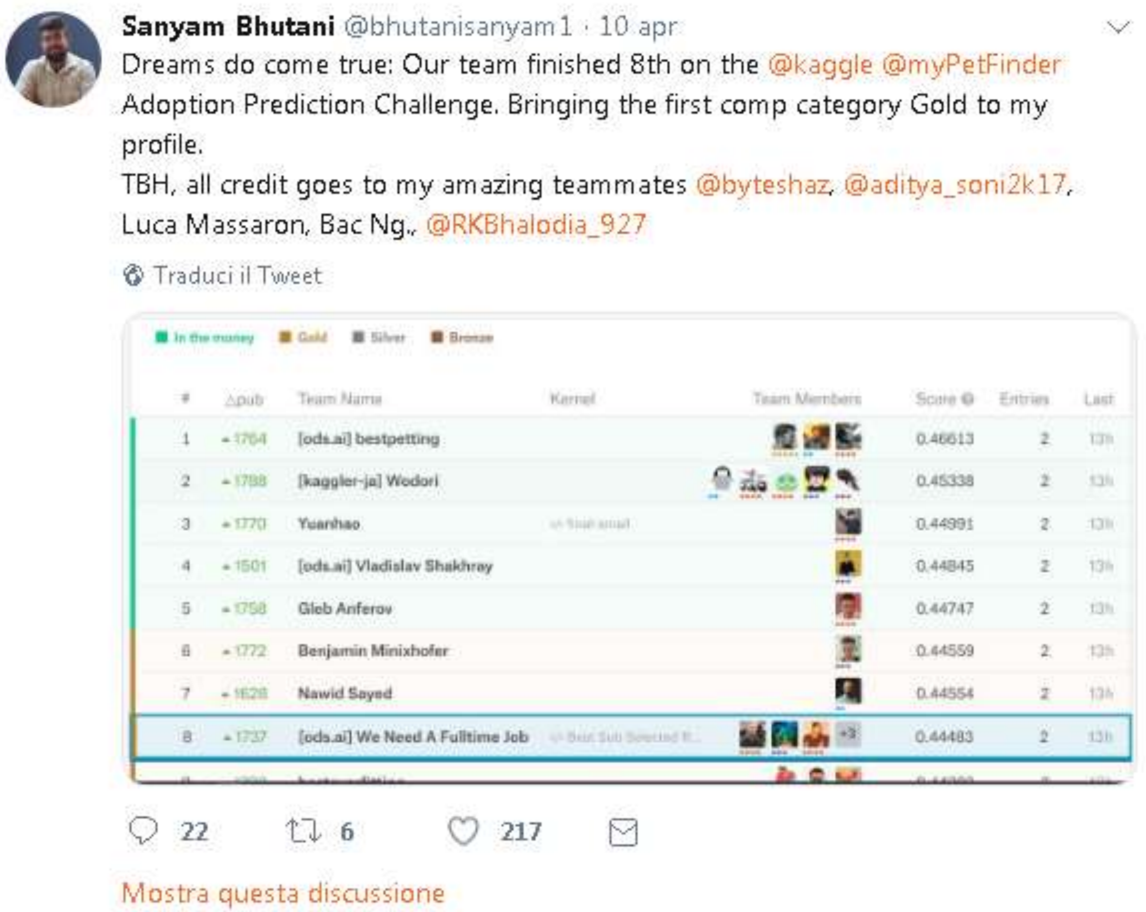


Team Members (6 of 8 maximum)

Luca Massaron (you)	Leader	https://www.linkedin.com/in/lmassaron/
Aditya Soni	Member	https://www.linkedin.com/in/aditya-soni-0505a9124/
Shahebaz	Member	https://www.linkedin.com/in/shaz13/
Sanyam Bhutani	Member	https://www.linkedin.com/in/sanyambhutani/
Rishi Bhalodia	Member	https://www.linkedin.com/in/rkbhalodia927/
Bac Nguyen	Member	https://www.linkedin.com/in/bac-nguyen-xuan-70340b66/

Team name: We Need A Fulltime Job

Wondering about the team name?



Sanyam Bhutani @bhutanisanyam1 · 10 apr

Dreams do come true: Our team finished 8th on the @kaggle @myPetFinder Adoption Prediction Challenge. Bringing the first comp category Gold to my profile.
TBH, all credit goes to my amazing teammates @byteshaz, @aditya_soni2k17, Luca Massaron, Bac Ng., @RKBhalodia_927

Traduci il Tweet

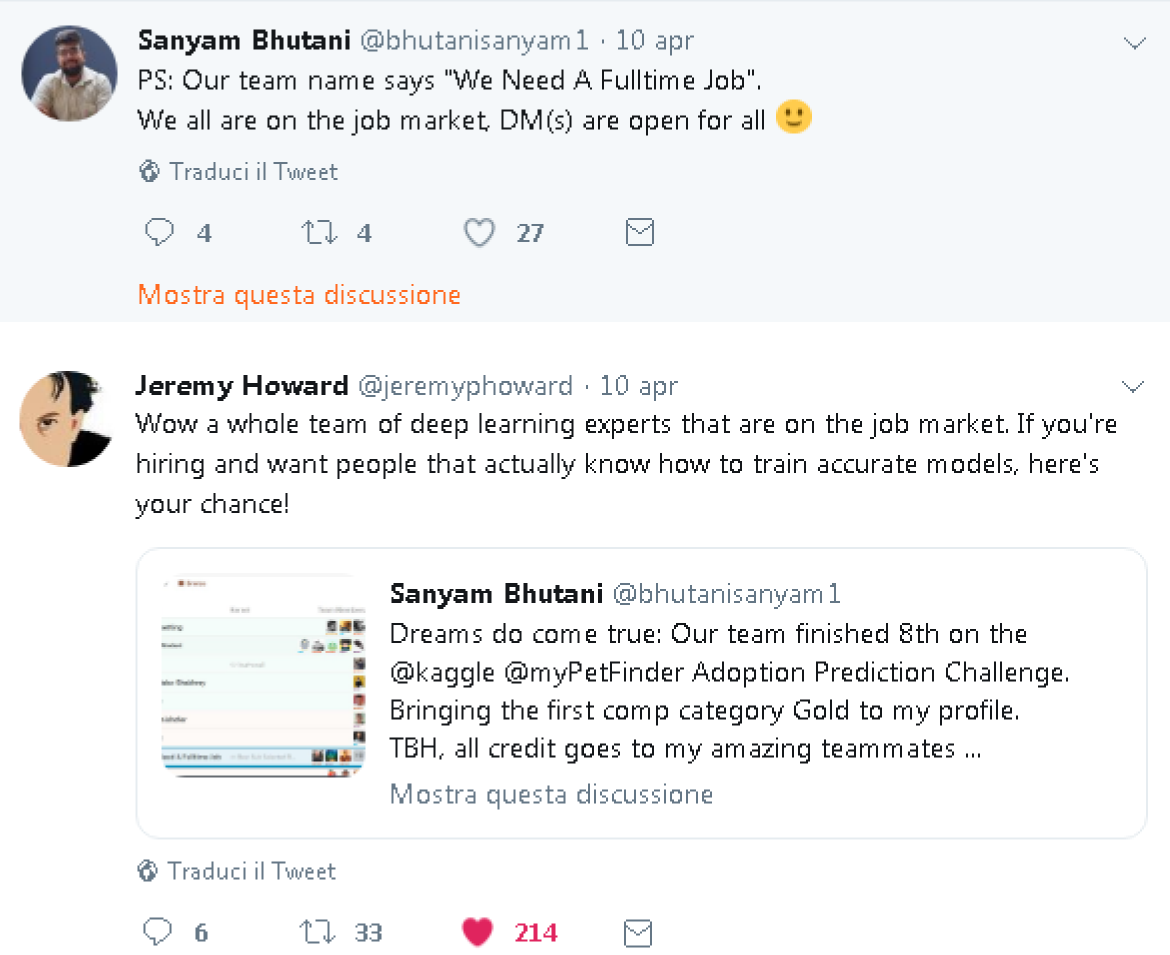
🟩 In the money 🟨 Gold ■ Silver 🟫 Bronze

#	Δpub	Team Name	Kernel	Team Members	Score	Entries	Last
1	▲ 1764	[ods.ai] bestpetting			0.46613	2	13h
2	▲ 1788	[kaggler-ja] Wodori			0.45338	2	13h
3	▲ 1770	Yuanhao	</> final small		0.44991	2	13h
4	▲ 1501	[ods.ai] Vladislav Shakhray			0.44845	2	13h
5	▲ 1758	Gleb Anferov			0.44747	2	13h
6	▲ 1772	Benjamin Minixhofer			0.44559	2	13h
7	▲ 1628	Nawid Sayed			0.44554	2	13h
8	▲ 1737	[ods.ai] We Need A Fulltime Job	</> Best Sub Selected R...	+3	0.44483	2	13h

22 6 217

Mostra questa discussione

As you are busy, meanwhile on Twitter…



Sanyam Bhutani @bhutanisanyam1 · 10 apr

PS: Our team name says "We Need A Fulltime Job".
We all are on the job market. DM(s) are open for all 🙂

Traduci il Tweet

4 4 27

Mostra questa discussione

Jeremy Howard @jeremyphoward · 10 apr

Wow a whole team of deep learning experts that are on the job market. If you're hiring and want people that actually know how to train accurate models, here's your chance!

Sanyam Bhutani @bhutanisanyam1

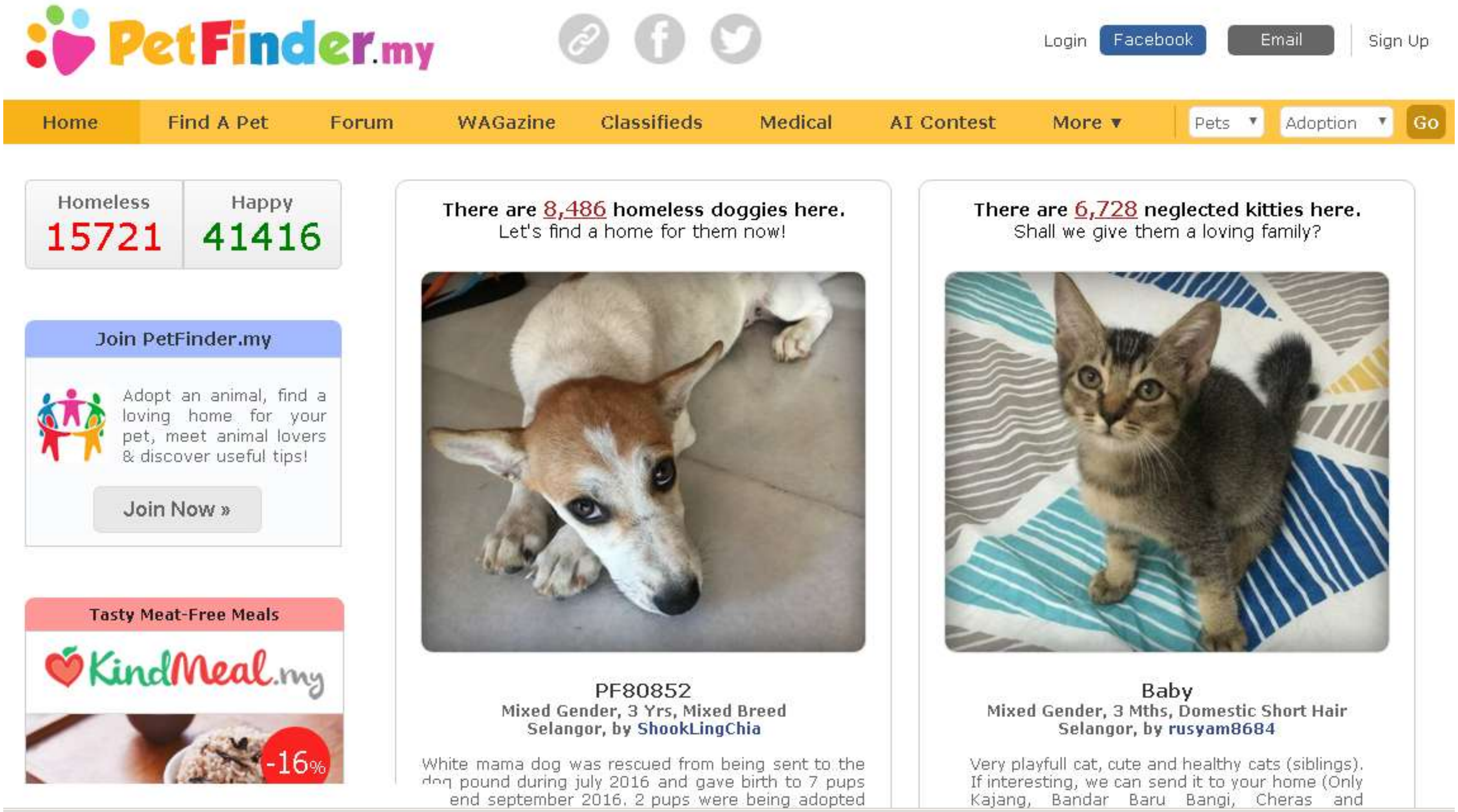
Dreams do come true: Our team finished 8th on the @kaggle @myPetFinder Adoption Prediction Challenge.
Bringing the first comp category Gold to my profile.
TBH, all credit goes to my amazing teammates ...

Mostra questa discussione

Traduci il Tweet

6 33 214

A look at the Website



Homeless	Happy
15721	41416

Join PetFinder.my

Adopt an animal, find a loving home for your pet, meet animal lovers & discover useful tips!

Tasty Meat-Free Meals

KindMeal.my

-16%

There are 8,486 homeless doggies here.
Let's find a home for them now!

PF80852
Mixed Gender, 3 Yrs, Mixed Breed
Selangor, by ShookLingChia

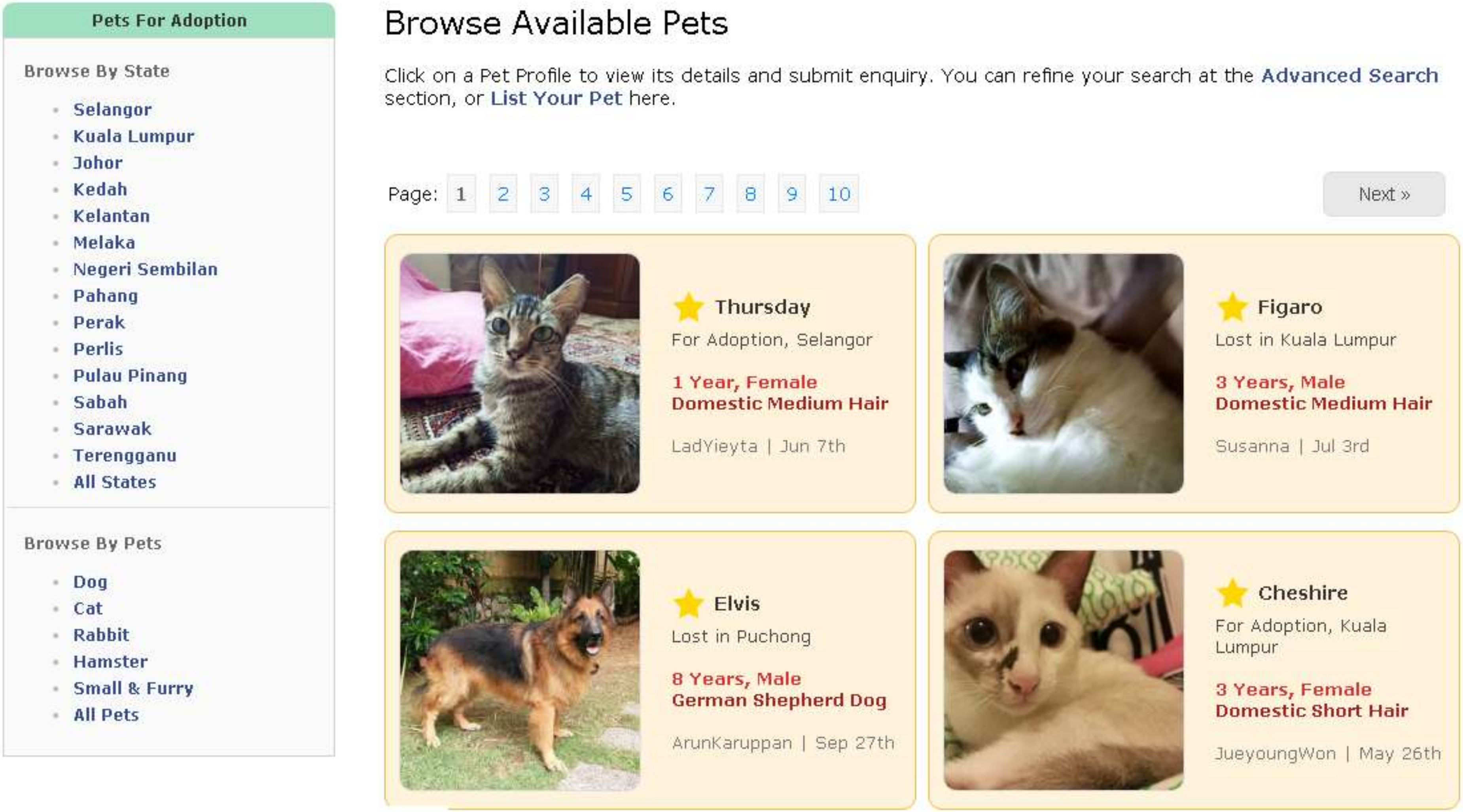
White mama dog was rescued from being sent to the dog pound during july 2016 and gave birth to 7 pups end september 2016. 2 pups were being adopted

There are 6,728 neglected kitties here.
Shall we give them a loving family?

Baby
Mixed Gender, 3 Mths, Domestic Short Hair
Selangor, by rusyam8684

Very playfull cat, cute and healthy cats (siblings). If interesting, we can send it to your home (Only Kajang, Bandar Baru Bangi, Cheras and

You have rankings for pets



Pets For Adoption

Browse By State

- Selangor
- Kuala Lumpur
- Johor
- Kedah
- Kelantan
- Melaka
- Negeri Sembilan
- Pahang
- Perak
- Perlis
- Pulau Pinang
- Sabah
- Sarawak
- Terengganu
- All States

Browse By Pets

- Dog
- Cat
- Rabbit
- Hamster
- Small & Furry
- All Pets

Browse Available Pets

Click on a Pet Profile to view its details and submit enquiry. You can refine your search at the **Advanced Search** section, or **List Your Pet** here.

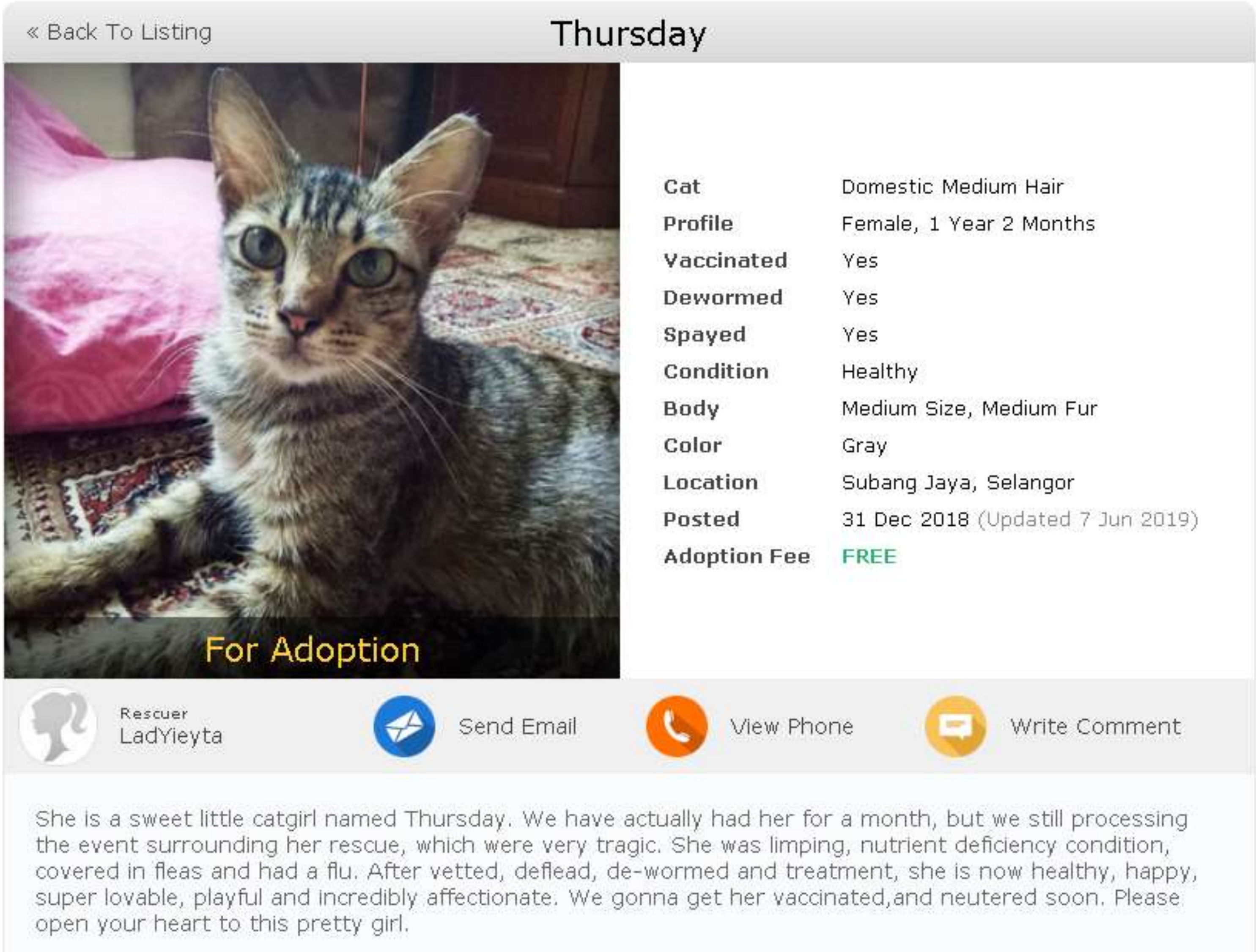
★ **Thursday**
For Adoption, Selangor
1 Year, Female
Domestic Medium Hair
LadYieyta | Jun 7th

★ **Figaro**
Lost in Kuala Lumpur
3 Years, Male
Domestic Medium Hair
Susanna | Jul 3rd

★ **Elvis**
Lost in Puchong
8 Years, Male
German Shepherd Dog
ArunKaruppan | Sep 27th

★ **Cheshire**
For Adoption, Kuala Lumpur
3 Years, Female
Domestic Short Hair
JueyoungWon | May 26th

Pets are listed

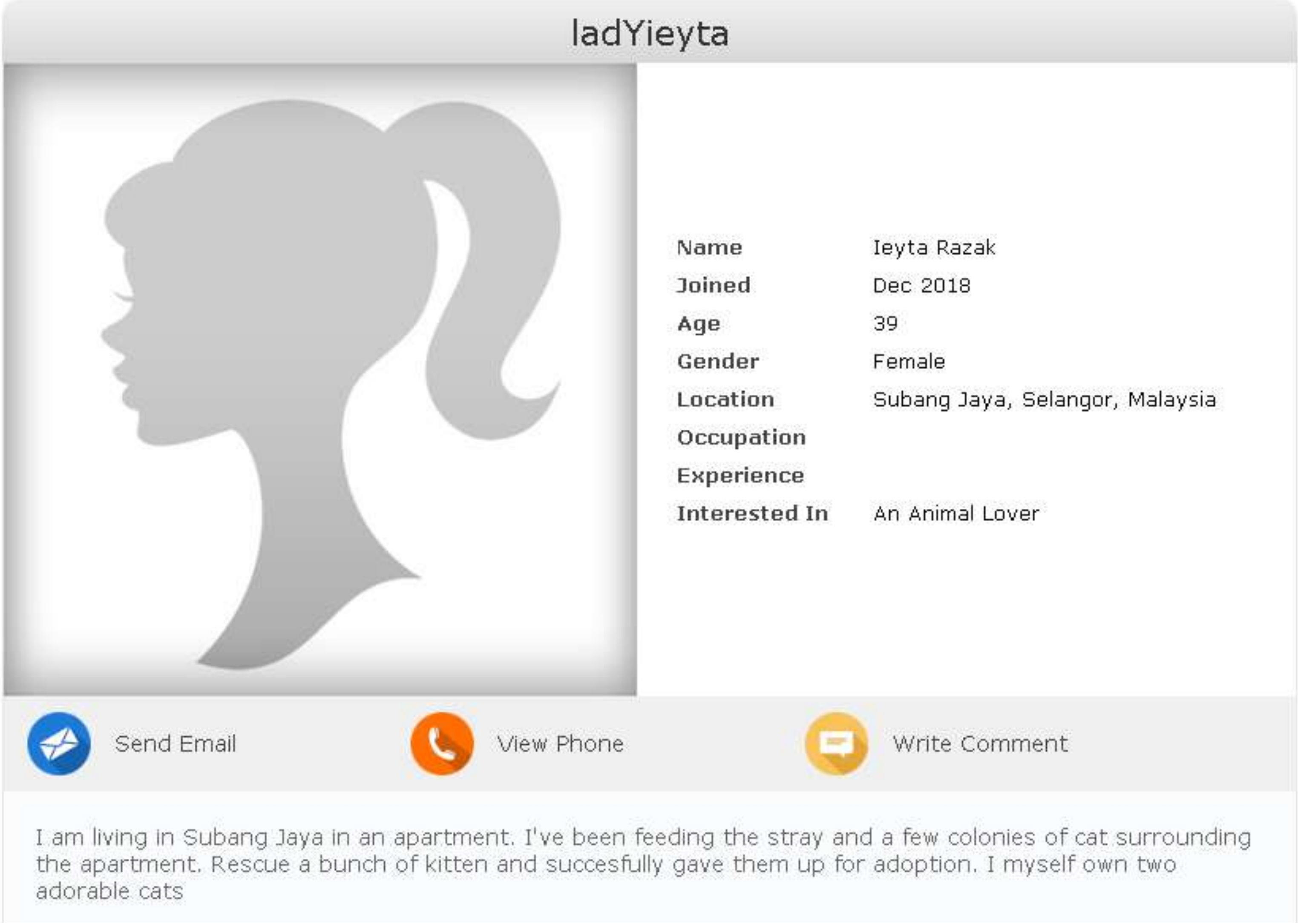


Thursday

Cat	Domestic Medium Hair
Profile	Female, 1 Year 2 Months
Vaccinated	Yes
Dewormed	Yes
Spayed	Yes
Condition	Healthy
Body	Medium Size, Medium Fur
Color	Gray
Location	Subang Jaya, Selangor
Posted	31 Dec 2018 (Updated 7 Jun 2019)
Adoption Fee	FREE

She is a sweet little catgirl named Thursday. We have actually had her for a month, but we still processing the event surrounding her rescue, which were very tragic. She was limping, nutrient deficiency condition, covered in fleas and had a flu. After vetted, deflead, de-wormed and treatment, she is now healthy, happy, super lovable, playful and incredibly affectionate. We gonna get her vaccinated,and neutered soon. Please open your heart to this pretty girl.

And so are rescurers

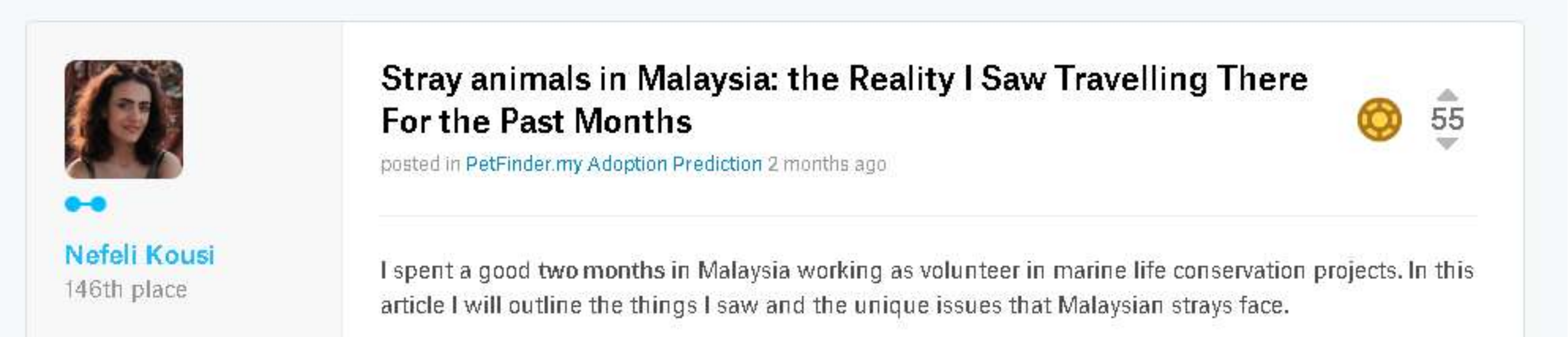


ladYieyta

Name	Ieyta Razak
Joined	Dec 2018
Age	39
Gender	Female
Location	Subang Jaya, Selangor, Malaysia
Occupation	
Experience	
Interested In	An Animal Lover

I am living in Subang Jaya in an apartment. I've been feeding the stray and a few colonies of cat surrounding the apartment. Rescue a bunch of kitten and succesfully gave them up for adoption. I myself own two adorable cats

Lots of insights to keep account of



Stray animals in Malaysia: the Reality I Saw Travelling There For the Past Months

posted in PetFinder.my Adoption Prediction 2 months ago

I spent a good two months in Malaysia working as volunteer in marine life conservation projects. In this article I will outline the things I saw and the unique issues that Malaysian strays face.

https://www.kaggle.com/c/petfinder-adoption-prediction/discussion/86581#latest-505147

- The stumpy tailed cats of Malaysia. Are a local breed of cats with short tails, often twisted at the end. A lot of people consider cats with full tails *"cutter"* and prefer them as pets.
- There a cultural / religious reasons for considering not acceptable having a dog as a pet. Dogs have generally a harder life than cats.
- Moreover generally cats seemed to be considered as "pets" while dogs were seen more as "useful", so people tend to prefer bigger dogs.
- Can you see both eyes in the picture? (a picture of a dog that looks straight in the camera signifies friendliness and good behaviour). Is the fur intact? Is the tail shown in the picture?

A glance at the features (1)

- PetID - Unique hash ID of pet profile
- AdoptionSpeed - Categorical speed of adoption. Lower is faster. This is the value to predict.
- Type - Type of animal *(1 = Dog, 2 = Cat)*
- Name - Name of pet *(Empty if not named)*
- Age - Age of pet when listed, in months
- Breed1 - Primary breed of pet *(Refer to BreedLabels dictionary)*
- Breed2 - Secondary breed of pet, if pet is of mixed breed *(Refer to BreedLabels dictionary)*
- Gender - Gender of pet *(1 = Male, 2 = Female, 3 = Mixed, if profile represents group of pets)*
- Color1 - Color 1 of pet *(Refer to ColorLabels dictionary)*
- Color2 - Color 2 of pet *(Refer to ColorLabels dictionary)*
- Color3 - Color 3 of pet *(Refer to ColorLabels dictionary)*
- MaturitySize - Size at maturity *(1 = Small, 2 = Medium, 3 = Large, 4 = Extra Large, 0 = Not Specified)*
- FurLength - Fur length *(1 = Short, 2 = Medium, 3 = Long, 0 = Not Specified)*

A glance at the features (2)

- Vaccinated - Pet has been vaccinated *(1 = Yes, 2 = No, 3 = Not Sure)*
- Dewormed - Pet has been dewormed *(1 = Yes, 2 = No, 3 = Not Sure)*
- Sterilized - Pet has been spayed / neutered *(1 = Yes, 2 = No, 3 = Not Sure)*
- Health - Health Condition *(1 = Healthy, 2 = Minor Injury, 3 = Serious Injury, 0 = Not Specified)*
- Quantity - Number of pets represented in profile
- Fee - Adoption fee *(0 = Free)*
- State - State location in Malaysia *(Refer to StateLabels dictionary)*
- RescuerID - Unique hash ID of rescuer
- VideoAmt - Total uploaded videos for this pet
- PhotoAmt - Total uploaded photos for this pet
- Description - Profile write-up for this pet. The primary language used is English, with some in Malay or Chinese.

A glance at the texts

The text is contained in json files processed by Google API:

```
{       "text": {       "content": "Cherry loves to be indoor, loves to be near
human, loves human touches, loves other dogs.",       "beginOffset": -1     },
"sentiment": {       "magnitude": 0.8,       "score": 0.8     }    },
```

```
{     "text": {       "content": "Don't be mistaken, Cherry is very alert at
strangers and noises at the gate, but being a watch dog should not be her full
time 'job'.",       "beginOffset": -1     },     "sentiment": {       "magnitude": 0.5,
"score": -0.5     }    },
```

```
"tokens": [],  "entities": [    {      "name": "Cherry",      "type": "PERSON",
"metadata": {},      "salience": 0.703432,      "mentions": [       {         "text": {
"content": "Cherry",           "beginOffset": -1         },         "type": "PROPER"
},
```

A glance at the pictures

Breed: Mixed_Breed

Breed: Golden_Retriever

Breed: Labrador_Retriever

Breed: Rottweiler

Breed: German_Shepherd_Dog

Breed: Domestic_Short_Hair

Breed: Domestic_Medium_Hair

Breed: Tabby

Breed: Domestic_Long_Hair

Breed: Persian

Breed: Mixed_Breed

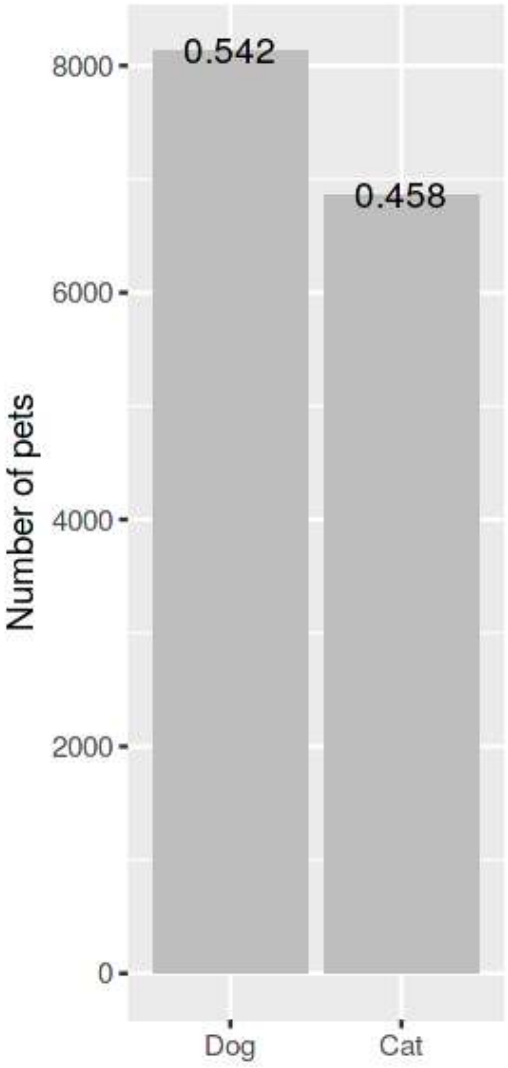
Breed: Shih_Tzu

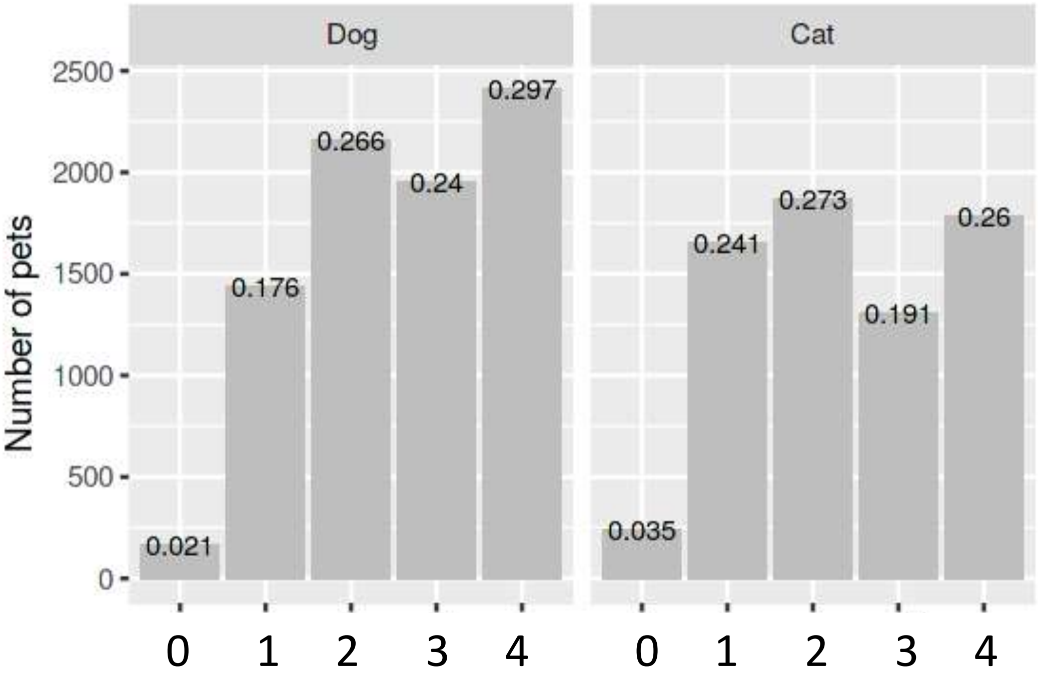
Breed: Poodle

Breed: Miniature_Pinscher

Breed: Schnauzer

Target



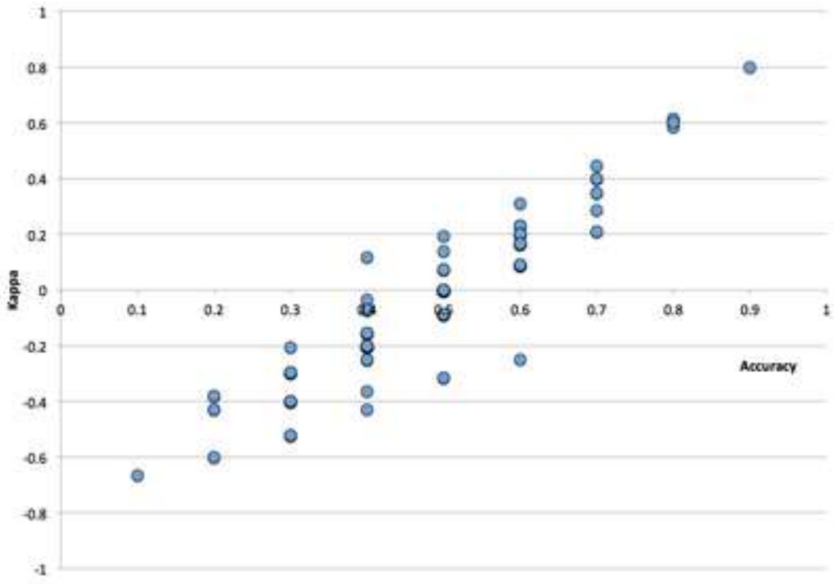


- 0 -Pet was adopted on the same day as it was listed.
- 1 - Pet was adopted between 1 and 7 days (1st week) after being listed.
- 2- Pet was adopted between 8 and 30 days (1st month) after being listed.
- 3 - Pet was adopted between 31 and 90 days (2nd & 3rd month) after being listed.
- 4 - No adoption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

Evaluation function

Submissions are scored based on the **quadratic weighted kappa**, which measures the agreement between two ratings.

This metric typically varies from 0 (random agreement between raters) to 1 (complete agreement between raters). In the event that there is less agreement between the raters than expected by chance, the metric may go below 0.



Source: https://en.wikipedia.org/wiki/Cohen%27s_kappa

```
from sklearn.metrics import cohen_kappa_score

def quadratic_weighted_kappa (y_true, y_pred):
   return cohen_kappa_score(y_true, y_pred, weights='quadratic')
```

Our optimization

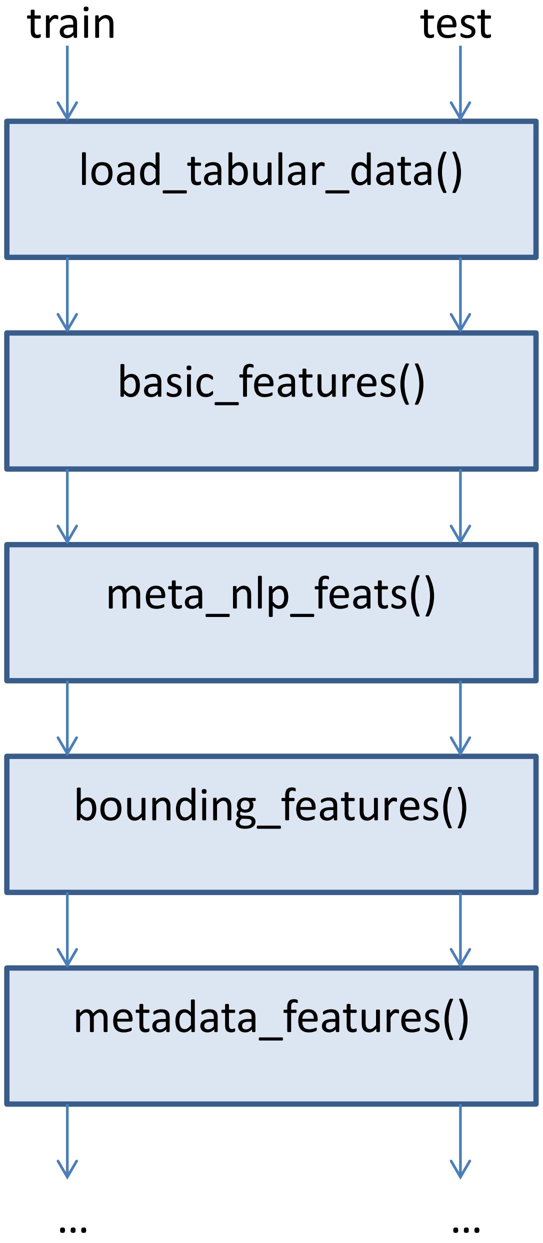
Solution: we optimize first for rmse, thus handling the problem as a regression problem, then we tune the solution using the out of fold predictions in order to set a numeric threshold and correctly guess the 5 classes and maximize the **quadratic weighted kappa**

```
class OptimizedRounder(object):


…
def fit(self, X, y):
        loss_partial = partial(self._kappa_loss, X=X, y=y)
        initial_coef = [0.5, 1.5, 2.5, 3.5]
        self.coef_ = sp.optimize.minimize(loss_partial,  initial_coef,
                                          method='nelder-mead')
```

* functools.partial returns the inputted function with predefined positional parameters

Data pipeline



train test

Loading train, test, breed, color, state labels

load_tabular_data()

TRAIN: (14993, 24)
Wall time: 230 ms

Feature engineering aiming at transformng, grouping, averaging features

basic_features()

TRAIN: (14993, 396)
Wall time: 1min 6s

Basic text features such as length, number of words, smileys

meta_nlp_feats()

TRAIN: (14993, 408))
Wall time: 2.51 s

processing Google's Vision API general image data present on -1.json files

bounding_features()

TRAIN: (14993, 418)
Wall time: 43 s

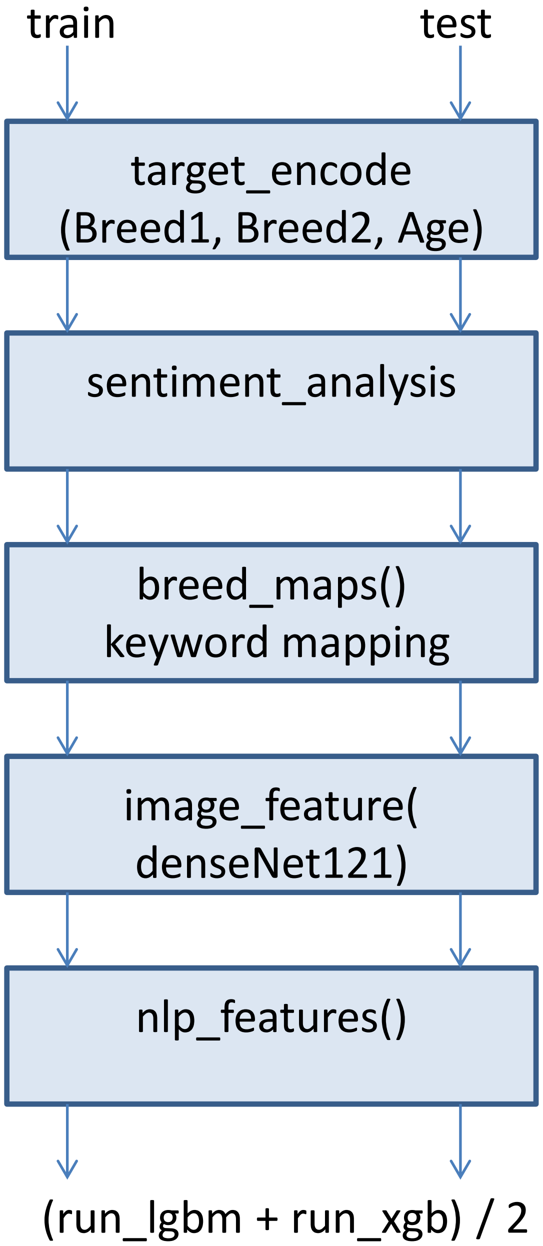
processing all metadata fromGoogle's Vision API and Google's Natural Language API

metadata_features()

TRAIN: (14993, 447)
Wall time: 24min 40s

... ...

Data pipeline



train

test

Target encoding of key variables

target_encode
(Breed1, Breed2, Age)

TRAIN: (14993, 450)
Wall time: 255 ms

Each pet is matched with a score, magnitude, negative score

sentiment_analysis

TRAIN: (14993, 453)
Wall time: 13.3 s

We create indicator variables for textual keywords and join external data with breeds stats

breed_maps()
keyword mapping

TRAIN: (14993, 458)
Wall time: 759 ms

Using Imagenet pretrained denseNet121, we extract 256 image features

image_feature(
denseNet121)

TRAIN: (14993, 714)
Wall time: 14min 57s

Extracting 50 components from SVD and NMF applied to all the different texts available

nlp_features()

TRAIN: (14993, 1009)
Wall time: 1min 7s

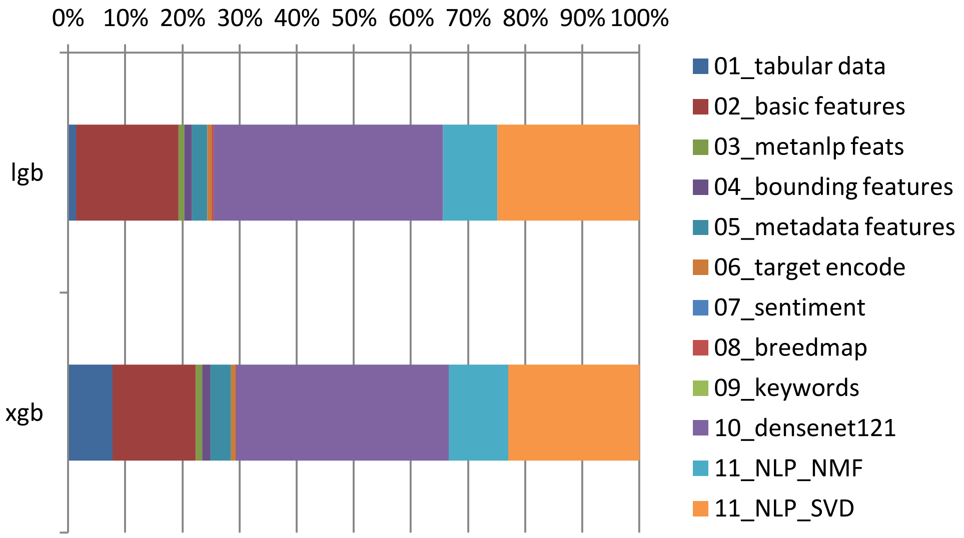
Adoption speed by blending solutions from XGBoost and LightGBM

(run_lgbm + run_xgb) / 2

Wall time: 53min 7s

Importance of feature blocks

Feature block	n. features	Lgb splits	Lgb gain	Xgb splits
01_tabular data	19	1,40%	3,33%	7,73%
02_basic features	372	17,88%	28,82%	14,66%
03_metanlp feats	12	1,07%	0,93%	1,06%
04_bounding features	10	1,33%	2,12%	1,47%
05_metadata features	27	2,65%	2,47%	3,60%
06_target encode	3	0,83%	1,46%	0,76%
07_sentiment	3	0,02%	0,02%	0,01%
08_breedmap	4	0,32%	2,44%	0,10%
09_keywords	1	0,00%	0,00%	0,01%
10_densenet121	256	40,15%	32,60%	37,20%
11_NLP_NMF	150	9,50%	7,24%	10,51%
11_NLP_SVD	150	24,85%	18,58%	22,90%
	1007	100,0%	100,0%	100,0%



For comparison reasons we mostly used the importance given by the number of splits that involved a feature in the iterations of the GBMs.

However, splits don't tell all the story, since features with less levels may need lto be less splitted or simply a single split may hid a huge gain in the cost function.

A few simple key ingredients

1. Handmade feature engineering together with some business understanding

2. Target encoding (reduce cardinality)

3. A pre-trained network, denseNet121, for generating features from images

4. NLP by SVD (LSA) and NMF (Topic Modelling)

5. Two power horses such as XGBoost and LightGBM

6. Solving it as a regression problem, on a linear continuum, then optimally discretized accordingly to the competition’s metrics

But remember that “There is no free lunch”

basic_features

First we apply basic feature engineering for better separablity by:

1. Transforming variables
   weeks, Feature_SecondaryColors, Feature_MonoColor, total_img_video,

2. Grouping/clustering variables
   L_Breed1_Siamese, L_Breed1_Persian, L_Breed1_Labrador_Retriever, L_Breed1_Terrier, shorthair_hairless_domestic_hair, top_dogs, top_cats

3. Taking averages of groups and them
   Feature_avg_age_breed1_fee, Feature_age_breed1_maturity_sz, Feature_age_breed1_fur, Feature_state_breed1_age_freq, Feature_avg_type_age_breed1_fee, Feature_age_type_breed1_fur …

4. Taking more complex stats
   RescuerID, State expressed as nunique, mean, **var**, **max**, **min**, **skew**, **median of many variables**

5. Ranking (by **seo_value** a proxy based on photo & video) inside the group
   State, Animal, Type, Breed1, Gender

Seo value

```
def seo_value(cols):
        photos = cols[0]
        videos = cols[1]
        seo = .7 * videos + .3 * photos
        return seo

alldata['InstaFeature'] = alldata[['PhotoAmt', 'VideoAmt']].apply(seo_value, axis=1)

def rankbyG(alldata, group):
        rank_telemetry = pd.DataFrame()
        for unit in (alldata[group].unique()):
            tf = alldata[alldata[group] == unit][['PetID', 'InstaFeature', group]]
            col_name = "Insta" + str(group).title() + "Rank"
            tf[col_name] = tf['InstaFeature'].rank(method='max')
            rank_telemetry = pd.concat([rank_telemetry, tf[['PetID', col_name]]])
            del tf
        alldata = pd.merge(alldata, rank_telemetry, on=['PetID'], how='left')
        return alldata
```

Photos and videos availability were treated as a proxy of ranking in the website to use in order to rank within different groups

Target encoding

High cardinality variables are processed using an encoding function which is computed accordingly to the following paper by Daniele Micci-Barreca:

Micci-Barreca, Daniele. "A preprocessing scheme for high-cardinality categorical attributes in classification and prediction problems." ***ACM SIGKDD Explorations Newsletter*** **3.1 (2001): 27-32**.

Code:
https://gist.github.com/lmassaron/6695171ff45bae7ef7ddcdad2ad493ca

Inputs:

trn_series : training categorical feature as a pd.Series
tst_series : test categorical feature as a pd.Series
target : target data as a pd.Series
min_samples_leaf (int) : minimum samples to take category average into account
smoothing (int) : smoothing effect to balance categorical average vs prior

The idea behind target encoding

$$X_i \rightarrow S_i \cong P(Y|X=X_i) \qquad S_i = \frac{n_{iY}}{n_i}$$

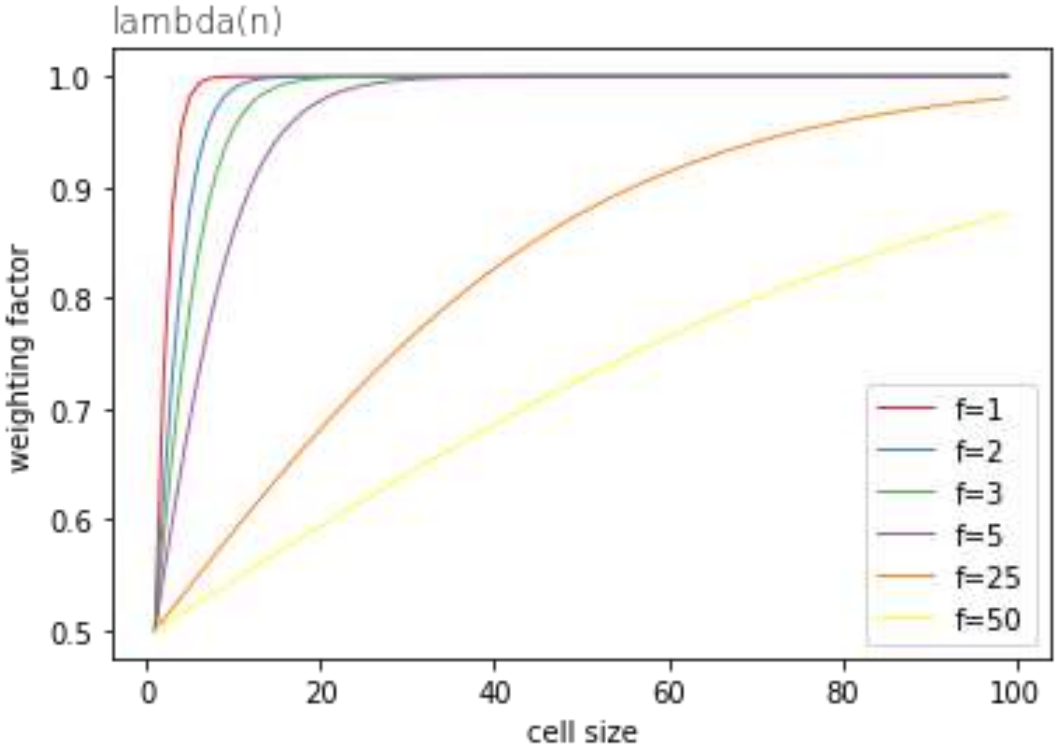
For a level i, we are looking for an approximate value that can help us predict better the target using a single encoded variable. Replacing the level by the observed conditional probability could be the solution, but for the levels with few observations.

$$S_i = \lambda(n_i)\frac{n_{iY}}{n_i} + (1-\lambda(n_i))\frac{n_Y}{n_{TR}}$$

The solution is to blend the observed posterior probability on that level (probability of Y given X=Xi) with the a-priori probability (probability of Y) by a lambda factor (Empirical Bayesian approach).

The idea behind target encoding

$$\lambda(n) = \frac{1}{1 + e^{-\frac{(n-k)}{f}}}$$



Given a fix k (usually it is 1, implying a minimum cell frequency of 2), higher values of f dictate less trust in the observed empirical frequency and more reliance on the empirical probability for all cells.

denseNet121

DenseNet is a network architecture where each layer is directly connected to every other layer in a feed-forward fashion (within each *dense block*). For each layer, the feature maps of all preceding layers are treated as separate inputs whereas its own feature maps are passed on as inputs to all subsequent layers.

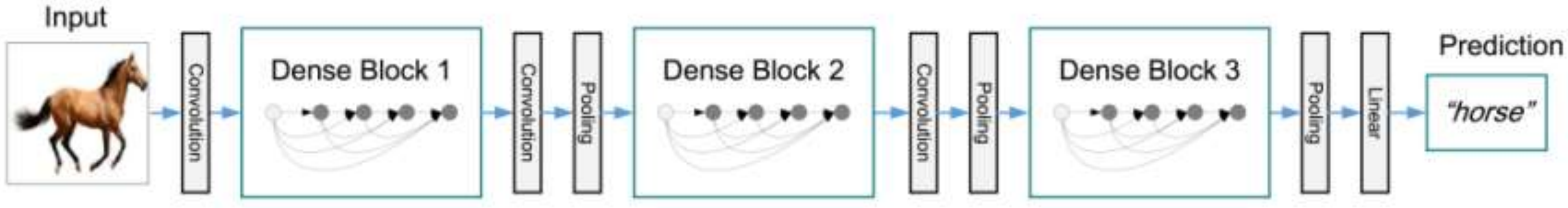
This connectivity pattern yields state-of-the-art accuracies on CIFAR10/100 (with or without data augmentation) and SVHN. On the large scale ILSVRC 2012 (ImageNet) dataset, DenseNet achieves a similar accuracy as ResNet, but using less than half the amount of parameters and roughly half the number of FLOPs.

Source : https://github.com/liuzhuang13/DenseNet

Extracting features from denseNet121

```
def build_model(shape=(256, 256, 3),
  weights_path="../input/densenet-keras/DenseNet-BC-121-32-no-top.h5"):
   inp = Input(shape)
   backbone = DenseNet121(input_tensor=inp,
                                             weights=weights_path,
                                             include_top=False)
   x = backbone.output
   x = GlobalAveragePooling2D()(x)
   x = Lambda(lambda x: K.expand_dims(x, axis=-1))(x)
   x = AveragePooling1D(4)(x)
   out = Lambda(lambda x: x[:, :, 0])(x)
   model = Model(inp, out)
   return model
```

Glancing at the architecture



```
...
________________________________________________________________________________________________
bn (BatchNormalization) (None, 8, 8, 1024) 4096 conv5_block16_concat[0][0]
________________________________________________________________________________________________
relu (Activation) (None, 8, 8, 1024) 0 bn[0][0]
________________________________________________________________________________________________
global_average_pooling2d_1 (Glo (None, 1024) 0 relu[0][0]
________________________________________________________________________________________________
lambda_1 (Lambda) (None, 1024, 1) 0 global_average_pooling2d_1[0][0]
________________________________________________________________________________________________
average_pooling1d_1 (AveragePoo (None, 256, 1) 0 lambda_1[0][0]
________________________________________________________________________________________________
lambda_2 (Lambda) (None, 256) 0 average_pooling1d_1[0][0]
================================================================================================
Total params: 7,037,504 Trainable params: 6,953,856 Non-trainable params: 83,648
```

NLP processing

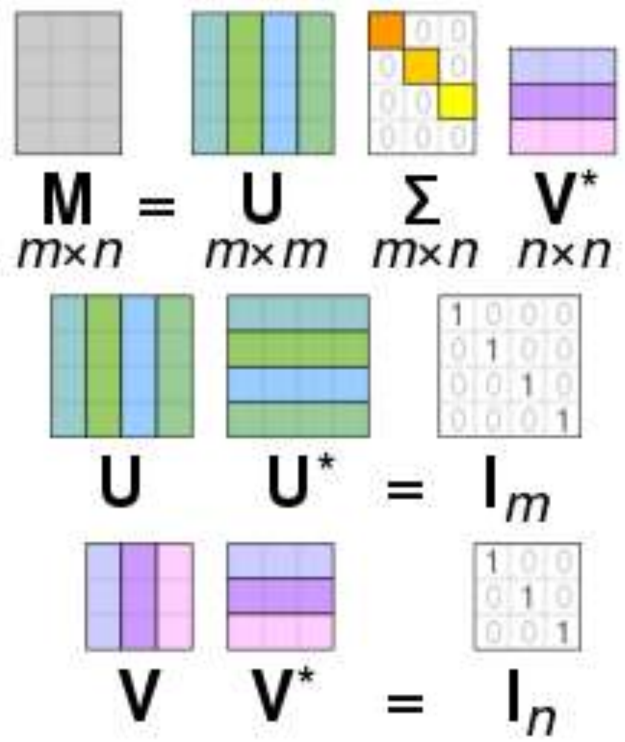
Basic indicator extracted from textual information:

1. Length
2. Capitals
3. caps_vs_length
4. num_exclamation_marks
5. num_question_marks
6. num_punctuation
7. num_symbols
8. num_words
9. num_unique_words
10. words_vs_unique
11. num_smilies (**':-)'**, **':)'**, **';-)'**, **';)'**)
12. num_sad (**':-<'**, **':()'**, **';-()'**, **';('**)))

We couldn’t use embeddings or even BERT because of the competition constraints and because as many descriptions were in English, some were also in Malay and Chinese (and we noticed that adoption speed drops for these two languages)

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD, NMF
n_components = 50
svd_ = TruncatedSVD(n_components=n_components, random_state=1337)
nmf_ = NMF(n_components=n_components, random_state=1337)
tfidf_col = TfidfVectorizer().fit_transform(X_text.loc[:, i].values)
svd_col = svd_.fit_transform(tfidf_col)
nmf_col = nmf_.fit_transform(tfidf_col)
```

SVD (LSA)



Latent semantic analysis (LSA) is a technique in natural language processing, in particular distributional semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms.

- data clustering, document classification
- cross language retrieval
- synonymy and polysemy
- information retrieval
- expand the feature space of machine learning / text mining systems

SOURCE:
https://en.wikipedia.org/wiki/Singular_value_decomposition
https://en.wikipedia.org/wiki/Latent_semantic_analysis

NMF for topic modelling

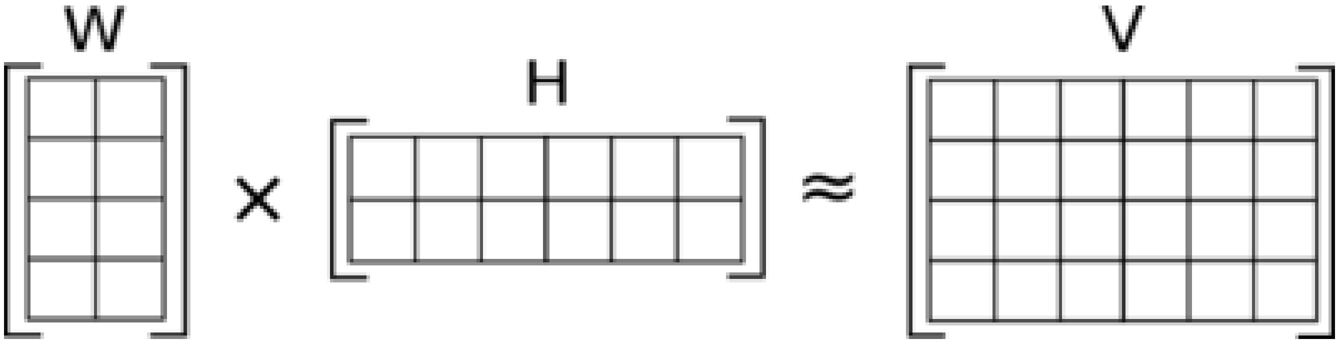


Illustration of approximate non-negative matrix factorization: the matrix **V** is represented by the two smaller matrices **W** and **H**, which, when multiplied, approximately reconstruct **V**.

NMF can be used for text mining applications. In this process, a document-term matrix is constructed with the weights of various terms (typically weighted word frequency information) from a set of documents. This matrix is factored into a term-feature and a feature-document matrix. The features are derived from the contents of the documents, and **the feature-document matrix describes data clusters of related documents**.

SOURCE:
https://en.wikipedia.org/wiki/Non-negative_matrix_factorization

XGBoost

XGBoost stands for eXtreme Gradient Boosting, an open source project by Tianqui Chen, Tong He, and Carlos Guestrin that has gained gained momentum and popularity in datascience competitions such as Kaggle and the KDD-cup 2015.

1. level-wise and leaf-wise splitting strategies (The level-wise strategy maintains a balanced tree, whereas the leaf-wise strategy splits the leaf that reduces the loss the most.)
2. Weighted Quantile Sketch for determining how to make splits in a decision tree (candidate splits)
3. Sparsity-aware Split finding introduces a default direction in each tree node, so when some data is missing, the direction of the split is automatically predermined, thus reducing complexity row-wise

```
params = {'eta': 0.0123, 'subsample': 0.7, 'colsample_bytree': 0.75,
          'tree_method': 'gpu_hist', 'gamma' : 8, 'max_depth' : 7}
early_stop = 500
num_rounds = 10000
```

LightGBM

The high-performance LightGBM algorithm is capable of being distributed and of fast-handling large amounts of data. It has been developed by a team at Microsoft as an open source project on GitHub (there is also an academic paper).

1. leaf-wise splitting startegy
2. Gradient-based One-Side Sampling (GOSS) which inspects the most informative samples while skipping the less informative samples
3. Exclusive Feature Bundling which takes advantage of sparse datasets by grouping features in a near lossless way (basically it combines combines similar columns)

```
params = {'num_leaves': 70, 'max_depth': 9, 'learning_rate': 0.01,
          'bagging_fraction': 0.6, 'feature_fraction': 0.6, 'min_split_gain': 0.02,
          'min_child_samples': 150, 'min_child_weight': 0.02,
          'lambda_l2': 0.0475}
early_stop = 500
num_rounds = 10000
```

CV strategy

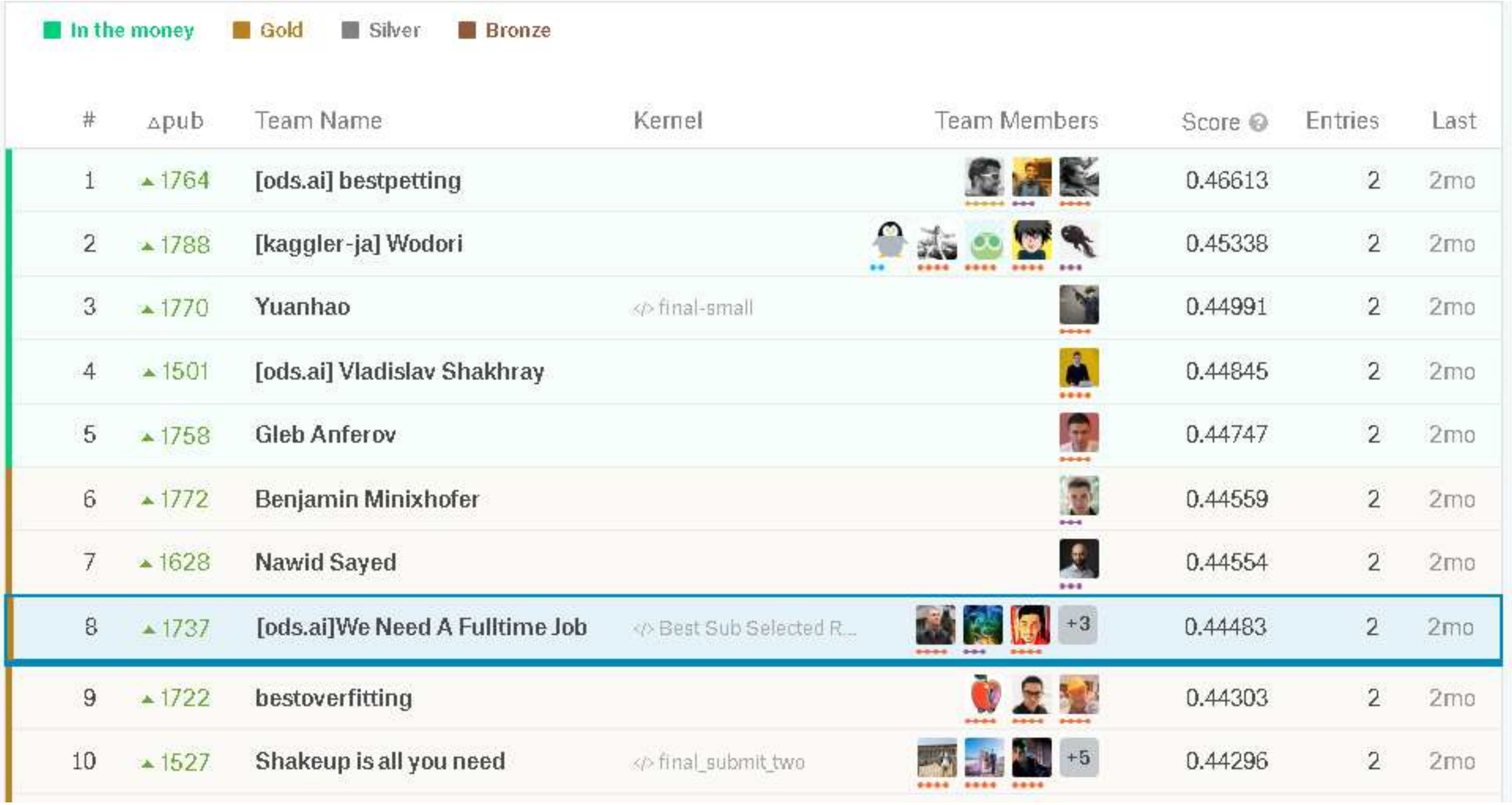
```
n_splits = 10
kfold = StratifiedKFold(n_splits=n_splits, random_state=1337)
rescuer_gb_mean = (X_train.groupby('RescuerID')['AdoptionSpeed']
                          .agg("mean").reset_index())
rescuer_as_mean = rescuer_gb_mean['AdoptionSpeed_mean'].values

for train_index, valid_index in kfold.split(rescuer_ids,
rescuer_as_mean.astype(np.int)):
    rescuser_train_ids = rescuer_ids[train_index]
    rescuser_valid_ids = rescuer_ids[valid_index]
    # Train model, predict on fold, predict on test
    # Store fold predictions in oof, stack test predictions
```

The rescurer in the test set are unknown in the train set. We cannot rely on such information, yet we can stratify by the information that the rescurer carry associated with them, the adoption speed, and replicate such a distribution in our predictions.

The result are the average (corr=0.943) of the averaged predictions of two models, an XGBoost and a LightGBM, trained on 10 cv folds.

Conclusions



🟩 In the money 🟫 Gold ⬜ Silver 🟫 Bronze

#	∆pub	Team Name	Kernel	Team Members	Score	Entries	Last
1	▲1764	[ods.ai] bestpetting			0.46613	2	2mo
2	▲1788	[kaggler-ja] Wodori			0.45338	2	2mo
3	▲1770	Yuanhao	</> final-small		0.44991	2	2mo
4	▲1501	[ods.ai] Vladislav Shakhray			0.44845	2	2mo
5	▲1758	Gleb Anferov			0.44747	2	2mo
6	▲1772	Benjamin Minixhofer			0.44559	2	2mo
7	▲1628	Nawid Sayed			0.44554	2	2mo
8	▲1737	[ods.ai]We Need A Fulltime Job	</> Best Sub Selected R...	+3	0.44483	2	2mo
9	▲1722	bestoverfitting			0.44303	2	2mo
10	▲1527	Shakeup is all you need	</> final_submit_two	+5	0.44296	2	2mo

8th Place Solution Code

Python script using data from multiple data sources · 875 views · 2mo ago · multiple data sources

https://www.kaggle.com/adityaecdrid/8th-place-solution-code

Ask me any question!

Thank you