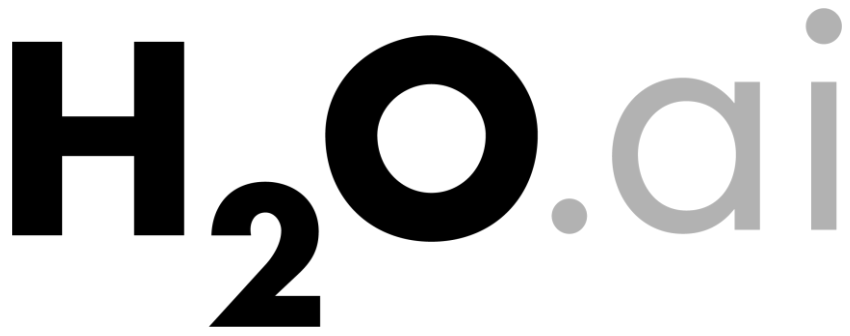
From Kaggle to H_2O

The true story of a civil engineer turned data geek



Jo-fai (Joe) Chow

Data Scientist

joe@h2o.ai

@matlabulous

SV Big Data Science at H2O.ai

28th February, 2017

About Me

- Civil (Water) Engineer

  2010 – 2015

  - Consultant (UK)
    - Utilities
    - Asset Management
    - Constrained Optimization
  - Industrial PhD (UK)
    - Infrastructure Design Optimization
    - Machine Learning + Water Engineering
    - Discovered H_2O in 2014

- Data Scientist

  2015

  - Virgin Media (UK)
  - Domino Data Lab (Silicon Valley)

  2016 – Present

  - H_2O.ai (Silicon Valley)

Agenda

- My Data Science Journey
  - Life as a Water Engineer
  - Massive Open Online Course
  - Kaggle
  - New Skills
  - Side Projects
  - New Opportunities
  - Discovery of H_2O & Domino
- To Kaggle, or not to Kaggle
  - Joy, Pain, Fear, Gain …
  - … and New Friends
- Life as a Data Scientist
- Using H_2O for Kaggle
  - Rossmann Store Sales
  - Santander Products Recommendation
- Conclusions

Life as a Water Engineer

Joe the Outlier

Joe (Water Engineer)

http://www.h2o.ai/gartner-magic-quadrant/

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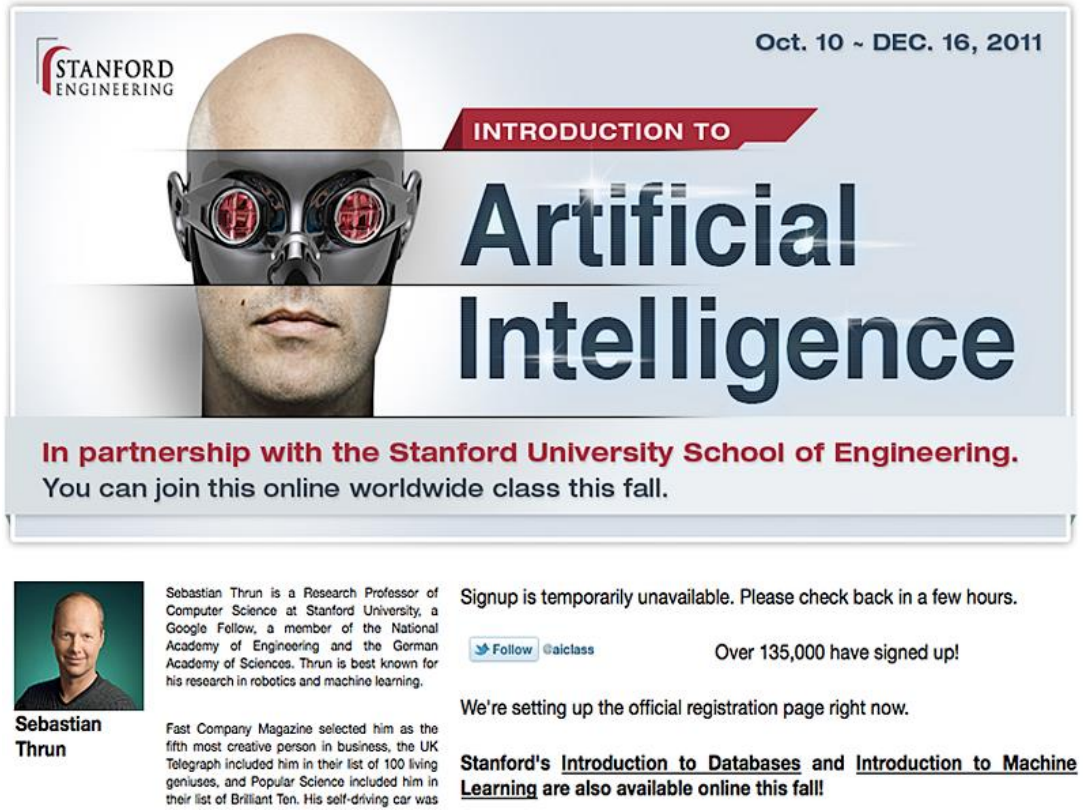
Massive Open Online Course (MOOC)

My First MOOC Experience

- Introduction to AI (2011)
  - One of the first MOOCs
- Key messages from Sebastian Thrun:
  - “Just dive into it.”
  - “Get your hands dirty.”
- Met new friends
  - Decided to collaborate for fun
  - “How about Kaggle?”
  - “What is Kaggle?”



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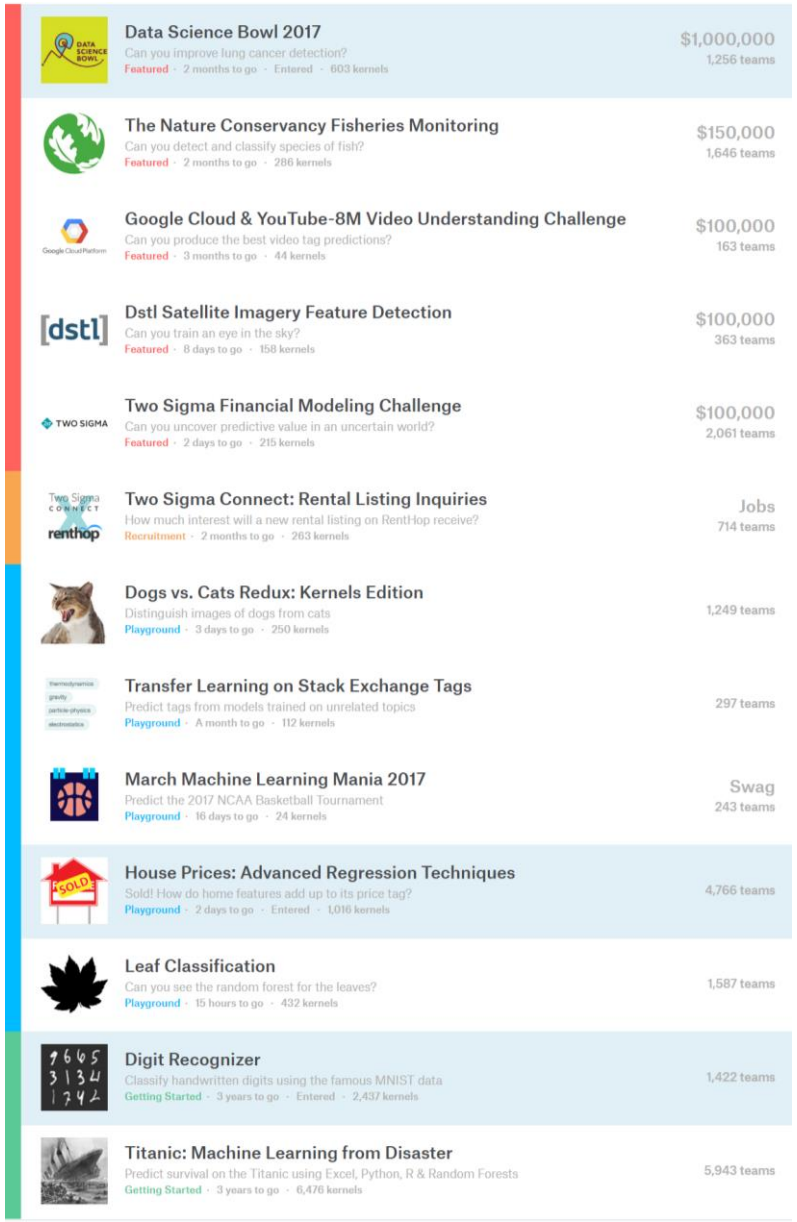
About Kaggle

- World's biggest data mining competition platform
- Competition Types:
  - Featured (w/ Prize)
  - Recruitment
  - Playground
  - Beginner (101)



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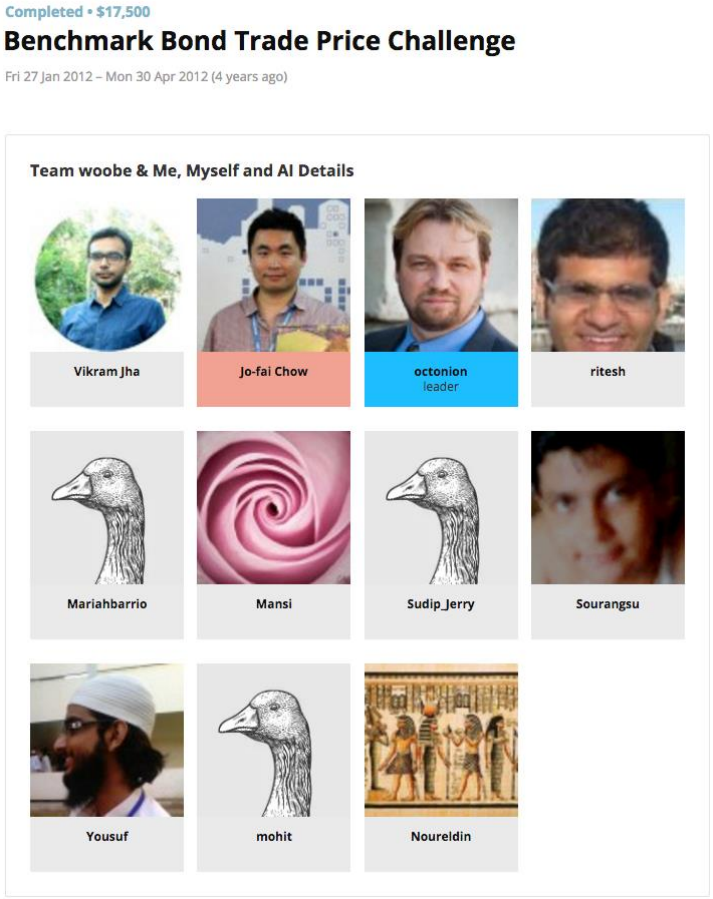
My Very First Kaggle Experience

- Predict Bond Trade Price
  - No domain knowledge
  - Lots of numbers (I couldn't open the CSV in Excel)
- Regression Models
  - Random Forest
  - Support Vector Machine
  - Neural Networks
- Black Magic or Data Science?
  - Still, I wasn't so sure



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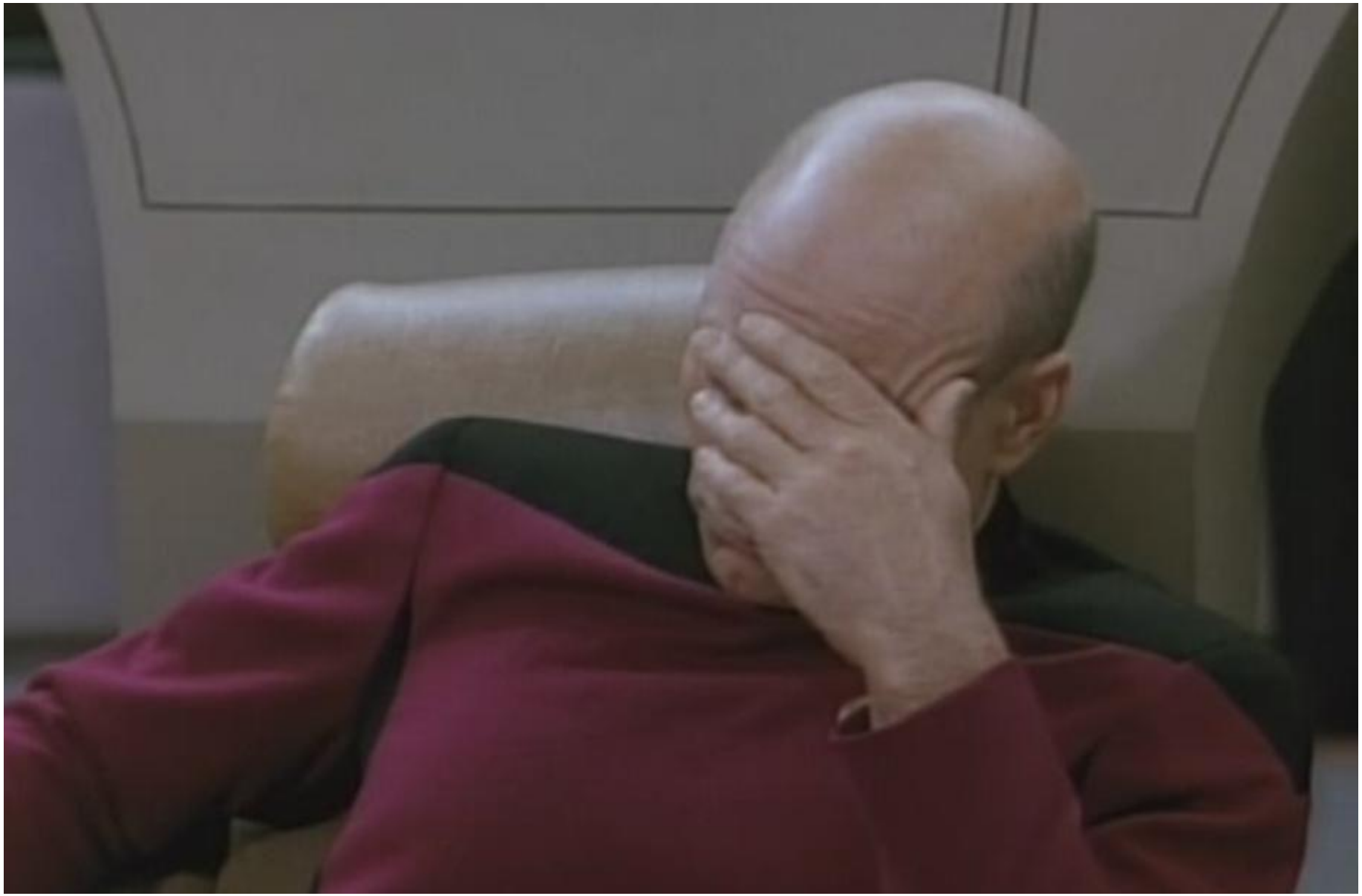
Teamwork

- Problems
  - “Hey Joe, you are a nice guy.”
  - “… but we can’t work together.”
  - “Okay, wait … why?
  - “You love MATLAB so much.”
  - “You even have a fan boy twitter handle!”

Jo-fai (Joe) Chow
@matlabulous

- Problems
  - “We prefer open source tools like R or Python.”
  - “Wait … you guys can use Octave”
  - “Thanks, but no thanks …”
- Solution
  - I kept using MATLAB
  - Lone wolf
  - ZERO collaboration

87th/264



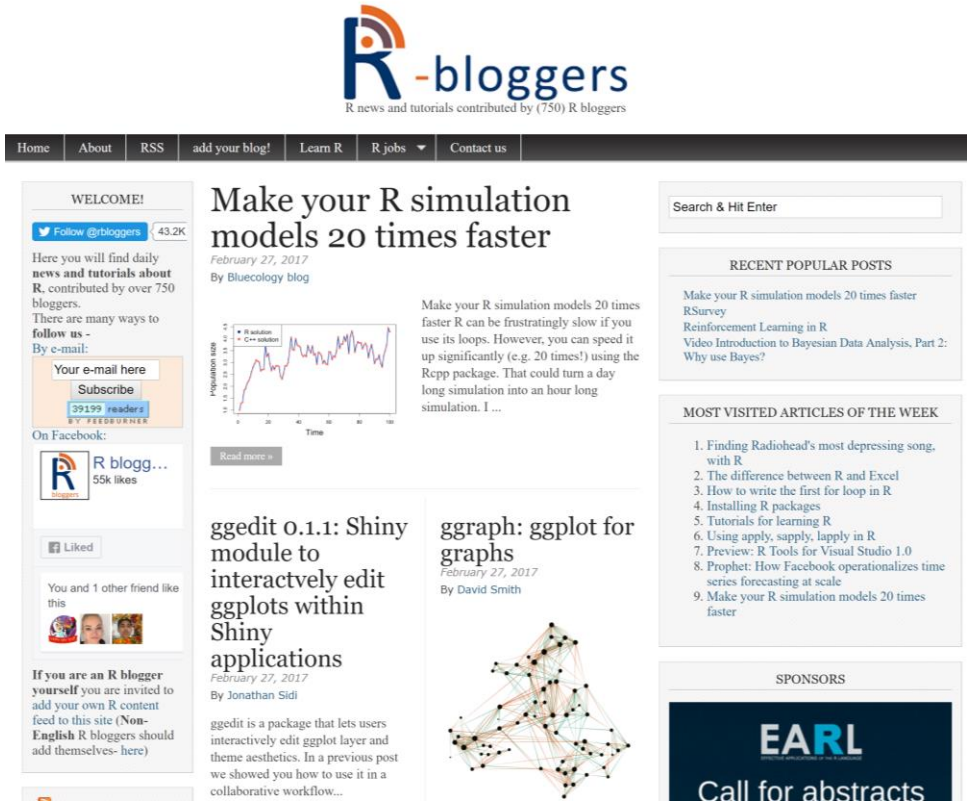
Adapt or Die

If you can't change ~~the world~~ your friends, change yourself.

Identifying Skill Gaps

- Obvious Skill Gaps
  - Open-source Programming Languages
  - Machine Learning Techniques
  - Big Data
  - Collaboration
- Kind of Related
  - Data Visualization
  - Explaining Results

- Where to Start?



https://www.r-bloggers.com/

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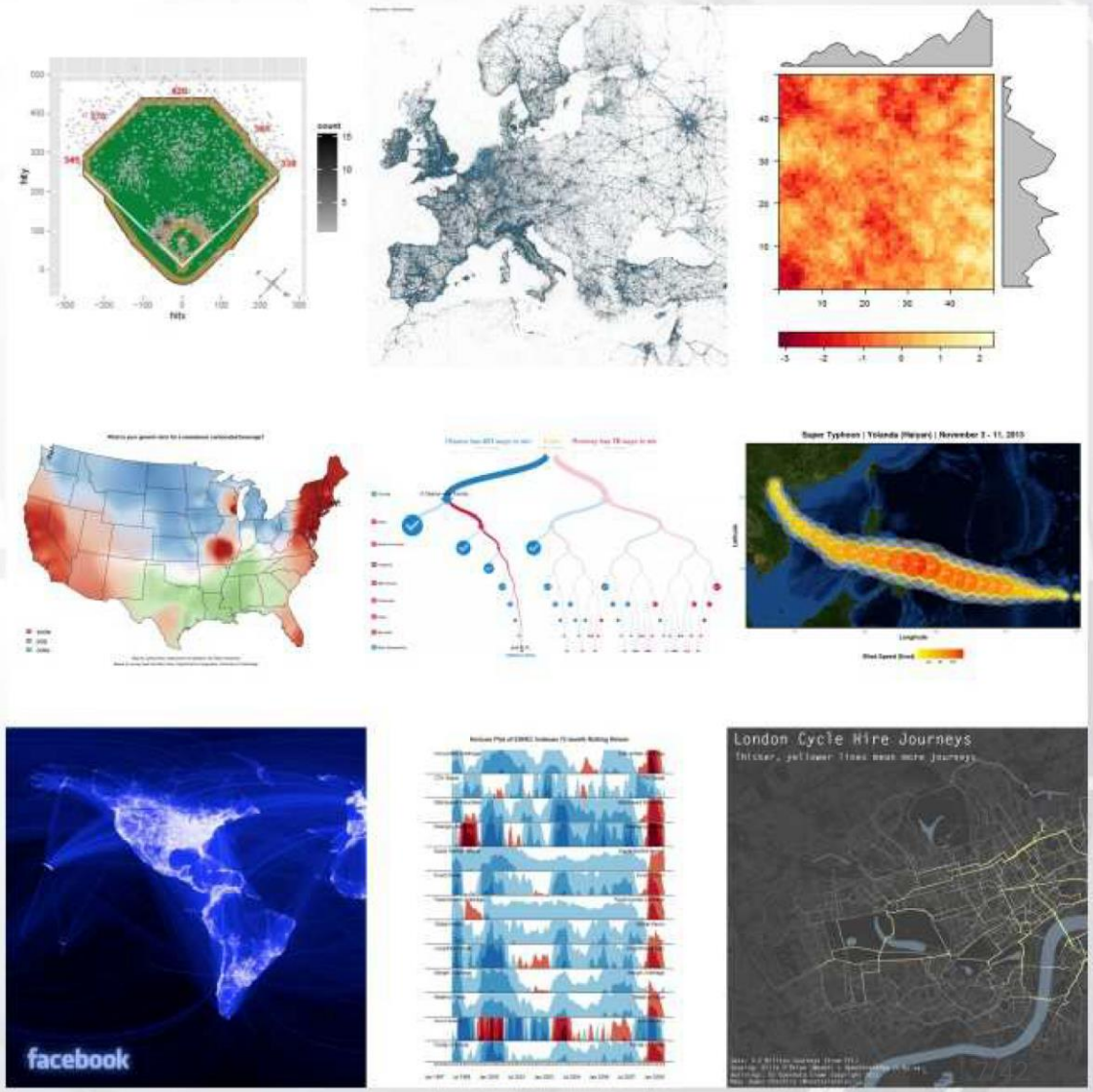
R Can Do That ?

... and more !?

Thanks to Tal Galili's

R-bloggers

R news and tutorials contributed by (452) R bloggers



http://www.jofaichow.co.uk/2014_03_11_LondonR/

Learn

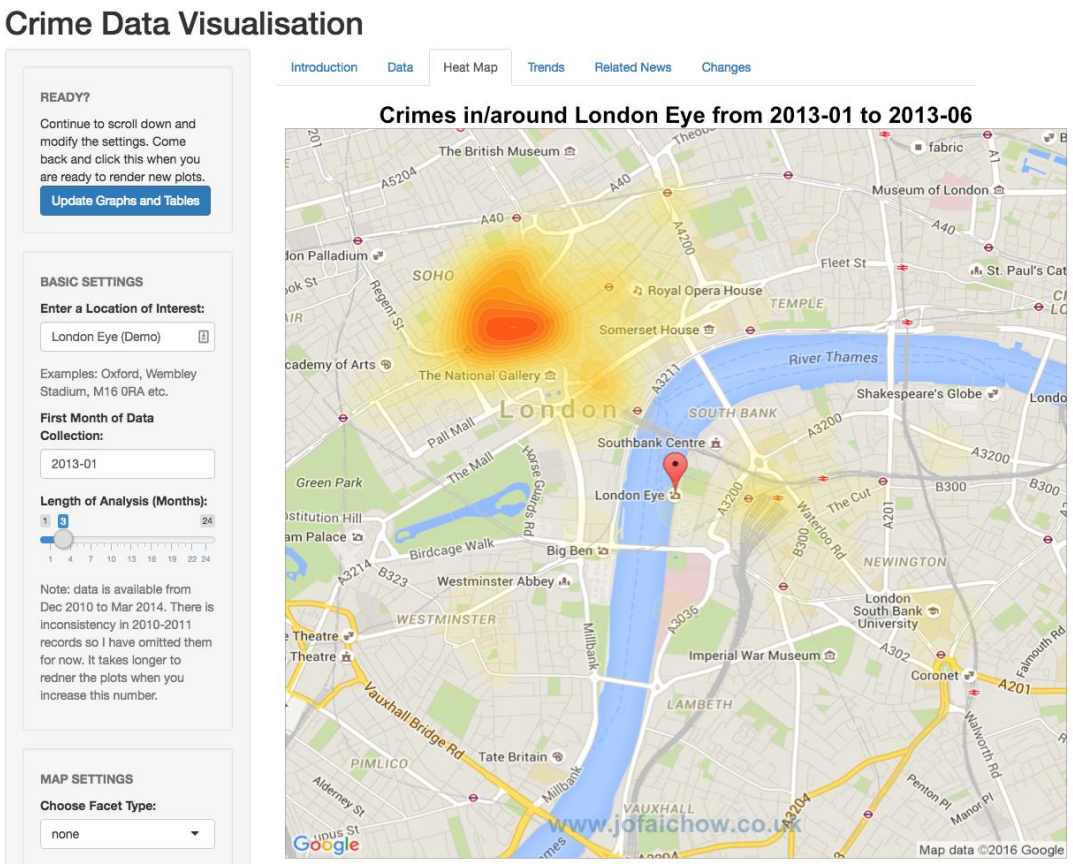
- More MOOCs
  - Machine Learning
    - Andrew Ng (Coursera)
    - MATLAB / Octave
  - Data Analysis
    - Jeff Leek (Coursera)
    - R
  - Intro to Programming
    - Dave Evans (Udacity)
    - Python

- Kaggle Forums
  - Tricks you can't learn from schools/books

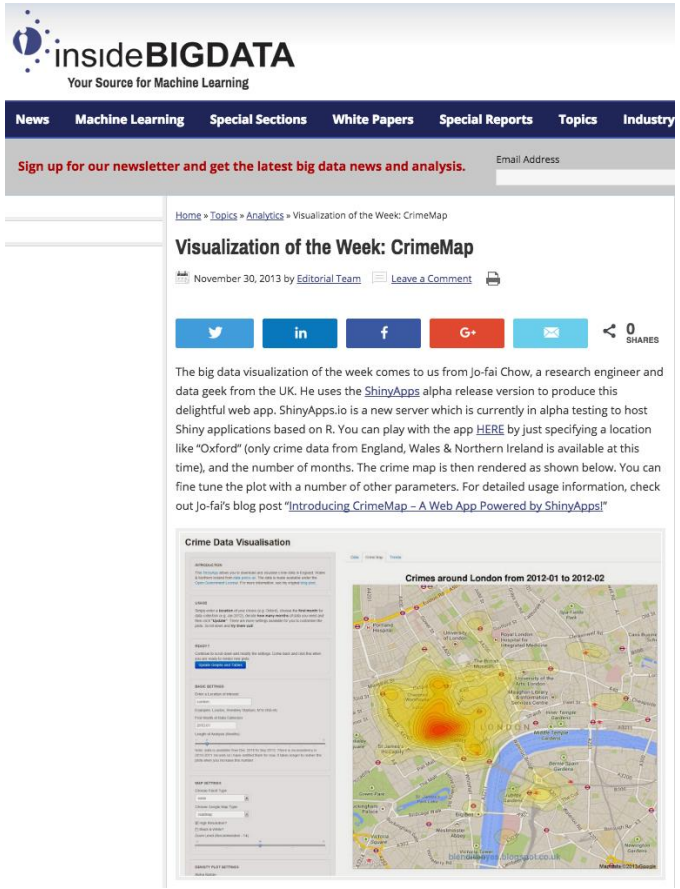
- Skills I also picked up
  - Linux – Ubuntu*
  - Git (I mean Git with GUI)
  - Cloud
  - HTML / CSS

**Ubuntu is an ancient African word that means "I can't configure Debian."*

Side Project #1 – Crime Data Visualization



https://github.com/woobe/rApps/tree/master/crimemap



http://insidebigdata.com/2013/11/30/visualization-week-crimemap/

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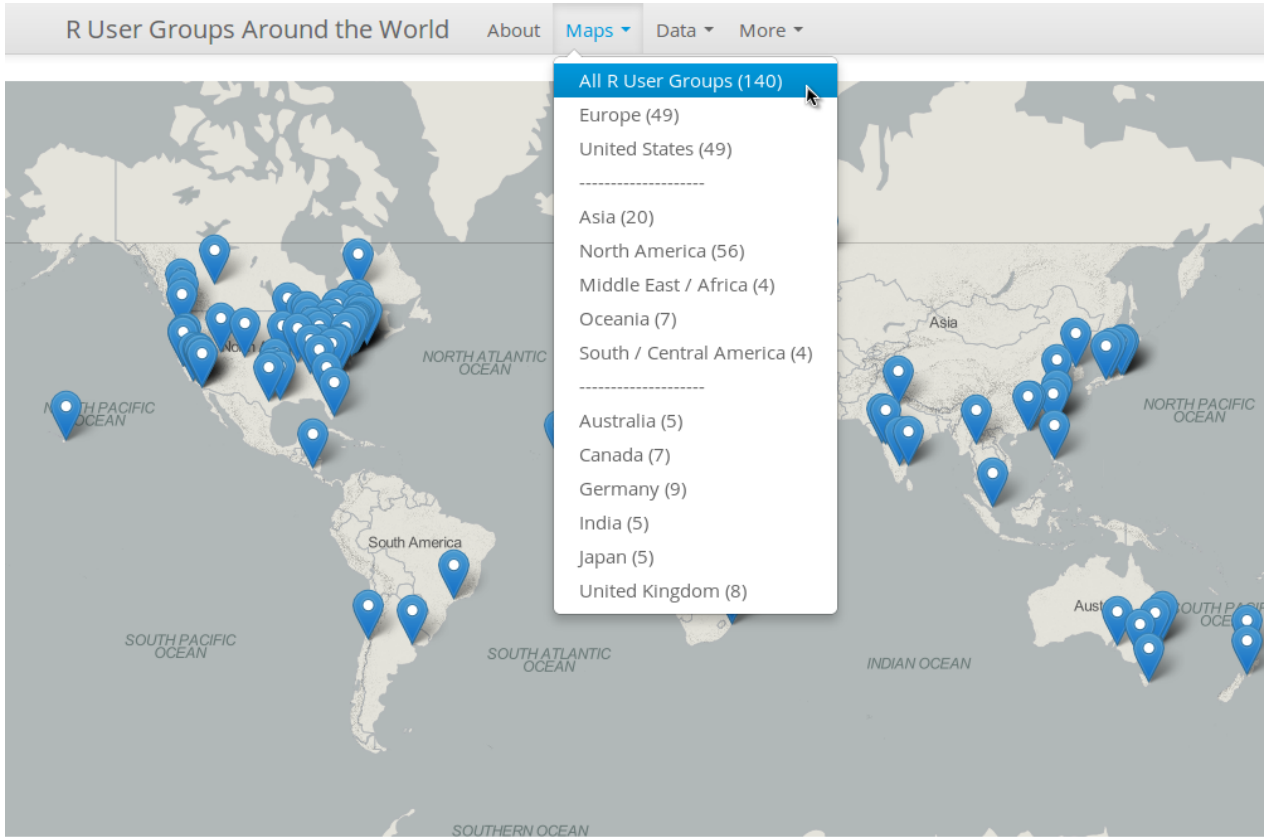
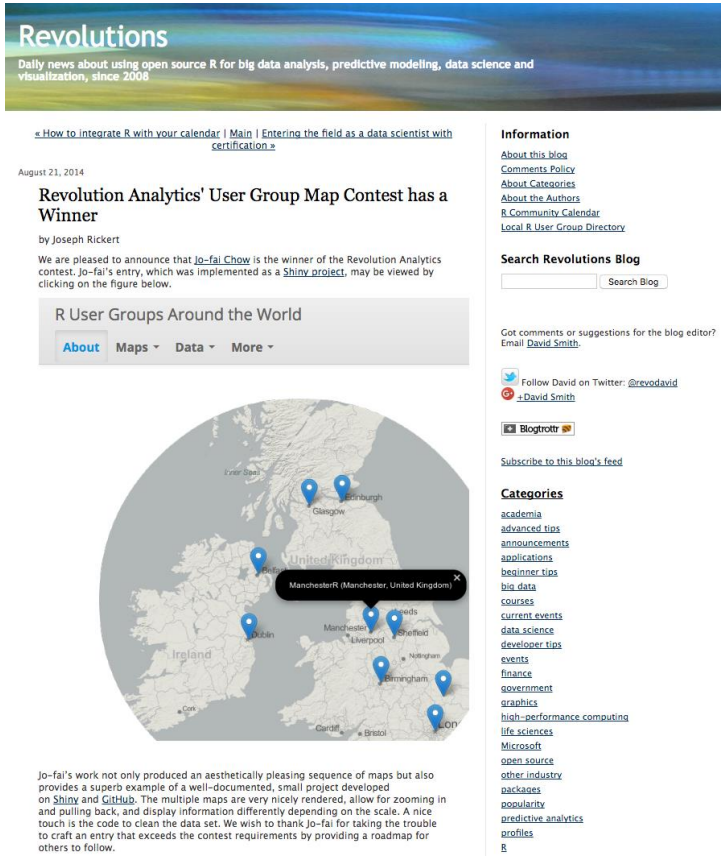
Side Project #2 – Data Visualization Contest





https://github.com/woobe/rugsmaps

http://blog.revolutionanalytics.com/2014/08/winner-for-revolution-analytics-user-group-map-contest.html

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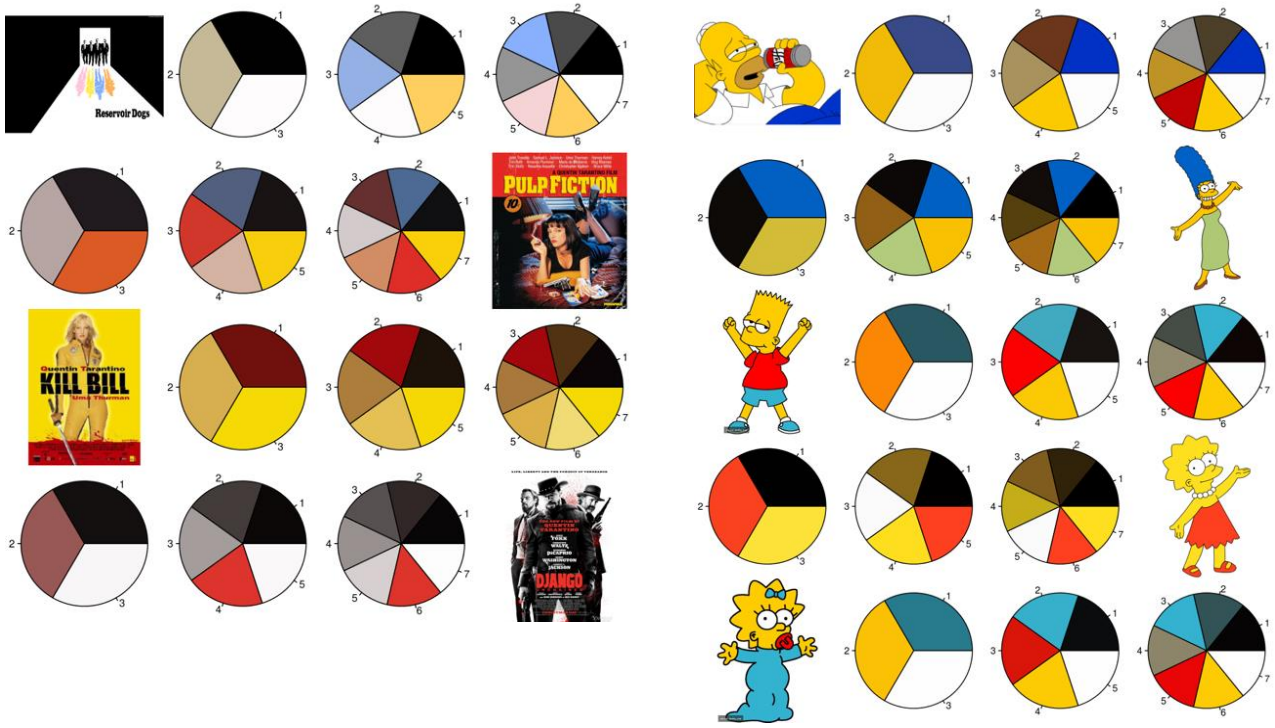
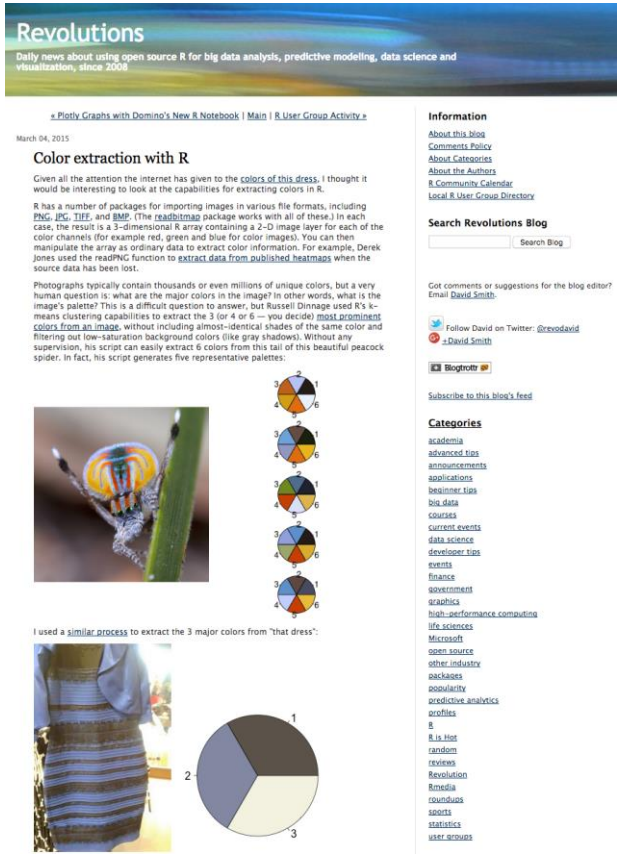
Side Project #3 – Color Extraction



https://github.com/woobe/rPlotter

#TheDress



http://blog.revolutionanalytics.com/2015/03/color-extraction-with-r.html

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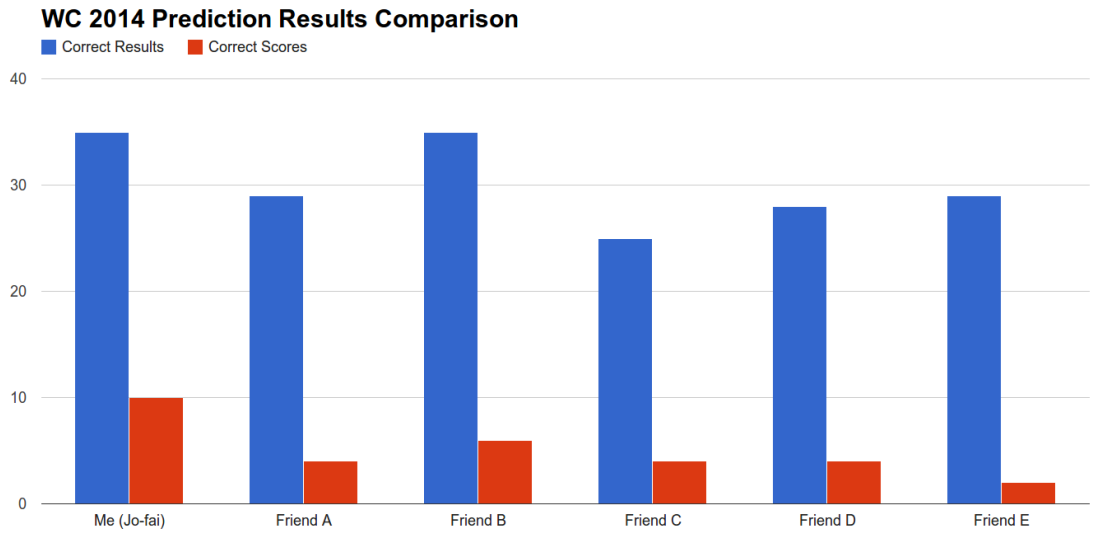
Side Project #4 – World Cup 2014 Prediction

- Joe (Machine Learning) vs. Friends
  - Correct Results (WDL)
    - ML: 35 / 64 (55%)
    - Friends (Avg): 29 / 64 (46%)
  - Correct Score
    - ML: 10 / 64 (16%)
    - Friends (Avg): 4 / 64 (6%)



https://github.com/woobe/wc2014

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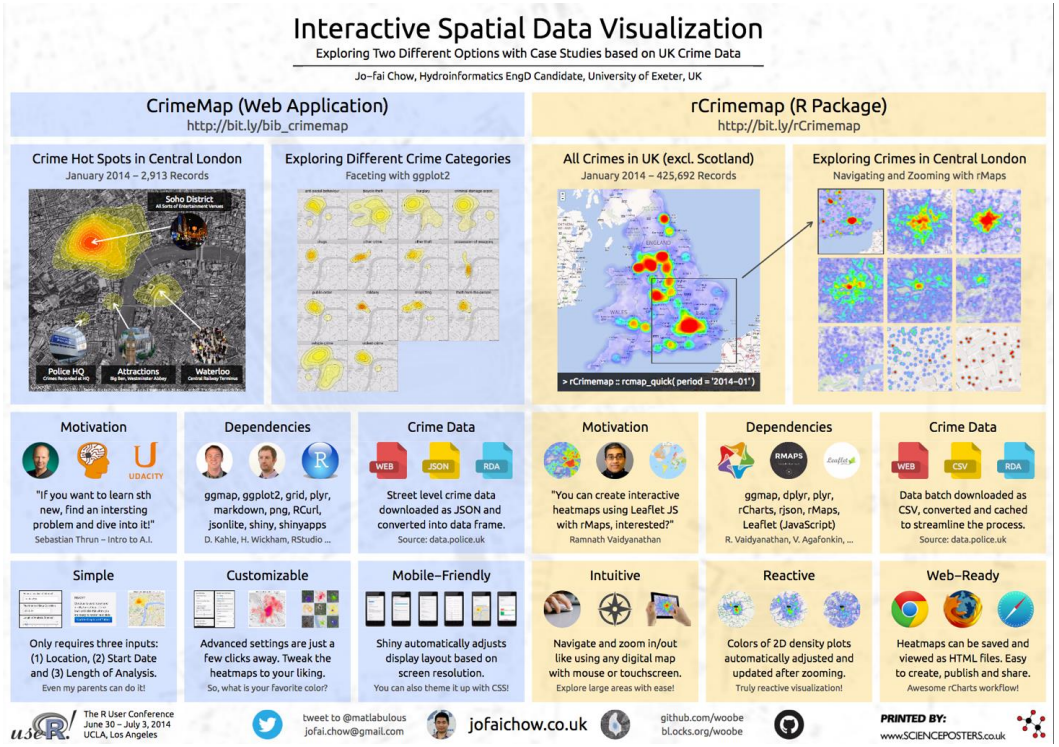
Open Up Myself

New Opportunities

R Community, H2O & Domino Data Lab

LondonR 2013 & useR! 2014



http://www.jofaichow.co.uk/2014_03_11_LondonR/

https://github.com/woobe/useR_2014

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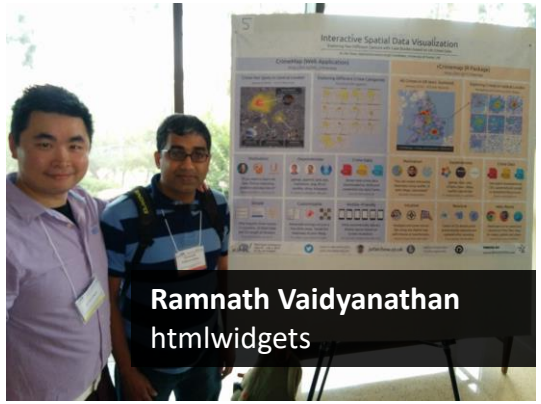
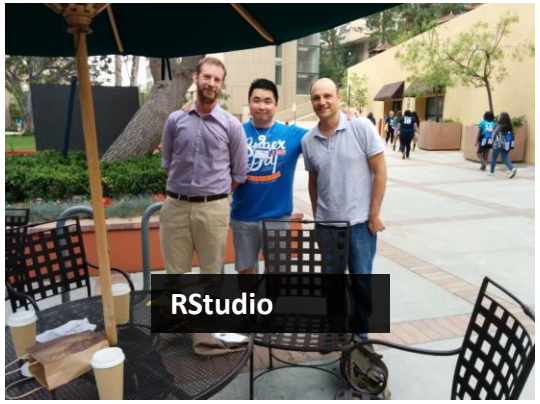
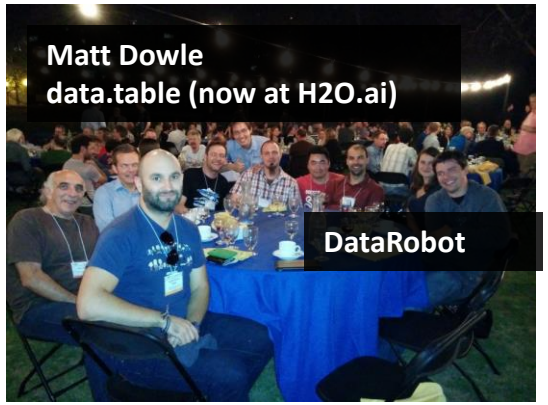
useR! 2014







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https://blog.dominodatalab.com/using-r-h2o-and-domino-for-a-kaggle-competition/

How to use R, H2O, and Domino for a Kaggle competition

data science R

by Nick Elprin on September 19th, 2014

SHARE

This is a guest post by Jo-Fai Chow

The sample project (code and data) described below is available on Domino.

If you're in a hurry, feel free to skip to:

- Tutorial 1: Using Domino
- Tutorial 2: Using H2O to Predict Soil Properties
- Tutorial 3: Scaling up your analysis

Introduction

Dear Kaggle

Joy, Pain, Fear, Gain … and New Friends ☺

Kaggle – The Joy

kaggle | Customer Solutions | Competitions | Community ▾

$8,000 • 413 teams

Africa Soil Property Prediction Challenge

Enter/Merge by

Wed 27 Aug 2014 — Tue 21 Oct 2014 (40 days to go)

Dashboard

Leaderboard - Africa Soil Property Prediction Challenge

This leaderboard is calculated on approximately 13% of the test data.
The final results will be based on the other 87%, so the final standings may be different.

See someone using multiple accounts?
Let us know.

#	Δ3d	Team Name * in the money	Score	Entries	Last Submission UTC (Best – Last Submission)
1	↑13	**Jo-fai Chow @ blenditbayes! + h2o.ai + Domino ***	0.40406	23	Thu, 11 Sep 2014 21:12:59 (-14.5h)

Your Best Entry

Number One!

You jumped into first by improving your score by 0.00638.

H2O.ai

Kaggle – The Pain & The Fear

513	▼ 449	Jo-fai Chow @ blenditbayes! + H2...		0.51401	133	2y

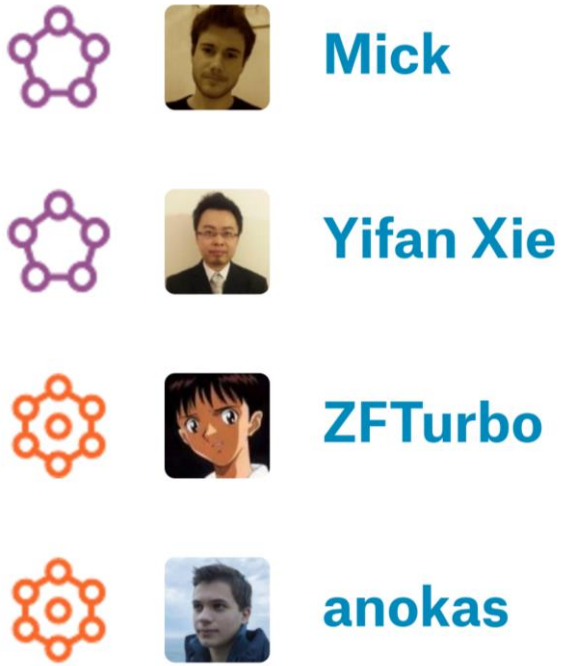
H2O.ai

Kaggle – The Gain

- New Skills
  - Exploratory Data Analysis
  - Machine Learning Algorithms
  - Feature Engineering
  - Model Stacking
  - Communication

  - **THE FEAR OF OVERFITTING!**

- New Friends
  - London Kaggle Meetup



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Life as a Data Scientist

Toy (In-Class) vs. Kaggle vs. Real-World Data

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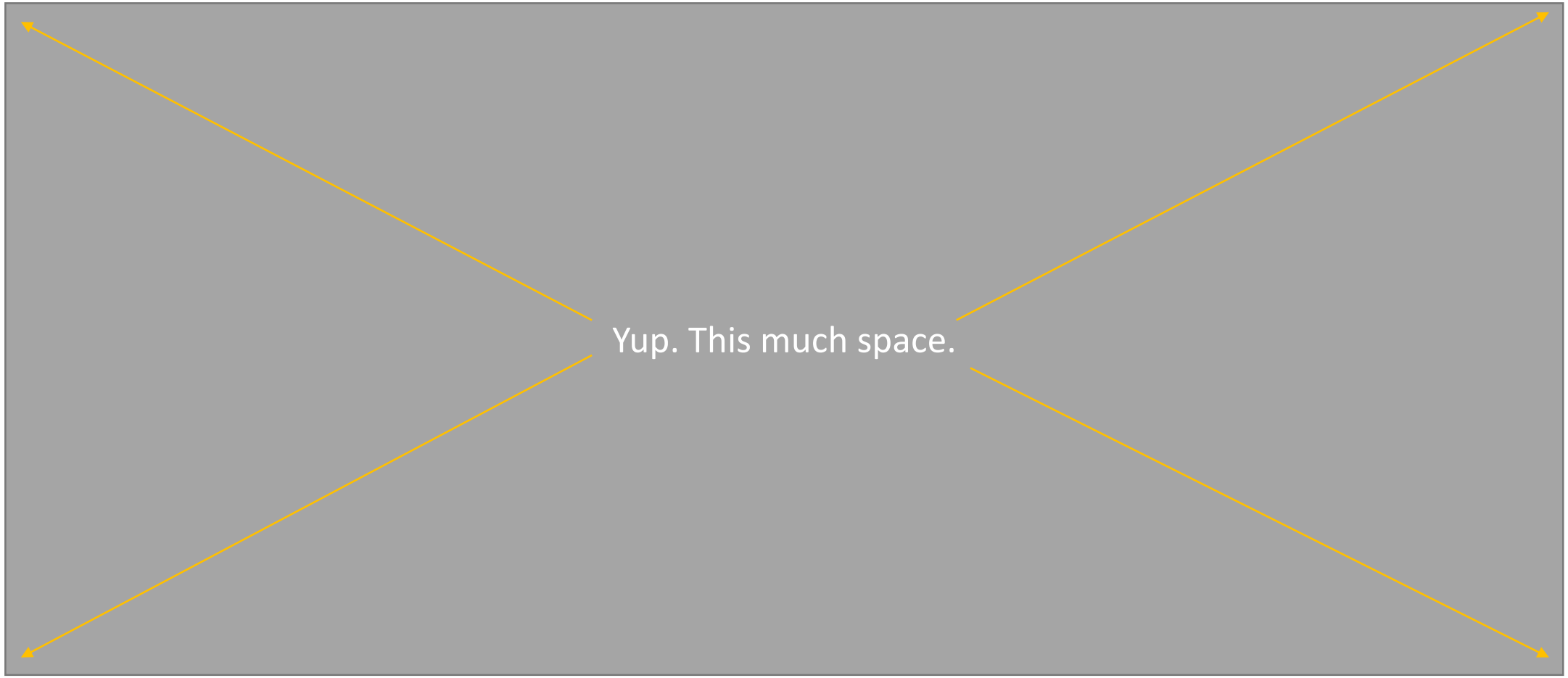
Story Telling

H2O.ai

Story Telling with One Single Slide



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Using H_2O for Kaggle

Jo-fai Chow

Data Scientist at H2O.ai

London, England, United Kingdom

Joined 5 years ago · last seen in the past day

http://www.jofaichow.co.uk/

Competitions Expert

Competitions Expert

Current Rank	Highest Rank
818 of 54,344	181

0	2	5

Santander Product Recom... · 2 months ago · Top 3%	38th of 1787
Rossmann Store Sales · a year ago · Top 2%	57th of 3303
Personality Prediction Base... · 5 years ago · Top 24%	21st of 89

Kernels Contributor

Unranked

0	0	0

XGB_test_001 a year ago	0 votes
H2O Starter GBM a year ago	0 votes
Testing a year ago	0 votes

Discussion Contributor

Unranked

1	1	12

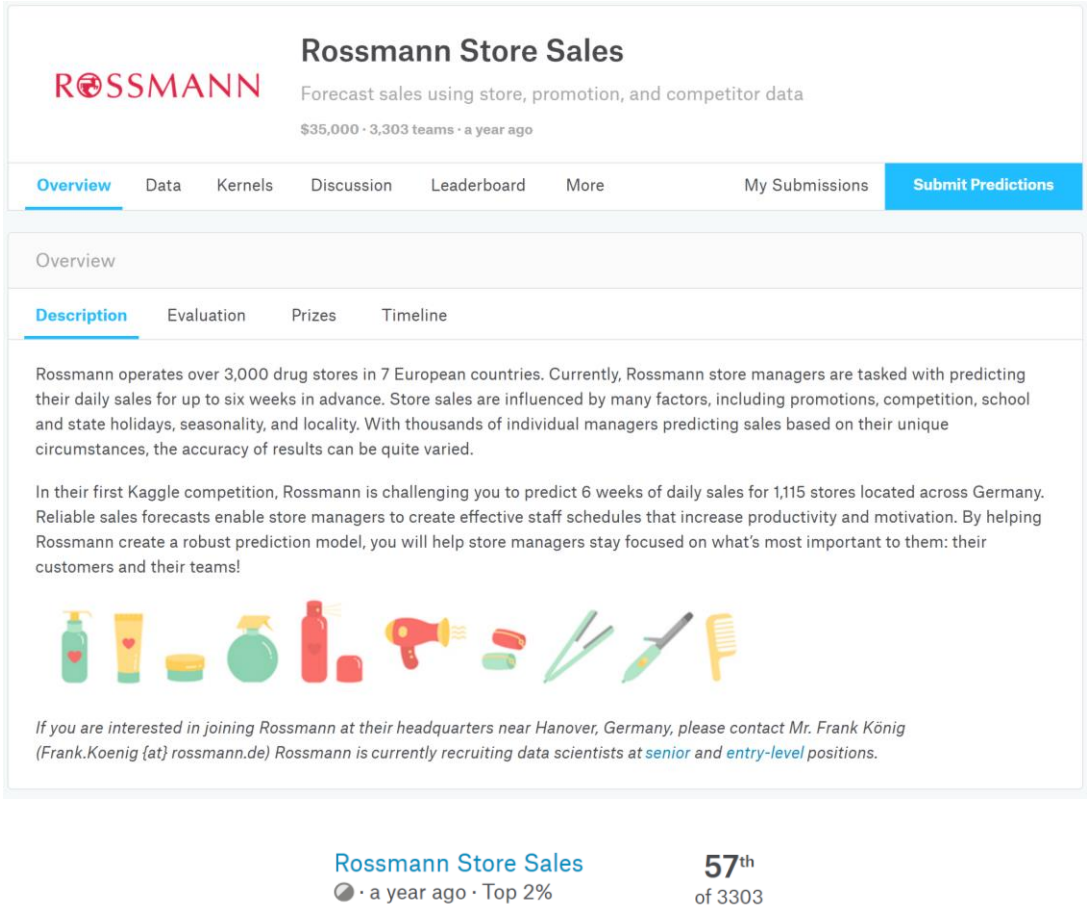
H2O Deep Learning Starte... · 2 years ago	21 votes
Best Ensemble References? · 2 years ago	7 votes
Leaderboard scores · 2 years ago	4 votes

Bio

Edit

Rossmann Store Sales

- Stuck at top 10% for a long time
- Final Breakthrough (Mickael)
  - Added external data – weather in different cities
  - 48 hours left
- Model Stacking (Joe)
  - H_2O Deep Learning
  - Xgboost
  - Manual process (life before h2oEnsemble / Stacked Ensembles in H_2O)



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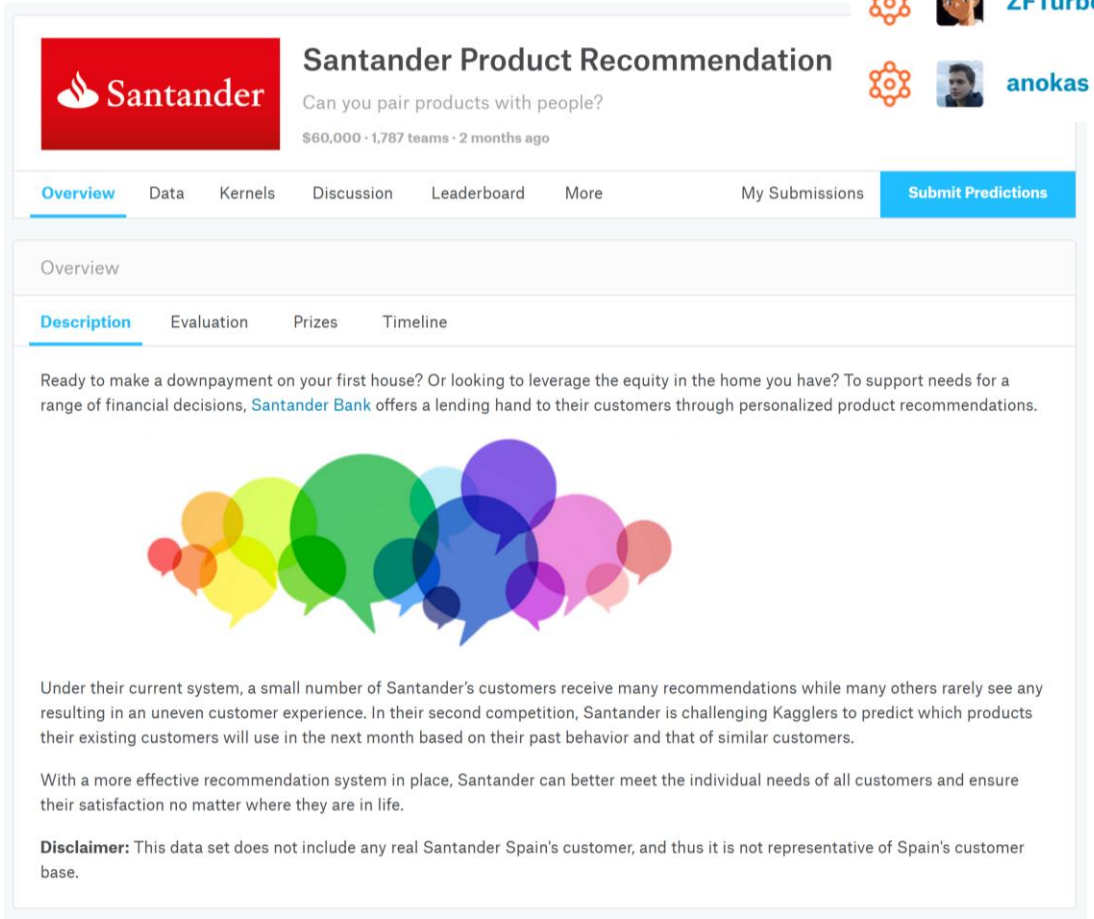
Santander Product Recommendation

- Predict new products that customers will add in the future
- Reframed as a Multiclass Classification (see next slide)
- Feature Engineering
  - Basic (Everyone)
  - Advanced (ZFTurbo, Yifan, Anokas)
  - Also see Yifan's slides
- Models
  - xgboost (ZFTurbo)
  - H_2O GBM (Joe) – Single Best Model



Santander Product Recom...
· 2 months ago · Top 3%
38th
of 1787

H2O.ai

Santander Product Recommendation

Can you pair products with people?

$60,000 · 1,787 teams · 2 months ago

BreakfastPirate
5th place

When Less is More

posted in Santander Product Recommendation 3 months ago

89

This might not be the best approach, but it seems to be working okay, and it is fairly fast since it does not use much data.

I'm only training on about 37,000 accounts – only the accounts that added a new product in June 2015. I found that the distribution of products added varied a lot by month, and June seemed to be an unusual month. Since we are predicting June 2016, I trained on only June 2015.

I only used accounts that added a new product in June 2015. We are not trying to determine who will add a new product, we are only trying to predict which products they would add **if they did**. So I excluded all accounts that didn't add a product.

I collapsed the multiple, binary dependent variables into a single multi-value dependent variable. If an account added multiple products in June 2015, then I simply had that line of data in my training set multiple times – once for each product added. So I ended up with about 46,000 rows in my training set. I then used multiclass classification (multi:softprob) to give me the probability that each product will be added, and I selected the 7 with the highest scores (and that also were not products that were owned in the previous month since those are by definition not new).

Options

kaggle-santander

Private

Show Menu

Backlog

- Date & time features (1)
- Encode categorical features (1)
- Create status feature
- Logistic regression on each product
- Add useful steps taken on previous winning solution to the backlog
- Antigüedad is the same for the 1st 7 months
- 223,967 clients never used any of the product
- Customer profile feature (1)
- Try xgboost on GPU

Add a card…

To Do

- Revisit H2O's GLRM
- Feature 2: Create linear regression on all sparse data predicting target variable independently. We again need to do so CV way. Split data on N=10 part and create linear regression validation predictions. So 24 columns in feature file.
- Generate frequency feature for categorical variables with high cardinality
- K-mean features: generate K-mean cluster feature for customer - product ownership
- total amount of time a product is owned by a customer
- Previous-month product purchase feature

Add a card…

Doing

- Feature 1: Minimum and average cosine sim between products vector for 5 previous months with any record where given product was added by customer. Since we use target variable here, we need to create this feature CV way. eg split all data on (N=10) parts. Choose one part as "validation" for which we calculate feature all other 9 as "train". Then calculate cosine sim for each record in "validation" against each record from "train" where given product was added. Find average and minimum value. Repeat for all 9 other splits. So at the end we will have 24*2 columns in feature file.
- Multi-class h2o stacking (final push only) (1)

Add a card…

Review

- Investigate the impact of surprisingly young customers (2) (1)
- k-means & PCA for customer info (without product info) (6) (1)
- Post-Prediction processing check list (0/3)
- Feature Engineering Check List

Add a card…

Done

- Basic data prep in R
- Removing highly correlated product lag features (1)
- Test and set up large scale features selection on Domino (1)
- Include May-16 for training and use kfold CV for early stopping
- Deal with outliers (3) (0/1)
- Try H2O GBM + DRF + DNN Ensemble and evaluate local validation set (1)
- Try H2O Deep Learning, RF, Deep

Add a card…

Submissions

Add a card…

kaggle-santander

File Edit View Insert Format Data Tools Add-ons Help Last edit was on 20 December 2016

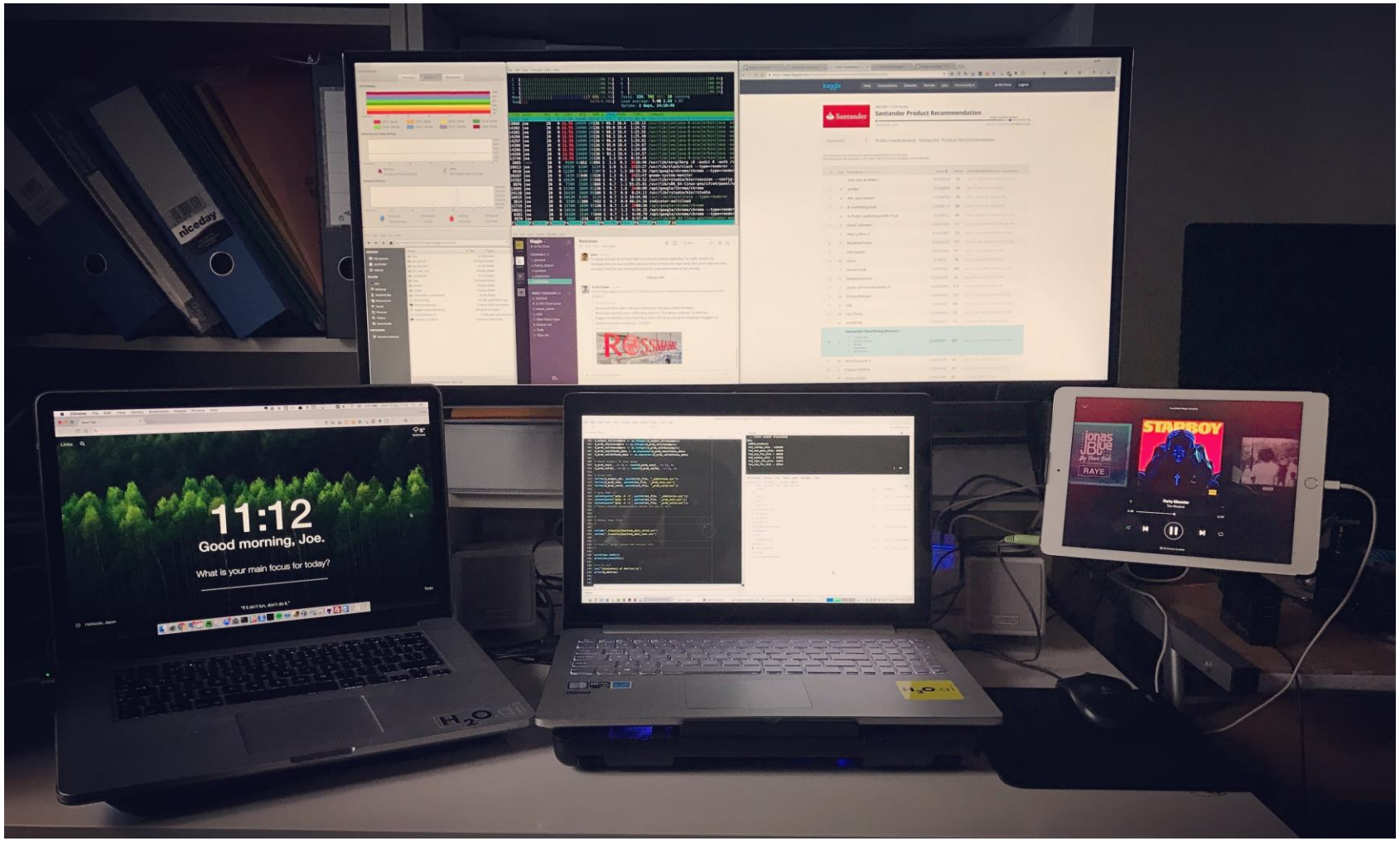
joe_gbm_038

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	run	data source	preprocessing	training	validation	lag	algo	ntrees / epochs	learn_rate	row_samp	col_samp	max depth	pred noise bw	run time	early stopping	mlogloss		mean per class error		overall class error		Public LB	Public LB (20/21 fix)
2																train	valid	train	valid	train	valid		
40		v8 start from raw data, only with Joe's features (with flag_closed_acc) = NEW BASELINE MODEL!!!																					
41	joe_gbm_032	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	672	0.05	0.9	0.5	5	0.00	2h33m	3/100/mpcerr	0.9154	0.9302	0.5373	0.5656	0.3443	0.3557	N/A	N/A
42	joe_gbm_033	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	693	0.05	0.8	0.8	5	0.00	2h37m	3/100/mpcerr	0.9138	0.9375	0.5246	0.5702	0.3437	0.3569	N/A	N/A
43	joe_gbm_034	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	350	0.05	0.9	0.5	5	0.00	48m	10/10/mpcerr	0.9107	0.9310	0.4886	0.5699	0.3432	0.3556	N/A	N/A
44	joe_gbm_035	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	360	0.05	0.8	0.8	5	0.00	52m	10/10/mpcerr	0.9103	0.9354	0.5195	0.5708	0.3432	0.3568	N/A	N/A
45	joe_gbm_036	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	205	0.05	0.9	0.5	5	0.00	38m	5/10/mpcerr	0.9190	0.9326	0.5408	0.5700	0.3449	0.3558	N/A	N/A
46	joe_gbm_037	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	170	0.05	0.8	0.8	5	0.00	38m	5/10/mpcerr	0.9281	0.9394	0.5415	0.5726	0.3469	0.3579	N/A	N/A
47	joe_gbm_038	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	350	0.05	0.9	0.5	5	0.00	55m	5/20/mpcerr	0.9107	0.9310	0.4886	0.5699	0.3432	0.3556	0.0303787	N/A
48	joe_gbm_039	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	360	0.05	0.8	0.8	5	0.00	1h1m	5/20/mpcerr	0.9103	0.9354	0.5195	0.5708	0.3432	0.3568	N/A	N/A
49		v9 = v8 + two features from Deep Autoencoder (recon_err and flag_outlier)																					
50	joe_gbm_040	Raw	data_prep_v009	Jun15-Apr16	May-2016	5	H2O_GBM	435	0.05	0.9	0.5	5	0.00	1h3m	5/20/mpcerr	0.9109	0.9359	0.5241	0.5636	0.3432	0.3571	N/A	N/A
51	joe_gbm_041	Raw	data_prep_v009	Jun15-Apr16	May-2016	5	H2O_GBM	305	0.05	0.9	0.5	5	0.00	48m	5/20/mpcerr	0.9125	0.9383	0.5296	0.5709	0.3454	0.3570	N/A	N/A
52	joe_gbm_042	Raw	data_prep_v009	Jun15-Apr16	May-2016	5	H2O_GBM	355	0.05	0.9	0.5	5	0.00	53m	5/20/mpcerr	0.9129	0.9376	0.4848	0.5692	0.3457	0.3556	N/A	N/A
53		v8 + remove high corr																					
54	joe_gbm_043 - cutoff 0.95	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	390	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9274	0.9529	0.5712	0.6027	0.3481	0.3615	N/A	N/A
55	joe_gbm_044 - cutoff 0.90	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	400	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9578	0.9645	0.5975	0.6250	0.3578	0.3651	N/A	N/A
56	joe_gbm_045 - cutoff 0.85	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	335	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9818	0.9832	0.6075	0.6323	0.3649	0.3718	N/A	N/A
57	joe_gbm_046 - cutoff 0.80	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	370	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9827	0.9821	0.6104	0.6361	0.3651	0.3712	N/A	N/A
58	joe_gbm_047 - cutoff 0.75	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	350	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	1.0079	1.0039	0.6196	0.6330	0.3736	0.3774	N/A	N/A
59	joe_gbm_048 - cutoff 0.70	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	390	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	1.0720	1.0726	0.6346	0.6441	0.3958	0.4033	N/A	N/A
60	joe_gbm_049 - cutoff 0.95	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	385	0.05	0.8	0.8	5	0.00	59m	5/20/mpcerr	0.9266	0.9536	0.5738	0.6026	0.3480	0.3627	N/A	N/A
61	joe_gbm_050 - cutoff 0.90	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	375	0.05	0.8	0.8	5	0.00	56m	5/20/mpcerr	0.9575	0.9688	0.5968	0.6257	0.3580	0.3651	N/A	N/A
62	joe_gbm_051 - cutoff 0.85	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	335	0.05	0.8	0.8	5	0.00	50m	5/20/mpcerr	0.9807	0.9886	0.6072	0.6328	0.3643	0.3726	N/A	N/A
63	joe_gbm_052 - cutoff 0.80	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	340	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	0.9827	0.9868	0.6047	0.6314	0.3650	0.3717	N/A	N/A
64	joe_gbm_053 - cutoff 0.75	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	350	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	1.0056	1.0129	0.6066	0.6413	0.3731	0.3800	N/A	N/A
65	joe_gbm_054 - cutoff 0.70	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	385	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	1.0715	1.0773	0.6305	0.6446	0.3953	0.4050	N/A	N/A
66	joe_gbm_055 - cutoff 0.975	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	275	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	0.9157	0.9404	0.5352	0.5753	0.3443	0.3580	N/A	N/A
67	joe_gbm_056 - cutoff 0.99	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	325	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	0.9101	0.9339	0.5270	0.5712	0.3430	0.3575	N/A	N/A
68	joe_gbm_057 - cutoff 0.99	Raw	data_prep_v008	Jun15-Apr16	May-2016	5	H2O_GBM	375	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9116	0.9314	0.5325	0.5658	0.3434	0.3557	N/A	N/A
69		v10 = v8 + ZFTurbo's feat_group_ids_for_purchaised_products_detailed																					
70	joe_gbm_058	Raw	data_prep_v010	Jun15-Apr16	May-2016	5	H2O_GBM	300	0.05	0.9	0.5	5	0.00	51m	5/20/mpcerr	0.9036	0.9322	0.5060	0.5595	0.3411	0.3559	N/A	0.0304047
71	joe_gbm_059_rerun	Raw	data_prep_v010	Jun15-Apr16	May-2016	5	H2O_GBM	370	0.05	0.8	0.8	5	0.00	1h3m	5/20/mpcerr	0.9024	0.9350	0.4666	0.5623	0.3409	0.3553	N/A	ensemble 00
72	joe_gbm_060	Raw	data_prep_v010	Jun15-Apr16	May-2016	5	H2O_GBM	200	0.05	0.9	0.5	5	0.00	41m	5/20/mpcerr	0.9088	0.9347	0.5072	0.5678	0.3406	0.3535	N/A	N/A
73	joe_gbm_061	Raw	data_prep_v010	Jun15-Apr16	May-2016	5	H2O_GBM	200	0.05	0.8	0.8	5	0.00	44m	5/20/mpcerr	0.9167	0.9384	0.5181	0.5658	0.3413	0.3553	N/A	N/A
74		v11 = v8 with 6-month lag																					
75	joe_gbm_062	Raw	data_prep_v011	Jun15-Apr16	May-2016	6	H2O_GBM	360	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	0.9019	0.9251	0.5279	0.5622	0.3406	0.3525	N/A	N/A
76	joe_gbm_063	Raw	data_prep_v011	Jun15-Apr16	May-2016	6	H2O_GBM	340	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	0.8997	0.9302	0.5217	0.5662	0.3398	0.3531	N/A	N/A
77		v12 = v8 with 7-month lag																					
78	joe_gbm_064	Raw	data_prep_v012	Jun15-Apr16	May-2016	7	H2O_GBM	325	0.05	0.9	0.5	5	0.00	1h	5/20/mpcerr	1.0161	0.9949	0.5582	0.5967	0.3815	0.3817	N/A	N/A
79	joe_gbm_065	Raw	data_prep_v012	Jun15-Apr16	May-2016	7	H2O_GBM	305	0.05	0.8	0.8	5	0.00	1h	5/20/mpcerr	1.0141	1.0307	0.5509	0.6089	0.3811	0.3925	N/A	N/A
80		v13 = v8 starting from May2015																					
81	joe_gbm_066	Raw	data_prep_v013	May15-Apr16	May-2016	5	H2O_GBM	420	0.05	0.9	0.5	5	0.00		5/20/mpcerr	0.9165	0.9468	0.5382	0.5384	0.3445	0.3560	N/A	0.0303708
82	joe_gbm_067	Raw	data_prep_v013	May15-Apr16	May-2016	5	H2O_GBM	370	0.05	0.8	0.8	5	0.00		5/20/mpcerr	0.9145	0.9576	0.4881	0.5501	0.3439	0.3588	N/A	ensemble 00
83		v14 = v8 starting from Apr2015																					

h2o_gbm_results | joe_stacking | stacking_grid_ref | variable_importance | h2o_gbm_grid | features_selection | fea_eval_stage_1 | joe_data_prep | features | old_test_ignore_this

Sum: May-2017 Explore

When I Kaggle …



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Conclusions

To Kaggle, or not to Kaggle?

New Skills, New Friends & New Opportunities

Giphy is your friend when you don't have enough time for bullet points.

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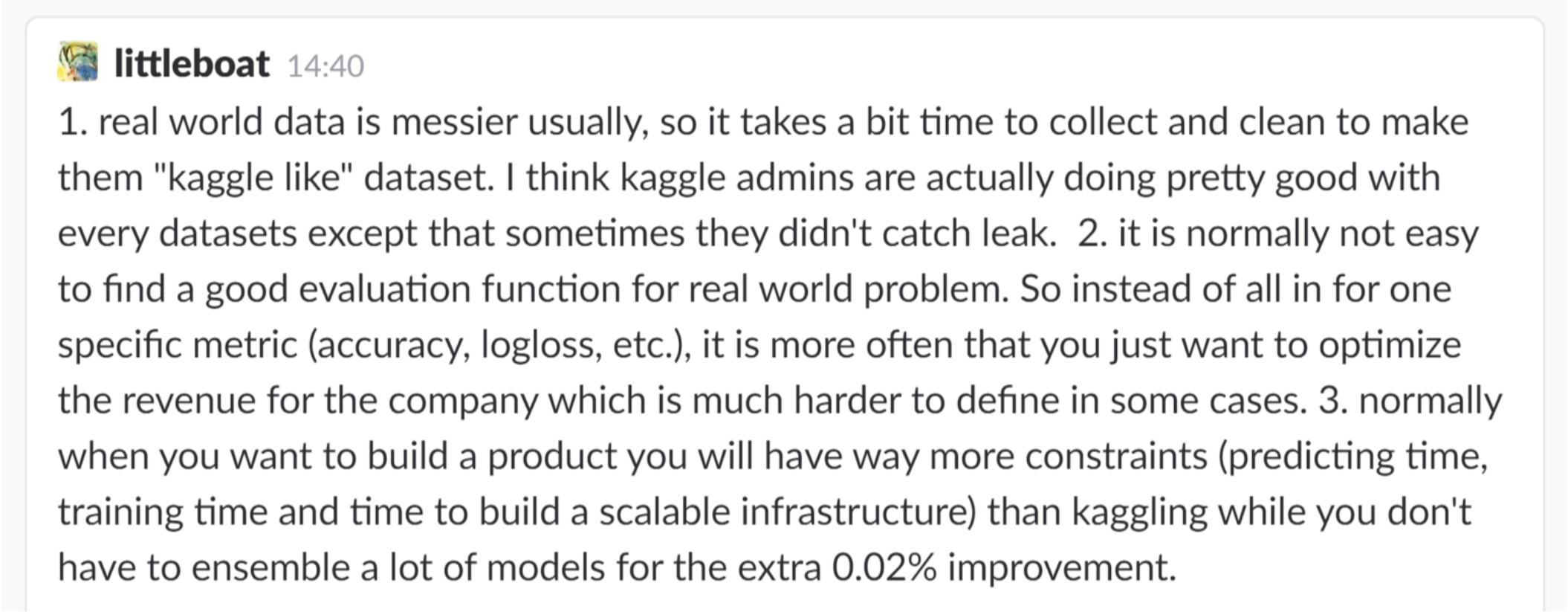
Differences between Kaggle & Data Science



Quote from Littleboat's AMA on Kagglenoobs Slack Channel

Thanks!

- People who have helped me along the way
  - Kaggle Friends
  - H_2O.ai
  - Domino Data Lab
  - Mango Solutions
- Slides
  - bit.ly/h2o_meetups
- Contact
  - joe@h2o.ai
  - @matlabulous
  - github.com/woobe

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Making Machine Learning Accessible to Everyone

Photo credit: Virgin Media