HONORARY PATRONAGE RECTOR OF





IMPROVING PREDICTIVE MODELING THE WAY FOR PERSONAL CARRIER

ADAM KARWAN, PHD

7 NOVEMBER 2017, WARSAW





Sponsor





Media Patronage





Kaggle

The Home of Data Science and Machine Learning

WHAT IS KAGGLE (Data Science as a Competition)

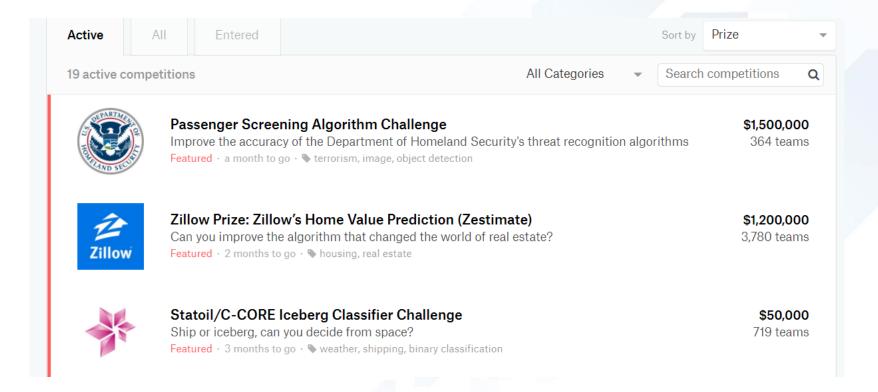




- Data Sets
- Contests

What is Kaggle

Competitions Datasets Kernels Discussion



- Self-Learning
- Recruitment
- Algorithm for Companies

Interview Task for Boeing Digital Aviation Research



Boeing Global Services

Digital Aviation & Analytics Lab Gdansk

BIKE SHARING CHALLENGE

https://www.kaggle.com/c/bike-sharing-demand

GOAL

to **forecast bike rental demand** in the Capital Bike Share Program in Washington, D.C.





BIKE SHARING CHALLENGE















Presentation

Personal Goal – create model in TOP100 best solutions in 7 days



- How to properly present a Data Mining project?
 - Start with big picture
 - Overview of process
 - Show the main outcome







Source http://algolytics.com/data-visualization-essentials-for-data-scientists



Exploratory Analysis Feature Engineering

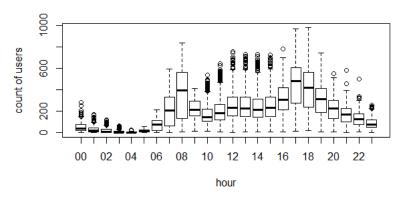
Experiments

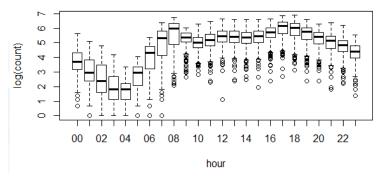
Fine Tuning Algorithm

No	Attribute	Description					
1	datetime	hourly date +timestamp					
2	season	1 = spring					
		2 = summer					
		3 = fall					
		4 = winter					
3	holiday	whether the day is considered a holiday (0; 1)					
4	workingday	whether the day is neither a weekend nor holiday (0; 1)					
5	weather	1: Clear, Few clouds, Partly cloudy, Partly cloudy					
		2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist					
		3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain +					
		Scattered clouds					
		4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog					
6	temp	temperature in Celsius					
7	atemp	"feels like" temperature in Celsius					
8	humidity	relative humidity					
9	windspeed	wind speed					
10	casual	number of non-registered user rentals initiated					
11	registered	number of registered user rentals initiated					
12	count	number of total rentals					

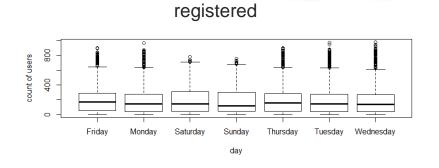
TRAIN 10886 TEST 6493

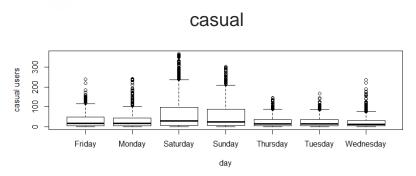
Hourly

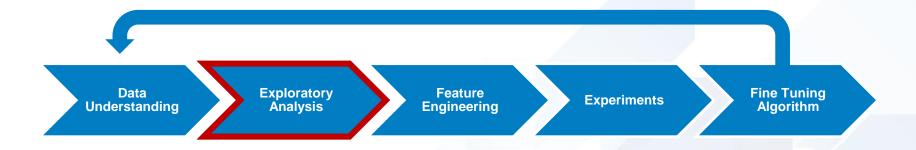


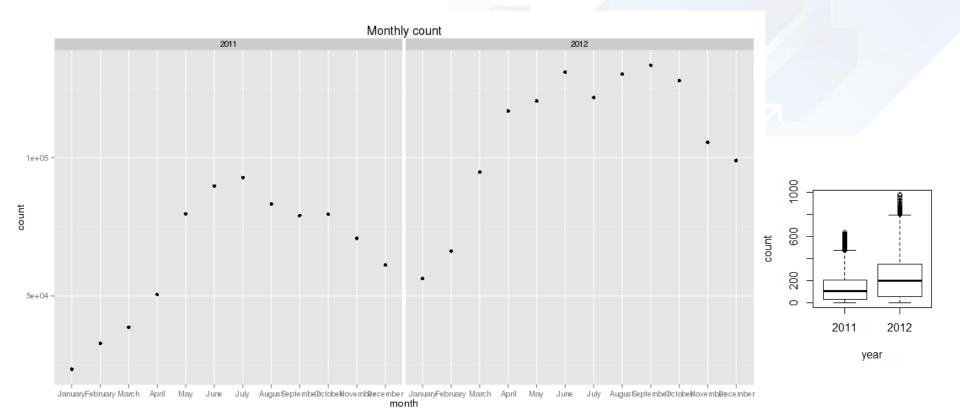


Daily

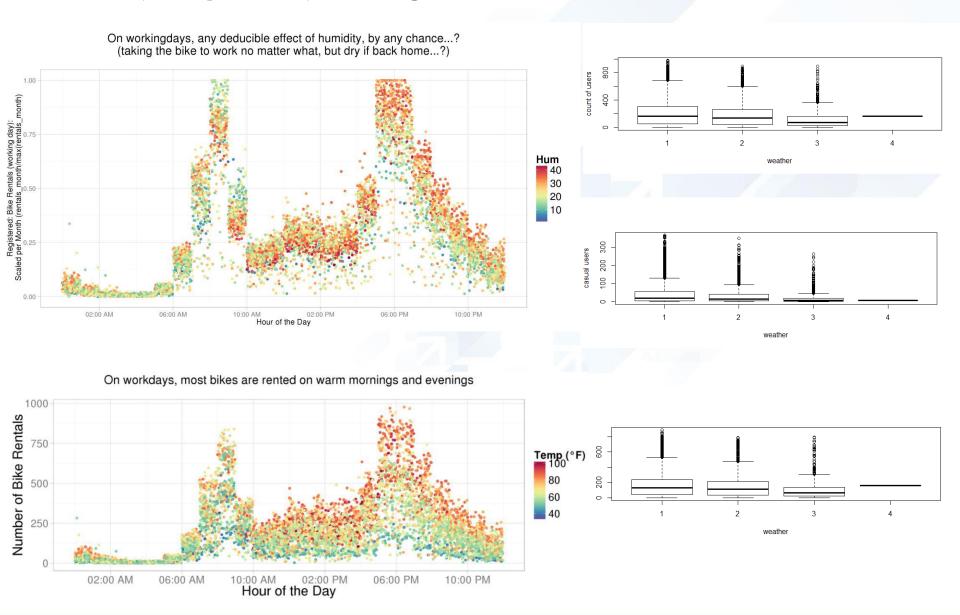






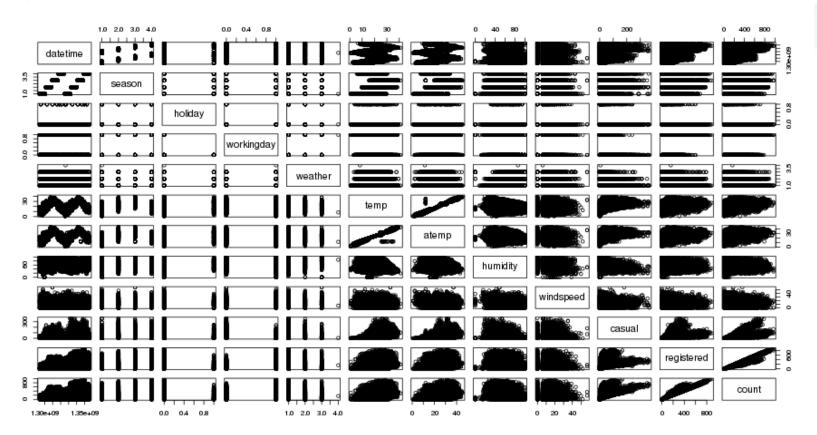


Weather, Temperature, Humidity

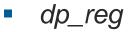


Correlations

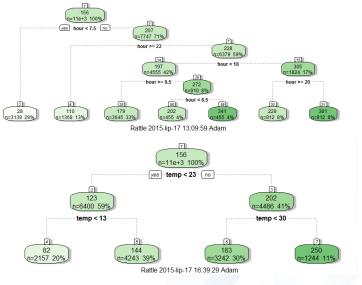
	train.registered	train.casual	train.count	train.temp	train.humiditv	train.atemp	train.windspeed
train.registered	1.00	0.50	0.97	0.32	-0.27	0.31	0.09
train.casual	0.50	1.00	0.69	0.47	-0.35	0.46	0.09
train.count	0.97	0.69	1.00	0.39	-0.32	0.39	0.10
train.temp	0.32	0.47	0.39	1.00	-0.06	0.98	-0.02
train.humidity	-0.27	-0.35	-0.32	-0.06	1.00	-0.04	-0.32
train.atemp	0.31	0.46	0.39	0.98	-0.04	1.00	-0.06
train.windspeed	0.09	0.09	0.10	-0.02	-0.32	-0.06	1.00

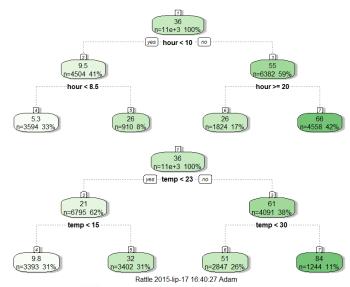


Data Understanding Exploratory Analysis Feature Engineering Experiments Fine Tuning Algorithm

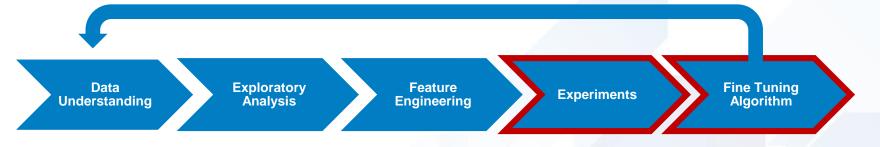


- dp_cas
- temp_reg
- temp_cas



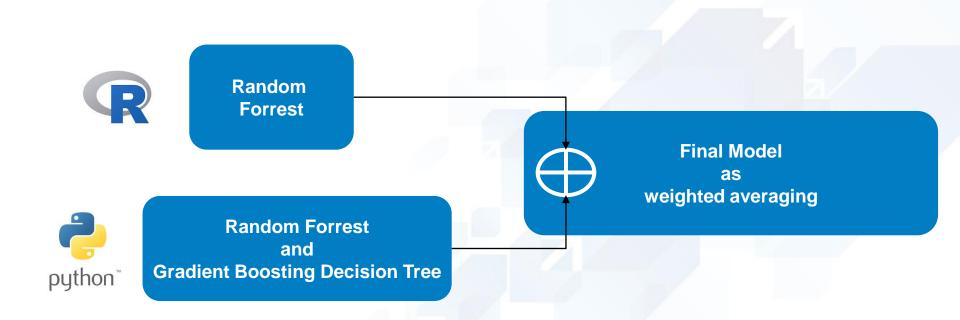


- day_type
 - Holiday [holiday=0 and workingday=0]
 - Weekend [holiday=1]
 - Working Day [holiday=0 and workingday=1]
- year_part
 - (1 − 8) from first quarter of 2011 till fourth of 2012

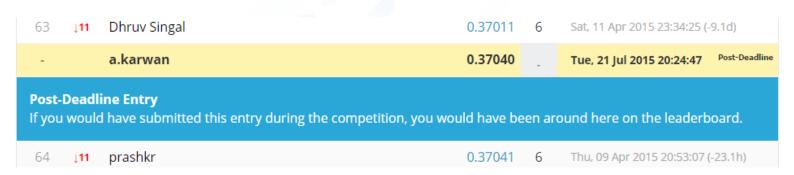


- R model bases on two separately computed Random Forests for casual and registered users. Final result is a sum of predicted values daily. Due to differences in count of users hourly we use logarithm to normalize values. Moreover each model was trained on 250 trees. In first model we estimate number of registered users therefore dp_reg and temp_reg are used, analogously dp_cas and temp_cas for second one. Other attributes used: hour, day, day_type, holiday, season, year, year_part, weekend, workingday, atemp, humidity, weather, windspeed.
- Python model bases on a combination of RF (Random Forrest) and GBDT (Gradient Boosting Decision Trees). Twelve attributes are used: hour, day, holiday, season, weekday, workingday, year, atemp, temp, humidity, weather, windspeed. Year is normalized by substraction 2011. GBDT is computed on 100 and RF on 1000 trees. Before computing final result we compute average regression of two instances for each approach RF and GBDT. For estimated variables logarithm is used to normalize results.

Ensamble Method



Final result 0.3704 that was 64 place out of 3252





A BOEING COMPANY

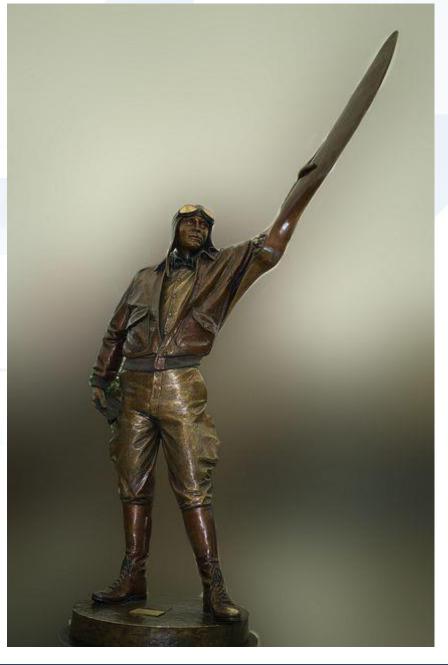


Boeing Global Services

Digital Aviation & Analytics Lab
Gdansk

DATA SCIENCE in AVIATION INDUSTRY

- PREDICTIVE MX
- POST FLIGHT ANALYTICS
- REAL TIME MACHINE LEARNING



Titanic Machine Learning from Disaster

https://www.kaggle.com/c/titanic

More likely to survive

- Females
- Children
- 1st Class Passengers
- · Traveling with Family

More likely to perish

- Males
- Adults
- 2nd and 3rd Class Passengers
- · Traveling alone





Trevor Stephens

Regular Data Scientist, Occasional Blogger.

- San Francisco, CA
- % Website
- Twitter
- in LinkedIn
- Github

43 1499 Total Recall

0.81340

Your Best Entry

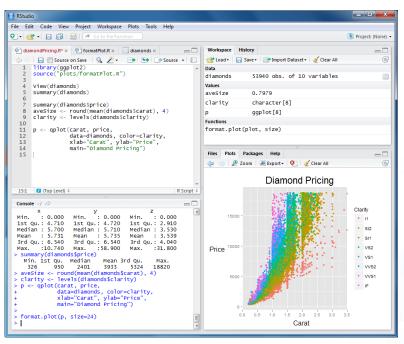
You improved on your best score by 0.01914. You just moved up 219 positions on the leaderboard.

Solution in Top 5%

Tutorial

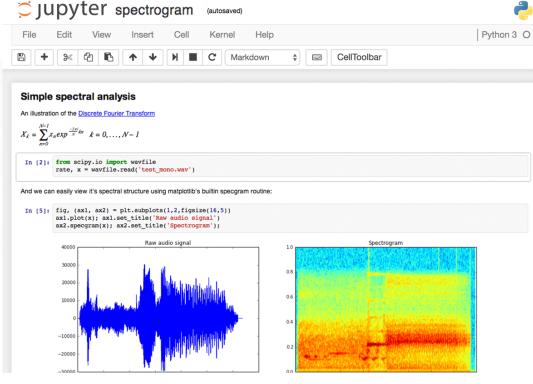
http://trevorstephens.com/kaggle-titanic-tutorial/getting-started-with-r

R Studio, Python Anaconda, Jupyter









Kaggle

Tips and tricks

- Be patient
- Understand data
- Think more, code less
- Follow other approaches (Kaggle Forum, Github, Slideshare)
- Fit appropriate algorithm to data



