A Data Oriented Approach to Recruitment

Wissem Belguidoum

Abstract

In this project we will try to leverage basic data analysis and machine learning techniques in order to help recruitment companies to find the top experts in a specific domain.

The dataset of choice is the Stack Overflow public dataset.

The main question that will be discussed is the following : How can we identify the top expert profiles regarding a specific domain of expertise, by analysing users behaviour on the Stack Overflow websites ?

In order to answer this question, we will train a machine learning model that predicts a reputation score of a user by observing his behaviour in the Stack Overflow web site, and we will apply this model to predict the reputation of users in a specific domain of knowledge.

Motivation

Hiring the right person for the right job is a very hard task, and what makes this task even harder is the increasing competition of companies in their quest to find the rare pearl that will meet all their expectations.

Hence the need of finding ways to spot and to approach the candidates as fast as possible. Here we can see a clear opportunity to leverage data science and machine learning techniques in order to achieve this objective.

In this project, we will try to deliver a very basic solution for this problem.

Dataset

- We will use the Stack Overflow database, which is published on the BigQuery cloud database (over 182 GB of data).
- This dataset is updated on a quarterly basis, and it includes an archive of the Stack Overflow content.
- The dataset includes :
  - Users (> 10 million rows) : name, overall reputation, view count ...
  - Posts (> 31 million rows) : title, content, score, tags, view count ...
  - Answers on posts (> 27 million rows) : content, score...
  - Comments (> 73 million rows) : content, score…
- A full description of this dataset can be found in Kaggle :
  - https://www.kaggle.com/stackoverflow/stackoverflow

Data Preparation and Cleaning

One of the biggest advantages of the Stack Overflow dataset is that it is clean and up to date.

All we had to do is to use BigQuery in order to aggregate the different tables, so we can compute an aggregated view ready to use.

We had also to exclude some of the columns that are not of interest to us in the scope of this project, like date fields and text fields.

Research Question(s)

By the end of this project we will hopefully answer the following question :

How can we spot the top experts in a given domain by analysing the behaviour of users on posts that are related to that domain ?

Methods

At first, we will explore the data and try to spot the parts of data that can depict the user’s behaviour.

After that, we will build a machine learning regression model that will take as input the behavioural data and that will predict a numerical metric (the reputation) that reflects the level of expertise of a user given his behaviour.

And lastly, we will use the built model in order to search for top experts in a very specific domain.

Findings

First, here is a non exhaustive list of the behavioural data that we spotted in the data set :

- **Posts count :** the number of posts a user created
- **Answers count :** the number of answers a user created
- **Answers score :** the total score that the user’s answers received
- **Post answers count :** the total number of answers in response to the user’s posts.

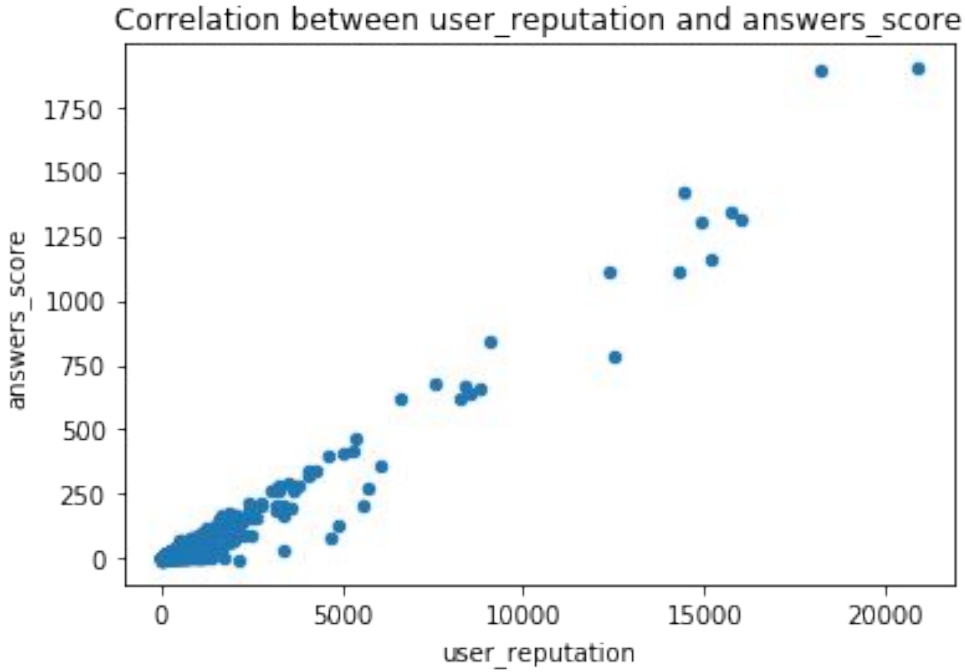
In overall, we spotted **13 columns** that are good candidates as input variables.

The target variable is the **user reputation** score that is computed by Stock Overflow for each user, and it reflects the overall impact of user on the community

Findings

The correlation between behavioural metrics and the user reputation metrics shows that some of the behavioural metrics were strongly correlated to the user reputation:

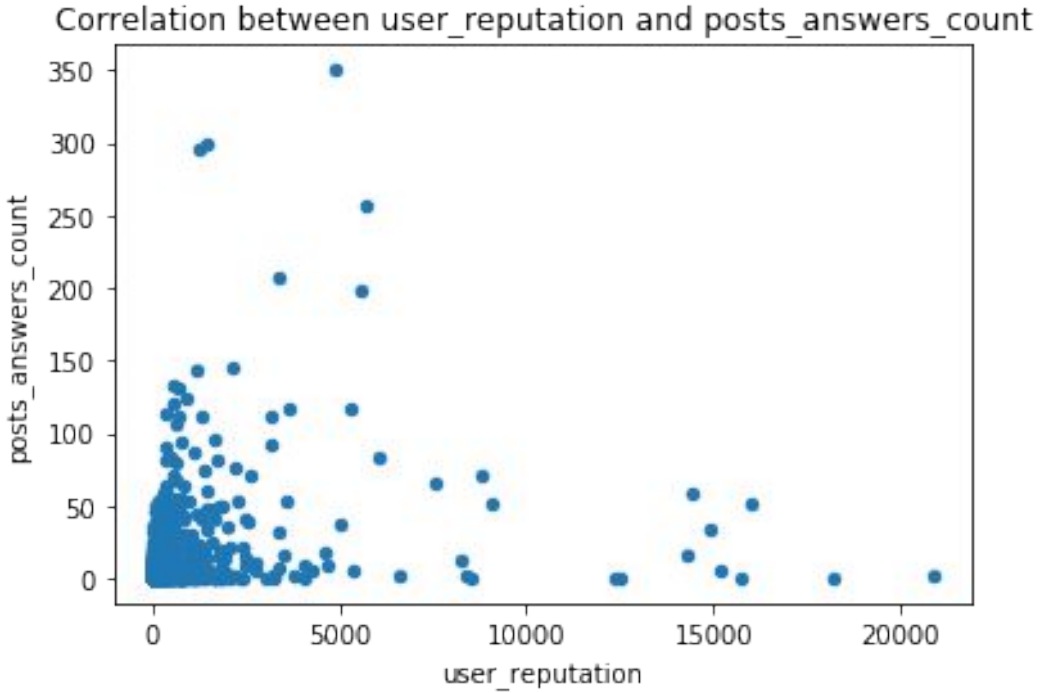
Correlation between (user reputation) and (answers score) is 99%



Findings

While some other behavioural metrics were much less correlated to the target variable.

Correlation between (user reputation) and (post answers count) is only 20%



Findings

Under the light of those findings, we excluded the 7 least correlated variables from the input variables, and we built a regression model based on the 6 remaining variables.

The application of the regression model showed a fairly satisfying result (see figure)

The calculation of RMSE shows a value of **1061.43**

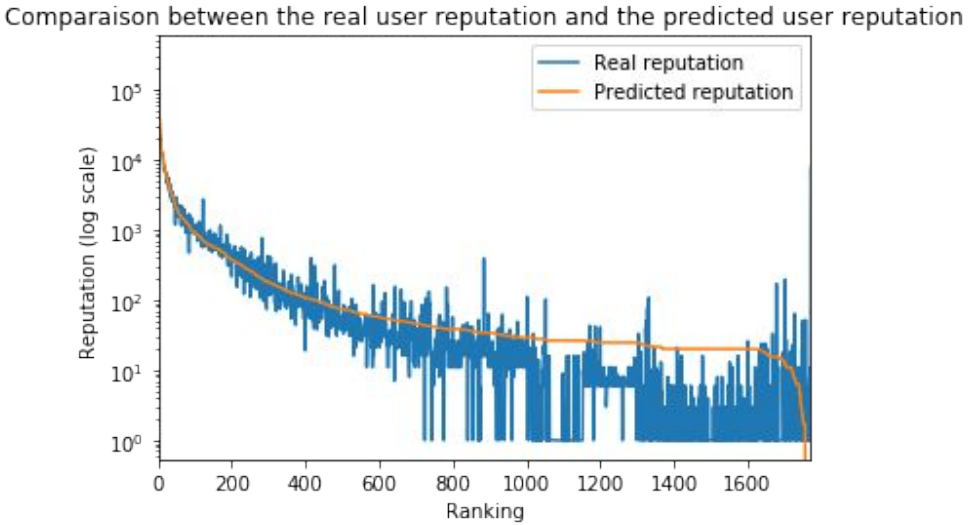
user_id	user_reputation	predicted_reputation
501557	270807.0	312701.176775
608772	53624.0	55889.444687
343088	42090.0	44200.055061
256793	41652.0	42507.485190
472792	34732.0	39579.336788
4955425	27499.0	23363.253819
1265660	19083.0	22197.602649
1569	20183.0	20218.634707
3661	17117.0	18689.254332
991085	12970.0	13507.087230
951860	12258.0	13095.801752
293403	12385.0	12922.433297
2780791	11779.0	12671.942343
64329	11255.0	12171.258744
1072150	10810.0	10589.278265
123951	8894.0	8562.660357
62237	7088.0	8458.216292
1376536	8185.0	8316.760439
61714	7677.0	8073.004075
330013	7272.0	7717.962785

Findings

RMSE is only useful to compare between two different models.

For this reason, we created this visualisation that enables us to compare between the predicted reputation and the observed reputation, the X axis is the ranking of users according to the predicted reputation (the lowest the ranking, the highest the reputation)

This plot shows that the range of error starts relatively small for the top ranked users, and it increases as the ranking increases, to reach a chaotic levels for the bottom ranked users.



Findings

Applying the model to spot TOP 10 experts of Pandas :

We used our regression model to calculate a Pandas reputation score for users and extract the Top 10 Pandas expert on Stack Overflow :

```
Expert # 1.0 :  Andy Hayden (https://stackoverflow.com/users/1240268/Andy Hayden)
Expert # 2.0 :  unutbu (https://stackoverflow.com/users/190597/unutbu)
Expert # 3.0 :  EdChum (https://stackoverflow.com/users/704848/EdChum)
Expert # 4.0 :  joris (https://stackoverflow.com/users/653364/joris)
Expert # 5.0 :  waitingkuo (https://stackoverflow.com/users/1426056/waitingkuo)
Expert # 6.0 :  BrenBarn (https://stackoverflow.com/users/1427416/BrenBarn)
Expert # 7.0 :  Alexander (https://stackoverflow.com/users/2411802/Alexander)
Expert # 8.0 :  Aman (https://stackoverflow.com/users/484596/Aman)
Expert # 9.0 :  behzad.nouri (https://stackoverflow.com/users/625914/behzad.nouri)
Expert # 10.0 :  ely (https://stackoverflow.com/users/567620/ely)
```

Limitations

This work was limited to the scope of stackoverflow data, in the future we can as well, extend this work to use other data sources like LinkedIn, Medium, Open Source repositories... etc

Conclusions

Despite the mediocre quality of the model, the result is still satisfying in the sense that we succeeded at extracting a list of real top experts in their domain.

There is more than one way to improve upon this work in the future :

- Tune the regression model and compare different regression methods
- Use other types of data to gain deeper knowledge of the users : use text of posts and comments, track user activity in time.
- Improve search capabilities : multi-tags search, search by synonym of tags, search by geographical location, search by date range
- Extend this work to use other data sources.

Acknowledgements

Many thanks to the UCSanDiegoX team who created this great courses.

References

- Course material : UCSanDiegoX - DSE200x

- Python documentation : https://docs.python.org/3/reference/index.html

- Pandas documentation : https://pandas.pydata.org/pandas-docs/version/0.21/index.html

- Matplotlib documentation : https://matplotlib.org/3.1.1/contents.html

- BigQuery user guide : https://cloud.google.com/bigquery/docs/

- Stack Overflow : https://stackoverflow.com

A Data Oriented Approach to Recruitment

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UCSanDiegoX : DSE200x
Final Project Submission

Table of content :

1. Abstract

In this project we will try to leverage basic data analysis and machine learning techniques in order to help recruitment companies to find the top experts in each domains.

The dataset of choice is the stackoverflow public dataset (please find a link to the source and to a description below).

The main question that will be discussed is the following : How can we identify the top expert profiles regarding a specific domain of expertise, by analysing users behaviour on the stackoverflow websites ?

In order to answer this question, we will train a regression model to predict a reputation score of a user by observing his behaviour in the stackoverflow web, and we will apply this model to predict the reputation of users in a specific domain of knowledge.

By the end of the notebook, we will identify a set of behavioural metrics that have the most impact in the reputation score.

Dataset Source : https://www.kaggle.com/stackoverflow/stackoverflow (https://www.kaggle.com/stackoverflow/stackoverflow)

Dataset Schema : https://meta.stackexchange.com/questions/2677/database-schema-documentation-for-the-public-data-dump-and-sede (https://meta.stackexchange.com/questions/2677/database-schema-documentation-for-the-public-data-dump-and-sede)

2. Initialisation

In [1]:
```
%matplotlib inline

import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
import time

from math import sqrt

from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

2.1. How to use BigQuery in Jupyter

Stackoverflow dataset is published in BigQuery in Google Cloud platform.

BigQuery is a cloud solution developed by Google that helps working with big amount of data without the need to download it locally.

BigQuery uses SQL to query the data. It also has a user interface that is accessible from the Google Cloud Console.

In this project we will access BigQuery from inside the Jupyter notebook. There is two different ways to do this :

- We can access using Python code. Here is a brief description of this method : https://jingsblog.com/2018/11/27/connect-your-jupyter-notebook-to-the-bigquery/ (https://jingsblog.com/2018/11/27/connect-your-jupyter-notebook-to-the-bigquery/)
- We can also send queries using cell magic as described in the following article : https://cloud.google.com/bigquery/docs/visualize-jupyter (https://cloud.google.com/bigquery/docs/visualize-jupyter)

We will now follow the steps, and we will use both methods of access depending on the need :

In [2]:
```
# Installing BigQuery Python packages :

!pip install --upgrade google-cloud-bigquery[pandas]
```

In [4]:
```
# Defining an environement variable that points to my BigQuery API credentials
 file :
%env GOOGLE_APPLICATION_CREDENTIALS=/home/wibe/Bureau/UCSDx1/ucsdx1-d232c1f77af
f.json

# Enabling the bigquery magic cell
%load_ext google.cloud.bigquery

# Importing bigquery package
from google.cloud import bigquery

# Creating a bigquery client that will be used in the rest of this notebook :
bigquery_client = bigquery.Client()
```

```
env: GOOGLE_APPLICATION_CREDENTIALS=/home/wibe/Bureau/UCSDx1/ucsdx1-d232c1f77af
f.json
The google.cloud.bigquery extension is already loaded. To reload it, use:
  %reload_ext google.cloud.bigquery
```

3. Data Exploration

In the links that we put in the abstract, there is a detailed description of the schema of this dataset, but in this section we will focus on a subset of the data that captures users information and users behaviour, because we will try to create a solution that filters users based on their behaviour and impact.

Let's first list all the tables available in the **bigquery-public-data.stackoverflow** database :

In [5]:
```
%%bigquery
SELECT *
FROM `bigquery-public-data.stackoverflow.INFORMATION_SCHEMA.TABLES`
```

Out[5]:

	table_catalog	table_schema	table_name	table_type	is_insertable_into	is_typed	
0	bigquery-public-data	stackoverflow	posts_answers	BASE TABLE	YES	NO	18
1	bigquery-public-data	stackoverflow	users	BASE TABLE	YES	NO	13
2	bigquery-public-data	stackoverflow	posts_orphaned_tag_wiki	BASE TABLE	YES	NO	16
3	bigquery-public-data	stackoverflow	posts_tag_wiki	BASE TABLE	YES	NO	16
4	bigquery-public-data	stackoverflow	stackoverflow_posts	BASE TABLE	YES	NO	13
5	bigquery-public-data	stackoverflow	posts_questions	BASE TABLE	YES	NO	15
6	bigquery-public-data	stackoverflow	comments	BASE TABLE	YES	NO	13
7	bigquery-public-data	stackoverflow	posts_tag_wiki_excerpt	BASE TABLE	YES	NO	15
8	bigquery-public-data	stackoverflow	posts_wiki_placeholder	BASE TABLE	YES	NO	16
9	bigquery-public-data	stackoverflow	posts_privilege_wiki	BASE TABLE	YES	NO	18
10	bigquery-public-data	stackoverflow	post_history	BASE TABLE	YES	NO	14
11	bigquery-public-data	stackoverflow	badges	BASE TABLE	YES	NO	13
12	bigquery-public-data	stackoverflow	post_links	BASE TABLE	YES	NO	13
13	bigquery-public-data	stackoverflow	tags	BASE TABLE	YES	NO	14
14	bigquery-public-data	stackoverflow	votes	BASE TABLE	YES	NO	13
15	bigquery-public-data	stackoverflow	posts_moderator_nomination	BASE TABLE	YES	NO	16

We will focus on the subset of the tables that contain data about users and data about their interactions : users, stackoverflow_posts, posts_answers, comments

In a nutshell :

- The users of stackoverflow can :
  - create posts : this information is stored in **stackoverflow_posts** table
  - respond to others' posts by posting an answer : this information is stored in **posts_answers** table
  - add a comment on others' posts : this information is stored in **comments** table
  - add a comment on others' answers : this information is also stored in **comments** table
- Users are associated with a reputation score stored in **users** table
- Comments can be linked to a user and either to a post, or to an answer

3.1. The *users* table

In [6]:
```
%%bigquery
SELECT *
FROM `bigquery-public-data.stackoverflow.users`
LIMIT 5
```

Out[6]:

	id	display_name	about_me	age	creation_date	last_access_date	location	re
0	292	shsteimer	I'm a senior consultant and technical archi...	None	2008-08-04 13:14:31.860000+00:00	2015-06-17 21:25:20.813000+00:00	Pittsburgh, PA	
1	669	quekshuy	None	None	2008-08-07 16:11:17.027000+00:00	2019-06-01 00:24:01.957000+00:00	None	
2	695	Saltire	Web developer since '98 for personal and co...	None	2008-08-07 23:02:44.527000+00:00	2019-05-31 14:50:53.973000+00:00	United Kingdom	
3	1123	Magnar	A happy front-end developer.	None	2008-08-12 14:20:20.517000+00:00	2019-05-23 06:26:10.333000+00:00	Norway	
4	1143	Quibblesome	nothing.	None	2008-08-12 18:58:24.510000+00:00	2019-05-31 17:25:22.403000+00:00	Cambridge, United Kingdom	

We will exclude some columns that will not be used in this project :

In [7]:
```
%%bigquery
SELECT id, display_name, location, reputation
FROM `bigquery-public-data.stackoverflow.users`
LIMIT 5
```

Out[7]:

	id	display_name	location	reputation
0	40	Kevin	Philadelphia, PA	9387
1	116	Mark Harrison	Piedmont, CA	177570
2	529	guitsaru	United States	578
3	905	Keith	New Brighton, Wallasey, UK	96750
4	968	Biri	Érd, Hungary	5999

Reputation is an overall score calculated by Stackoverflow, its value reflects the user overall impact on the community.

Let's learn more about the users table :

In [8]:
```
%%bigquery
SELECT count(*) users_count, min(reputation) min_reputation,
max(reputation) max_reputation, avg(reputation) avg_reputation
FROM `bigquery-public-data.stackoverflow.users`
```

Out[8]:

	users_count	min_reputation	max_reputation	avg_reputation
0	10528666	1	1109230	107.546489

- The database contains +10 millions users.
- Reputation values are in the range [1, 1109230], and the average reputation is 107

3.2. The *stackoverflow_posts* table

In [9]:
```
%%bigquery
SELECT *
FROM `bigquery-public-data.stackoverflow.stackoverflow_posts`
LIMIT 5
```

Out[9]:

	id	title	body	accepted_answer_id	answer_count	comment_count	community_ov
0	525063	Android Respond To URL in Intent	<p>I want my intent to be launched when the us...	525086	1	2	
1	14128723	Eclipse -- Progress windows don't show up any ...	<p>I used to see both Building and Cleaning ac...	14128762	1	0	
2	20728	What's the best way to create ClickOnce deploy...	<p>Our team develops distributed winform apps....	20806	2	0	
3	6531409	iOS: how to get image dimensions without openi...	<p>In an iOS app I need to provide image filte...	8731972	2	2	
4	593205	action delegate with zero parameters	<p>I see this line in many online examples of ...	593223	2	3	

In our analysis, we will not be interested in text fields like title and body, so we will remove them, along with some other fields that are irrelevant to our analysis.

We are especially interested in fields that hold information about the user behaviour and impact (number of posts, number of comments, number of views ..etc)

We are also interested in columns that help identify the user, the post or the domain: id, user id and the list of tags.

In [10]:
```
%%bigquery
SELECT id, owner_user_id, answer_count, comment_count, favorite_count, score, t
ags, view_count
FROM `bigquery-public-data.stackoverflow.stackoverflow_posts`
LIMIT 5
```

Out[10]:

	id	owner_user_id	answer_count	comment_count	favorite_count	score	
0	316861	26721.0	1	0	5	8	php|pdo|pdost
1	318489	40322.0	2	0	5	3	.net|http|encoding|tcp|cl e
2	277291	3827.0	2	0	7	8	java|eclipse| plugin|ecl
3	629024	75505.0	2	0	6	2	asp.net| mvc|deployment|aut
4	1037604	NaN	2	0	7	5	iphor

- owner_user_id : the id of the user who created the post,
- answer_count : the number of answers trying to bring a solution to the problem described in the post
- comment_count : the number of comments made on the post (answers are different from comments)
- favorite_count : the number of people who clicked the star on top of the post
- score : the result of the vote on the post (thumbs up - thumbs down)
- tags : a list of tags separated by |
- view_count : the number of times the post was viewed

Now let's apply some aggregations :

In [11]:
```
%%bigquery
SELECT count(*) posts_count, max(view_count) max_view_count,
       max(answer_count) max_answer_counts, max(comment_count) max_comments_cou
nt,
       max(favorite_count) max_fav_count, max(score) max_score
FROM `bigquery-public-data.stackoverflow.stackoverflow_posts`
```

Out[11]:

	posts_count	max_view_count	max_answer_counts	max_comments_count	max_fav_count	max_sco
0	31017889	3364629	518	133	7317	205

3.3. The *posts_answers* table

This table has the same structure as the posts table.

Some of the fields are always empty (like view_count). That's because those fields are used exclusively for posts and not for answers.

In [12]:
```
%%bigquery
SELECT *
FROM `bigquery-public-data.stackoverflow.posts_answers`
LIMIT 3
```

Out[12]:

	id	title	body	accepted_answer_id	answer_count	comment_count	community_own
0	12085147	None	In theory, System.exit is signal JVM to sto...	None	None	0	
1	12085148	None	Could you try to separate audio and video? ...	None	None	0	
2	12085149	None	You can use below query : \n\n<pre> <code...	None	None	0	

As usual, we will exclude some fields and keep the most important (identification fields + impact fields) :

In [13]:
```
%%bigquery
SELECT id, owner_user_id, parent_id, comment_count, score
FROM `bigquery-public-data.stackoverflow.posts_answers`
LIMIT 3
```

Out[13]:

	id	owner_user_id	parent_id	comment_count	score
0	55832858	7266317	6004032	0	0
1	55832872	5873109	55832746	3	0
2	55832876	5713047	16935965	0	0

- parent_id : is the id of the post that this answer is linked two.
- comment_count: users can also comment on answers, and this is the number of comments that this answer received

Let's do some aggregations over the answers table :

In [14]:
```
%%bigquery
SELECT count(*) answers_count, max(comment_count) max_comments_count, max(scor
e) max_score
FROM `bigquery-public-data.stackoverflow.posts_answers`
```

Out[14]:

	answers_count	max_comments_count	max_score
0	27107580	157	30199

3.4. The *comments* table

This table contains the comments that can be linked to a post or to an answer. Later, we will make difference between those two cases in our analysis, and count them as two different behaviours

In [15]:
```
%%bigquery
SELECT *
FROM `bigquery-public-data.stackoverflow.comments`
LIMIT 10
```

Out[15]:

	id	text	creation_date	post_id	user_id	user_display_name	score
0	40131403	Not sure why you got a downvote for this, its ...	2014-09-05 04:27:49.067000+00:00	23377188	None	user764357	4
1	40148193	@MatíasFidemraizer - he's shown his effort, wh...	2014-09-05 14:22:45.573000+00:00	25688029	None	user1017882	10
2	40157402	you can't use any `-` options inside a script ...	2014-09-05 19:30:54.393000+00:00	25692635	None	user3442743	6
3	40161850	You can have a form inside a `td` element but ...	2014-09-05 22:54:28.453000+00:00	25694862	None	user3559349	4
4	40163850	@kevin Yup, this is ghetto polling that will m...	2014-09-06 01:46:41.170000+00:00	21369398	None	user246672	4
5	40166469	`exit(0)` terminates the program. In order to ...	2014-09-06 06:39:59.647000+00:00	25697469	None	user3920237	4
6	40173648	@FredOverflow `char` and `unsigned char` alway...	2014-09-06 15:21:56.693000+00:00	25701418	None	user743382	9
7	40175635	It is confusing and misleading to call this a ...	2014-09-06 17:17:52.023000+00:00	17421508	None	user663031	12
8	40224481	Try `format(*row)`	2014-09-08 16:32:59.953000+00:00	25728901	None	user3960432	4
9	40254384	This: `fatal error: numpy/arrayobject.h: No su...	2014-09-09 12:44:23.180000+00:00	25744933	None	user707650	4

We exclude unused columns :

In [16]:
```
%%bigquery
SELECT id, post_id, user_id, score
FROM `bigquery-public-data.stackoverflow.comments`
LIMIT 3
```

Out[16]:

	id	post_id	user_id	score
0	40131403	23377188	None	4
1	40148193	25688029	None	10
2	40157402	25692635	None	6

- Some row have user_id null, we will exclude those in our analysis later :

Let's do some aggregations over the comments table :

In [17]:
```
%%bigquery
SELECT count(*) comments_count, max(score) max_score
FROM `bigquery-public-data.stackoverflow.comments`
```

Out[17]:

	comments_count	max_score
0	73799233	1366

4. Data Analysis

The aim of this section is to use the tables above in order to analyse the data and try find a way to take advantage of the data to correctly guide our search for the experts in a given domain.

- We will start by creating an aggregated view that represents the user information (id, reputation) combined with metrics that reflect the user interactions (number of posts, the total of the views over the user's posts, the total sum of the scores on the user's comments...etc)
- And then, we will run a set of correlation calculations

4.1 Agregated View 1 : User Posts

Here we will group posts of the each users, and aggregate the different posts field to end up with a user view of the those fields :

In [18]:
```
%%bigquery user_posts_df

SELECT user_id, avg(user_reputation) as user_reputation, count(*) as posts_coun
t,
      sum(post_favorite_count) as posts_favorite_count, sum(post_score) as post
s_score,
      sum(post_view_count) as posts_view_count, sum(post_answers_count) as post
s_answers_count,
      sum(post_comments_count) as posts_comments_count
FROM (
  SELECT users.id as user_id, users.reputation as user_reputation, posts.favori
te_count as post_favorite_count, posts.score as post_score, posts.view_count as
 post_view_count,
         posts.answer_count as post_answers_count,  posts.comment_count as post
_comments_count
  FROM `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = posts.
owner_user_id
  WHERE mod(users.id, 1023) = 0
) AS USER_POSTS
GROUP BY USER_POSTS.user_id
```

In [19]:
```
user_posts_df = user_posts_df.set_index('user_id')
user_posts_df.head(10)
```

Out[19]:

user_id	user_reputation	posts_count	posts_favorite_count	posts_score	posts_view_count	posts_ans
1763652	1422.0	162	20.0	114	135308.0	
117645	141.0	27	27.0	56	65067.0	
104346	76.0	6	5.0	9	8754.0	
182094	2210.0	58	22.0	208	22003.0	
3216312	8287.0	255	3.0	570	1476.0	
5987619	497.0	17	2.0	7	485.0	
1617363	32.0	5	NaN	1	3058.0	
3211197	841.0	41	6.0	49	9520.0	
1005609	1470.0	79	14.0	104	90129.0	
1193841	3180.0	110	19.0	234	132062.0	

- In order to limit the number of targeted users, we used the modulo operator over the user's id.
- Some values are null, we will clean them later

4.2 Agregated View 2 : User Answers

Here we will group answers of the each users, and compute aggregates in the same way we did for the posts :

In [20]:
```
%%bigquery user_answers_df

SELECT user_id, count(*) as answers_count, sum(answers_score) as answers_score,

       sum(answers_comments_count) as answers_comments_count
FROM (
  SELECT users.id as user_id, answers.score as answers_score,
        answers.comment_count as answers_comments_count
  FROM `bigquery-public-data.stackoverflow.posts_answers` as answers
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = answer
s.owner_user_id
  WHERE mod(users.id, 1023) = 0
) AS USER_ANSWERS
GROUP BY USER_ANSWERS.user_id
```

In [21]:
```
user_answers_df = user_answers_df.set_index('user_id')
user_answers_df.head(10)
```

Out[21]:

user_id	answers_count	answers_score	answers_comments_count
3480246	599	781	1193
1202025	2929	9135	8872
789756	144	200	212
5508855	16	17	18
1405602	27	15	28
2623995	12	10	17
292578	114	153	145
4800939	7	8	3
323268	20	59	31
1320693	232	642	326

- We used the same sampling method (modulo) and the same parameter (1023) as the last step, so we get the same users id that we got for the posts view

4.3 Agregated View 3 : User Comments made on posts

In [22]:
```
%%bigquery user_comments_on_posts_df

SELECT user_id, count(*) as comments_on_posts_count, sum(comment_score) as comm
ents_on_posts_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts on pos
ts.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
  WHERE mod(users.id, 1023) = 0
) AS USER_COMMENTS_ON_POSTS
GROUP BY USER_COMMENTS_ON_POSTS.user_id
```

In [23]:
```
user_comments_on_posts_df = user_comments_on_posts_df.set_index('user_id')
user_comments_on_posts_df.head(10)
```

Out[23]:

user_id	comments_on_posts_count	comments_on_posts_score
285417	633	178
348843	74	2
378510	28	1
471603	4	0
1372866	41	134
5922147	11	0
117645	32	0
2052138	30	6
2167737	2	0
2431671	8	3

4.4 Agregated View 4 : User comments made on answers

In [24]:
```
%%bigquery user_comments_on_answers_df

SELECT user_id, count(*) as comments_on_answers_count, sum(comment_score) as co
mments_on_answers_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.posts_answers` as answers on answer
s.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
  WHERE mod(users.id, 1023) = 0
) AS USER_COMMENTS_ON_ANSWERS
GROUP BY USER_COMMENTS_ON_ANSWERS.user_id
```

In [25]:
```
user_comments_on_answers_df = user_comments_on_answers_df.set_index('user_id')
user_comments_on_answers_df.head(10)
```

Out[25]:

user_id	comments_on_answers_count	comments_on_answers_score
5997849	2	0
8321082	26	2
1305348	9	1
8599338	2	0
272118	76	34
3218358	71	1
5031114	71	15
1241922	1	0
1007655	23	0
1720686	36	1

4.5 Merging & Cleaning

Now we will merge the previous results and create a single view combining all the informations

In [26]:
```
# Merging on user_id
merged_view = user_posts_df.join(user_answers_df, how='left')
merged_view = merged_view.join(user_comments_on_posts_df, how='left')
merged_view = merged_view.join(user_comments_on_answers_df, how='left')

# Cleaning : filling null values with zeroes
merged_view = merged_view.fillna(0)
print(merged_view.shape)
merged_view.head(5)
```

```
(2739, 14)
```

Out[26]:

user_id	user_reputation	posts_count	posts_favorite_count	posts_score	posts_view_count	posts_ans
1763652	1422.0	162	20.0	114	135308.0	
117645	141.0	27	27.0	56	65067.0	
104346	76.0	6	5.0	9	8754.0	
182094	2210.0	58	22.0	208	22003.0	
3216312	8287.0	255	3.0	570	1476.0	

The variables in this dataset can be splitted in two categories :

1. Behavioral variables (all the variables except user_reputation) : metrics collected directly from user interactions
2. Computed variables (user_reputation) : that is computed by Stackoverflow in a way that we ignore, but we know that it indicates how the user is active and impactful (in overall)

In the next section we will analyze the correlation between user_reputation and the behavioral variables.

4.6 Correlations Analysis

Now that we created our merged view, let's run a correlation analysis and observe the relationships between the variables :

In [27]:
```
correlations = merged_view.corr()
correlations
```

Out[27]:

	user_reputation	posts_count	posts_favorite_count	posts_score	posts_vi
user_reputation	1.000000	0.959187	0.435409	0.994311	
posts_count	0.959187	1.000000	0.429022	0.935099	
posts_favorite_count	0.435409	0.429022	1.000000	0.460623	
posts_score	0.994311	0.935099	0.460623	1.000000	
posts_view_count	0.302688	0.327824	0.860963	0.325092	
posts_answers_count	0.226851	0.295045	0.680419	0.243603	
posts_comments_count	0.905606	0.975840	0.359636	0.867457	
answers_count	0.955714	0.993345	0.371158	0.926473	
answers_score	0.996223	0.936071	0.413204	0.997542	
answers_comments_count	0.902436	0.967352	0.316413	0.860905	
comments_on_posts_count	0.914827	0.974290	0.367165	0.877898	
comments_on_posts_score	0.981466	0.927167	0.416188	0.984779	
comments_on_answers_count	0.927126	0.980991	0.400773	0.893547	
comments_on_answers_score	0.951190	0.877473	0.455267	0.961941	

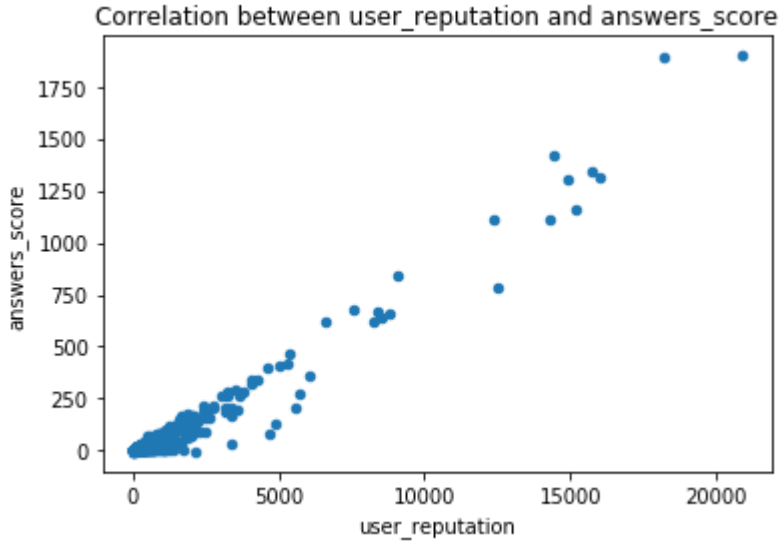
From the results above, we notice that user_reputation variable is highly correlated with some of the behavioral variable.

Let's visualize the correlation of user_reputation with two of the variables.

The most correlated variable with user_reputation is answers_score :

In [28]:
```
# We have to reduce the range of user_reputation in order to limit the dispersi
on :
filtered_view = merged_view[merged_view['user_reputation'] < 40000]
filtered_view.plot(kind='scatter', x='user_reputation', y='answers_score', titl
e='Correlation between user_reputation and answers_score')
```

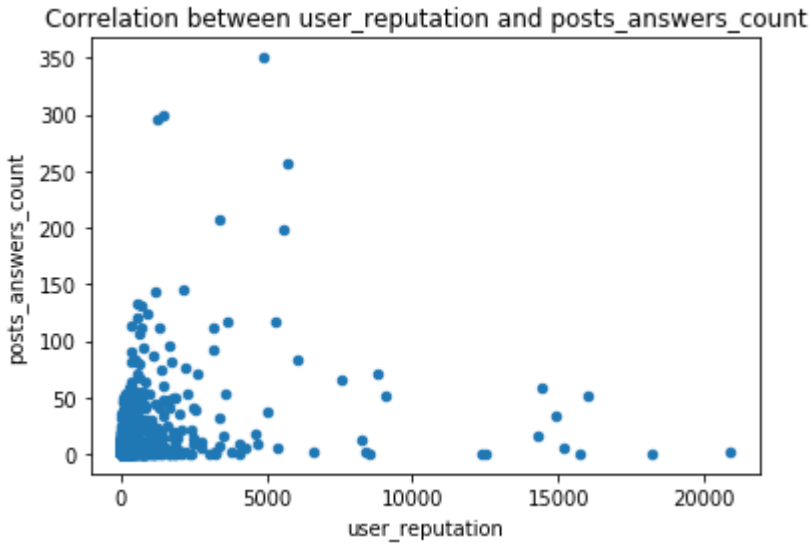
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45dfa37550>



The least correlated variable is posts_answers_count :

In [29]:
```
# We have to reduce the range of user_reputation in order to limit the dispersi
on :
filtered_view = merged_view[merged_view['user_reputation'] < 40000]
filtered_view.plot(kind='scatter', x='user_reputation', y='posts_answers_count'
, title='Correlation between user_reputation and posts_answers_count')
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f45df7aaa58>



4.7 Conclusion

Based on the observations above, we come to the conclusion that we can build a model to calculate user_reputation from a subset of the behavioural variables.

In order to find this subset, we will fix a lower threshold of correlation to 95% and take all the variables above this threshold :

In [30]:
```
selected_features = correlations[['user_reputation']][(correlations[['user_repu
tation']] > 0.95) & (correlations[['user_reputation']] < 1)].dropna().index.val
ues
selected_features
```

Out[30]:
```
array(['posts_count', 'posts_score', 'answers_count', 'answers_score',
       'comments_on_posts_score', 'comments_on_answers_score'],
      dtype=object)
```

5. Building a Model

At this point, we came to the conclusion that in order to predict the impact (the reputation) of a user by observing his behaviour, we need to create a model that predicts the value of the user_reputation variable by giving as input the values of variables that we already selected based on their correlation user_reputation.

In this section, we will build and test the model, and we will apply it in the next and final section.

Model Type :

Since user_reputation is an ordinal unlimited numerical value, we will opt for building a regression model.

We choose to build a **linear regressor**

But first, we need to write a python function, that will package the sampling steps that we saw earlier. Then, we can call this function to build a sample dataset :

In [31]:

```
# This function will be used to create dataset to train and test the model :

def build_sample_data(sampling_step) :

    # Step1 : Preparing queries

    USER_POSTS_QUERY = """
SELECT user_id, avg(user_reputation) as user_reputation, count(*) as posts_coun
t, sum(post_favorite_count) as posts_favorite_count, sum(post_score) as posts_s
core, sum(post_view_count) as posts_view_count,
sum(post_answers_count) as posts_answers_count, sum(post_comments_count) as pos
ts_comments_count
FROM (
  SELECT users.id as user_id, users.reputation as user_reputation, posts.favori
te_count as post_favorite_count, posts.score as post_score, posts.view_count as
 post_view_count,
         posts.answer_count as post_answers_count,  posts.comment_count as post
_comments_count
  FROM `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = posts.
owner_user_id
  WHERE mod(users.id, """ + str(sampling_step) + """) = 0
) AS USER_POSTS
GROUP BY USER_POSTS.user_id
"""
    USER_ANSWERS_QUERY = """
SELECT user_id, count(*) as answers_count, sum(answers_score) as answers_score,
 sum(answers_comments_count) as answers_comments_count
FROM (
  SELECT users.id as user_id, answers.score as answers_score, answers.comment_c
ount as answers_comments_count
  FROM `bigquery-public-data.stackoverflow.posts_answers` as answers
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = answer
s.owner_user_id
  WHERE mod(users.id, """ + str(sampling_step) + """) = 0
) AS USER_ANSWERS
GROUP BY USER_ANSWERS.user_id
    """

    USER_COMMENTS_ON_POSTS_QUERY = """
SELECT user_id, count(*) as comments_on_posts_count, sum(comment_score) as comm
ents_on_posts_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts on pos
ts.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
  WHERE mod(users.id, """ + str(sampling_step) + """) = 0
) AS USER_COMMENTS_ON_POSTS
GROUP BY USER_COMMENTS_ON_POSTS.user_id
    """

    USER_COMMENTS_ON_ANSWERS_QUERY = """
SELECT user_id, count(*) as comments_on_answers_count, sum(comment_score) as co
mments_on_answers_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.posts_answers` as answers on answer
s.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
  WHERE mod(users.id, """ + str(sampling_step) + """) = 0
```

```
) AS USER_COMMENTS_ON_ANSWERS
GROUP BY USER_COMMENTS_ON_ANSWERS.user_id
    """

    # Step2 : Querying data from bigquery
    user_posts_df = bigquery_client.query(USER_POSTS_QUERY).to_dataframe().set_
index('user_id')
    user_answers_df = bigquery_client.query(USER_ANSWERS_QUERY).to_dataframe().
set_index('user_id')
    user_comments_on_posts_df =  bigquery_client.query(USER_COMMENTS_ON_POSTS_Q
UERY).to_dataframe().set_index('user_id')
    user_comments_on_answers_df =  bigquery_client.query(USER_COMMENTS_ON_ANSWE
RS_QUERY).to_dataframe().set_index('user_id')

    # Step3 : Combining the results in a single dataframe
    result = user_posts_df.join(user_answers_df, how='left')
    result = result.join(user_comments_on_posts_df, how='left')
    result = result.join(user_comments_on_answers_df, how='left')

    # Step4 : Cleaning and returning the final result
    return result.fillna(0)
```

In [51]:
```
# Sampling the data with a step of 523 :

sample_data = build_sample_data(sampling_step = 523)
print(sample_data.shape)
sample_data.head(5)
```

```
(5371, 14)
```

Out[51]:

user_id	user_reputation	posts_count	posts_favorite_count	posts_score	posts_view_count	posts_ans
2446071	1903.0	117	19.0	166	139401.0	
618186	5187.0	98	26.0	412	168558.0	
169452	75.0	5	1.0	5	1211.0	
2960180	1.0	5	0.0	-5	193.0	
40794	81.0	5	4.0	9	1815.0	

Let's take a look at the sample data :

In [52]:
```
sample_data.describe()
```

Out[52]:

	user_reputation	posts_count	posts_favorite_count	posts_score	posts_view_count	posts_answ
count	5371.000000	5371.000000	5371.000000	5371.000000	5.371000e+03	53
mean	442.178551	11.816980	2.099981	27.261962	6.283558e+03	
std	4730.824538	67.066058	15.946707	337.191835	3.458810e+04	
min	1.000000	1.000000	0.000000	-13.000000	0.000000e+00	
25%	3.000000	1.000000	0.000000	0.000000	3.000000e+01	
50%	16.000000	2.000000	0.000000	1.000000	2.360000e+02	
75%	83.000000	5.000000	1.000000	5.000000	1.600500e+03	
max	270807.000000	3397.000000	795.000000	20770.000000	1.162686e+06	6

5.1 Training a linear regressor :

We will use the sample dataset, and the list of features that we selected earlier, to build a linear regression model that will be used to predict the value of user_reputation from the values of the selected behavioural features :

In [65]:
```
target = ['user_reputation']

X = sample_data[selected_features]

y = sample_data[target]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, rando
m_state=324)

regressor = LinearRegression()
regressor.fit(X_train, y_train)
regressor
```

Out[65]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

5.2 Testing the linear regressor :

In [66]:
```
# Testing the regressor
y_prediction = regressor.predict(X_test)
```

In [114]:
```
# We merge the predicted reputation and the observed reputation
# in the same dataframe in order to facilitate the comparaison :

comparaison = y_test.copy()
comparaison['predicted_reputation'] = y_prediction
comparaison.head()
```

Out[114]:

user_id	user_reputation	predicted_reputation
2055913	1.0	20.096500
990039	1.0	26.409444
3658385	51.0	48.266967
2806941	1.0	34.120071
2447640	11.0	29.289841

In [115]:
```
# We sort the comparaison dataframe in a descending order of predicted_reputation
comparaison = comparaison.sort_values(['predicted_reputation'], ascending=False)
comparaison.head(20)
```

Out[115]:

user_id	user_reputation	predicted_reputation
501557	270807.0	312701.176775
608772	53624.0	55889.444687
343088	42090.0	44200.055061
256793	41652.0	42507.485190
472792	34732.0	39579.336788
4955425	27499.0	23363.253819
1265660	19083.0	22197.602649
1569	20183.0	20218.634707
3661	17117.0	18689.254332
991085	12970.0	13507.087230
951860	12258.0	13095.801752
293403	12385.0	12922.433297
2780791	11779.0	12671.942343
64329	11255.0	12171.258744
1072150	10810.0	10589.278265
123951	8894.0	8562.660357
62237	7088.0	8458.216292
1376536	8185.0	8316.760439
61714	7677.0	8073.004075
330013	7272.0	7717.962785

- Although the values differs, but we can see that the order of ranking is almost preserved.

Let's now calculate the Root Mean Squared Error of the model :

In [110]:
```
# Calculating RMSE :
RMSE = sqrt(mean_squared_error(y_true = y_test, y_pred = y_prediction))
print(RMSE)
```

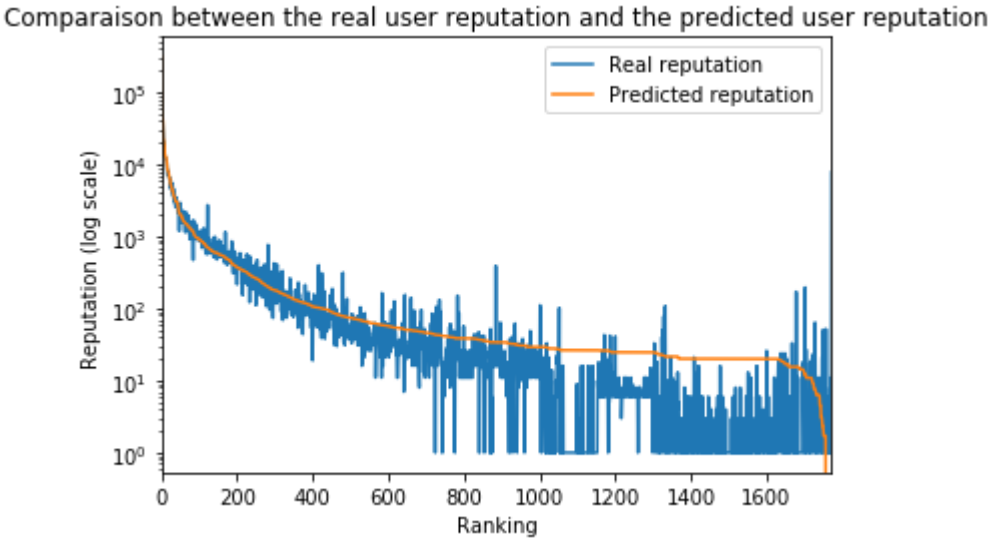
```
1061.4369735701096
```

The overall RMSE value is useful to compare between two different models. But per se, it gives few insight on the quality of the model.

We found out that by visualising the sorted comparaison dataframe, with a log scale over y axis, and by using the ranking as x axis, this gives a lot more insight on the quality of the model.

In [117]:
```
# Replace the index of the dataframe with row num :
comparaison.index = range(comparaison.shape[0])
comparaison.columns = ['Real reputation', 'Predicted reputation']

# Plotting the result :
ax1 = comparaison.plot(logy=True, title='Comparaison between the real user repu
tation and the predicted user reputation')
ax1.set_xlabel('Ranking')
ax1.set_ylabel('Reputation (log scale) ')
ax1.tick_params(axis='y')
```



With the graph above, we can make the following observations about the quality of the regressor :

1. The error is relatively small for the top ranking users, and it increases as the ranking increases, to reach a chaotic level of error by the end of the ranking axis.
2. The predicted reputation shows values that are less than 1, which is by definition not possible for a reputation in stackoverflow.
3. To the most right side we can spot some of the users that have a very high reputation in reality, yet their predicted reputation was one of the lowest.

5.3 Conclusion

This regressor is not good in overall, but since we are interested in finding only the top ranking profiles, this will moderate the risks of error.

In the next section, we will see how to apply this model to find the best experts in their domain of expertise.

6. Applying the Model

In this final section we use the model created in the last section, in order to look for the best of the best talents in their domain.

First we need to write a function similar to the sampling function, but that will build a dataset based on tags:

In [43]:

```
def search_users_data(tag) :

    # Step1 : Preparing queries

    USER_POSTS_BY_TAG_QUERY = """
SELECT user_id, count(*) as posts_count, sum(post_favorite_count) as posts_favo
rite_count, sum(post_score) as posts_score, sum(post_view_count) as posts_view_
count,
sum(post_answers_count) as posts_answers_count, sum(post_comments_count) as pos
ts_comments_count
FROM (
  SELECT users.id as user_id, posts.favorite_count as post_favorite_count, post
s.score as post_score, posts.view_count as post_view_count,
         posts.answer_count as post_answers_count,  posts.comment_count as post
_comments_count
  FROM `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = posts.
owner_user_id
  WHERE posts.tags like "%""" + tag + """%"
) AS USER_POSTS
GROUP BY USER_POSTS.user_id
"""
    USER_ANSWERS_BY_TAG_QUERY = """
SELECT user_id, count(*) as answers_count, sum(answers_score) as answers_score,
 sum(answers_comments_count) as answers_comments_count
FROM (
  SELECT users.id as user_id, answers.score as answers_score, answers.comment_c
ount as answers_comments_count
  FROM `bigquery-public-data.stackoverflow.posts_answers` as answers
  JOIN `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts on pos
ts.id = answers.parent_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = answer
s.owner_user_id
  WHERE posts.tags like "%""" + tag + """%"
) AS USER_ANSWERS
GROUP BY USER_ANSWERS.user_id
    """

    USER_COMMENTS_ON_POSTS_BY_TAG_QUERY = """
SELECT user_id, count(*) as comments_on_posts_count, sum(comment_score) as comm
ents_on_posts_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts on pos
ts.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
  WHERE posts.tags like "%""" + tag + """%"
) AS USER_COMMENTS_ON_POSTS
GROUP BY USER_COMMENTS_ON_POSTS.user_id
    """

    USER_COMMENTS_ON_ANSWERS_BY_TAG_QUERY = """
SELECT user_id, count(*) as comments_on_answers_count, sum(comment_score) as co
mments_on_answers_score
FROM (
  SELECT users.id as user_id, comments.score as comment_score
  FROM `bigquery-public-data.stackoverflow.comments` as comments
  JOIN `bigquery-public-data.stackoverflow.posts_answers` as answers on answer
s.id = comments.post_id
  JOIN `bigquery-public-data.stackoverflow.stackoverflow_posts` as posts on pos
ts.id = answers.parent_id
  JOIN `bigquery-public-data.stackoverflow.users` as users on users.id = commen
ts.user_id
```

```
  WHERE posts.tags like "%""" + tag + """%"
) AS USER_COMMENTS_ON_ANSWERS
GROUP BY USER_COMMENTS_ON_ANSWERS.user_id
    """

    # Step2 : Querying data from bigquery

    user_posts_df = bigquery_client.query(USER_POSTS_BY_TAG_QUERY).to_dataframe
().set_index('user_id')
    user_answers_df = bigquery_client.query(USER_ANSWERS_BY_TAG_QUERY).to_dataf
rame().set_index('user_id')
    user_comments_on_posts_df =  bigquery_client.query(USER_COMMENTS_ON_POSTS_B
Y_TAG_QUERY).to_dataframe().set_index('user_id')
    user_comments_on_answers_df =  bigquery_client.query(USER_COMMENTS_ON_ANSWE
RS_BY_TAG_QUERY).to_dataframe().set_index('user_id')

    # Step3 : Combining the results in a single dataframe
    result = user_posts_df.join(user_answers_df, how='left')
    result = result.join(user_comments_on_posts_df, how='left')
    result = result.join(user_comments_on_answers_df, how='left')

    return result.fillna(0)
```

6.1 Creating an Input dataset

Now, we are ready to apply the model.

Let's for example look for the best experts in the domain of **Pandas** (Data Science library for Python).

To do so, we first create a dataset based on the tag (pandas).

In [45]:
```
experts = search_users_data(tag='pandas')
print(experts[selected_features].shape)
experts[selected_features].head()
```

```
(9337, 6)
```

Out[45]:

user_id	posts_count	posts_score	answers_count	answers_score	comments_on_posts_score	comme
327702	1	0	0.0	0.0	0.0	
1377107	1	18	4.0	8.0	0.0	
5539711	1	0	0.0	0.0	1.0	
649920	1	0	0.0	0.0	0.0	
1639671	1	1	1.0	0.0	0.0	

- We have found 9337 users who have made at least one action (posting, answering, commenting), on a post that is tagged as a 'pandas' post.

6.2 Applying the regressor to the input dataset

Now, using the created dataset of pandas experts, let's use the our regressor in order to associate a "Pandas expert reputation" with each user in the dataset :

In [46]:
```
prediction = regressor.predict(experts[selected_features])
```

In [47]:
```
experts['predicted_reputation'] = prediction
```

6.3 Getting the list of the TOP 10 best talents :

In [97]:
```
# Sorting by predicted reputation, and taking the first 10 users
top10_experts = experts.sort_values(['predicted_reputation'], ascending=False)[
0:10]
top10_experts['ranking'] = [x + 1 for x in range(10)]
top10_experts[['predicted_reputation', 'ranking', *selected_features]]
```

Out[97]:

user_id	predicted_reputation	ranking	posts_count	posts_score	answers_count	answers_score	comm
1240268	138053.045102	1	2	108	1217.0	15715.0	
190597	111958.834043	2	3	15	1070.0	12566.0	
704848	111862.707916	3	1	6	1958.0	12711.0	
653364	45778.744011	4	5	32	449.0	5281.0	
1426056	29203.725904	5	6	32	123.0	3338.0	
1427416	27387.271434	6	5	37	242.0	3172.0	
2411802	25252.777460	7	9	20	921.0	2434.0	
484596	19838.798051	8	3	11	18.0	2301.0	
625914	18920.032137	9	3	29	216.0	2121.0	
567620	18781.506403	10	21	114	76.0	2173.0	

Let's take a look at the experts we found.

But first, we need to write a utility function that allows as to seek users from bigquery database by id :

In [98]:
```
def get_user_by_id(user_id) :
    QUERY = """
    SELECT *
    FROM `bigquery-public-data.stackoverflow.users`
    WHERE id = """ + str(user_id) + """
    """
    return bigquery_client.query(QUERY).to_dataframe()
```

Now, we can display each expert and a link to his stackoverflow profile (those are real users, you can check their Stack Overflow profiles by following the links) :

In [99]:
```
for index, topexpert in top10_experts.iterrows():
    user = get_user_by_id(index)
    name = user['display_name'][0]
    ranking = topexpert['ranking']
    print("Expert #", ranking,": ", name, "(https://stackoverflow.com/users/{0}
/{1})".format(index, name))
```

```
Expert # 1.0 :  Andy Hayden (https://stackoverflow.com/users/1240268/Andy Hayde
n)
Expert # 2.0 :  unutbu (https://stackoverflow.com/users/190597/unutbu)
Expert # 3.0 :  EdChum (https://stackoverflow.com/users/704848/EdChum)
Expert # 4.0 :  joris (https://stackoverflow.com/users/653364/joris)
Expert # 5.0 :  waitingkuo (https://stackoverflow.com/users/1426056/waitingkuo)
Expert # 6.0 :  BrenBarn (https://stackoverflow.com/users/1427416/BrenBarn)
Expert # 7.0 :  Alexander (https://stackoverflow.com/users/2411802/Alexander)
Expert # 8.0 :  Aman (https://stackoverflow.com/users/484596/Aman)
Expert # 9.0 :  behzad.nouri (https://stackoverflow.com/users/625914/behzad.nour
i)
Expert # 10.0 :  ely (https://stackoverflow.com/users/567620/ely)
```

At this point, our work is done, and the recruitment company extracted successfully a list of top 10 experts in the domain of Pandas. The next action is to get in touch with the candidates in order to make a job offer.

7. Limitations and future works

Despite the medium quality of the model, the result is still satisfying in the sense that we succeeded in extracting a list of real top experts in their domain.

There is more than one way to improve upon this work:

- Use other sources to gain deeper knowledge of the users : use text of posts and comments, track user activity in time.
- Improved search : multi-tags search, synonym of tags search, search by geographical location, search by date range
- This work was limited to the scope of stackoverflow data, in the future we can as well, extend this work to use other data sources like LinkedIn, Medium, Open Source repositories... etc

In [ ]:
```
```