

# analisis

December 10, 2018

## Trabajo Final

```
<h2 style="text-align: center; font-weight: bold; font-size: 20px; padding: 10px 20px; background-color: #f2f2f2;">
<div style="width: 450px; margin: 0 auto 30px;">
  <div style="overflow: hidden; border-bottom: 1px solid #d2d2d2;">
    <div style="float: left; width: 300px; padding-left: 8px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 18px; font-weight: bold;">
    </div>
    <div style="float: left; width: 150px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 18px; font-weight: bold;">
    </div>
  </div>
  <div style="overflow: hidden; border-bottom: 1px solid #d2d2d2;">
    <div style="float: left; width: 300px; padding-left: 8px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 16px; color: #363636; line-height: 1.2;">
    </div>
    <div style="float: left; width: 150px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 16px; color: #363636; line-height: 1.2;">
    </div>
  </div>
  <div style="overflow: hidden; border-bottom: 1px solid #d2d2d2; ">
    <div style="float: left; width: 300px; padding-left: 8px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 16px; color: #363636; line-height: 1.2;">
    </div>
    <div style="float: left; width: 150px;">
      <p style="font-family: 'Open Sans', sans-serif; font-size: 16px; color: #363636; line-height: 1.2;">
    </div>
  </div>
</div>
```

```
In [1]: import pandas as pd
import numpy as np
import matplotlib
import seaborn as sns
import sklearn
from matplotlib import pyplot as plt
```

```
import plotly.offline as py
from plotly import tools
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
from plotly import tools
```

```
import warnings
warnings.filterwarnings("ignore")
```

```
In [2]: apps = pd.read_csv('data/AppleStore.csv')
desc = pd.read_csv('data/appleStore_description.csv')
```

Con millones de aplicaciones en la actualidad, el siguiente conjunto de datos se ha convertido en la clave para obtener las mejores aplicaciones en la tienda de aplicaciones iOS. Este conjunto de datos contiene más de 7000 detalles de aplicaciones móviles de Apple iOS. Los datos se extrajeron de la API de búsqueda de iTunes en el sitio web de Apple Inc.

Fecha de recolección de datos (de API); Julio 2017

Dimensión del conjunto de datos; 7197 filas y 18 columnas (17 columnas + 1 de descripción que está en un archivo aparte).

```
In [3]: apps.shape
```

```
Out[3]: (7197, 17)
```

```
In [4]: apps.dtypes
```

```
Out[4]: Unnamed: 0      int64
id                    int64
track_name           object
size_bytes           int64
currency             object
price                float64
rating_count_tot     int64
rating_count_ver     int64
user_rating          float64
user_rating_ver      float64
ver                  object
cont_rating          object
prime_genre          object
sup_devices.num      int64
ipadSc_urls.num      int64
lang.num             int64
vpp_lic              int64
dtype: object
```

*vpp\_lic: The Apple Volume Purchase Program (VPP) is a service that allows organizations that have registered for the Apple VPP to purchase iOS apps in bulk, but not at discounted prices.*

*After making a bulk purchase, the organization receives redemption codes for each app bought. The organization can then distribute app codes to individual users, who use the codes to "purchase" the app from the Apple App Store.*

source: <https://searchmobilecomputing.techtarget.com/definition/Apple-Volume-Purchase-Program-Apple-VPP>

```
In [5]: # borramos la primer columna, Unnamed: 0, que en el file original funciona como indice
apps.drop('Unnamed: 0', axis=1, inplace=True)
```

```
In [6]: apps.head()
```

```
Out[6]:
```

	id	track_name	size_bytes	\
0	281656475	PAC-MAN Premium	100788224	
1	281796108	Evernote - stay organized	158578688	
2	281940292	WeatherBug - Local Weather, Radar, Maps, Alerts	100524032	
3	282614216	eBay: Best App to Buy, Sell, Save! Online Shop...	128512000	
4	282935706	Bible	92774400	

	currency	price	rating_count_tot	rating_count_ver	user_rating	\
0	USD	3.99	21292	26	4.0	
1	USD	0.00	161065	26	4.0	
2	USD	0.00	188583	2822	3.5	
3	USD	0.00	262241	649	4.0	
4	USD	0.00	985920	5320	4.5	

	user_rating_ver	ver	cont_rating	prime_genre	sup_devices.num	\
0	4.5	6.3.5	4+	Games	38	
1	3.5	8.2.2	4+	Productivity	37	
2	4.5	5.0.0	4+	Weather	37	
3	4.5	5.10.0	12+	Shopping	37	
4	5.0	7.5.1	4+	Reference	37	

	ipadSc_urls.num	lang.num	vpp_lic
0	5	10	1
1	5	23	1
2	5	3	1
3	5	9	1
4	5	45	1

```
In [7]: # remove repeated columns from description file
desc.drop(['track_name', 'size_bytes'], axis=1, inplace=True)
```

```
In [8]: desc.head()
```

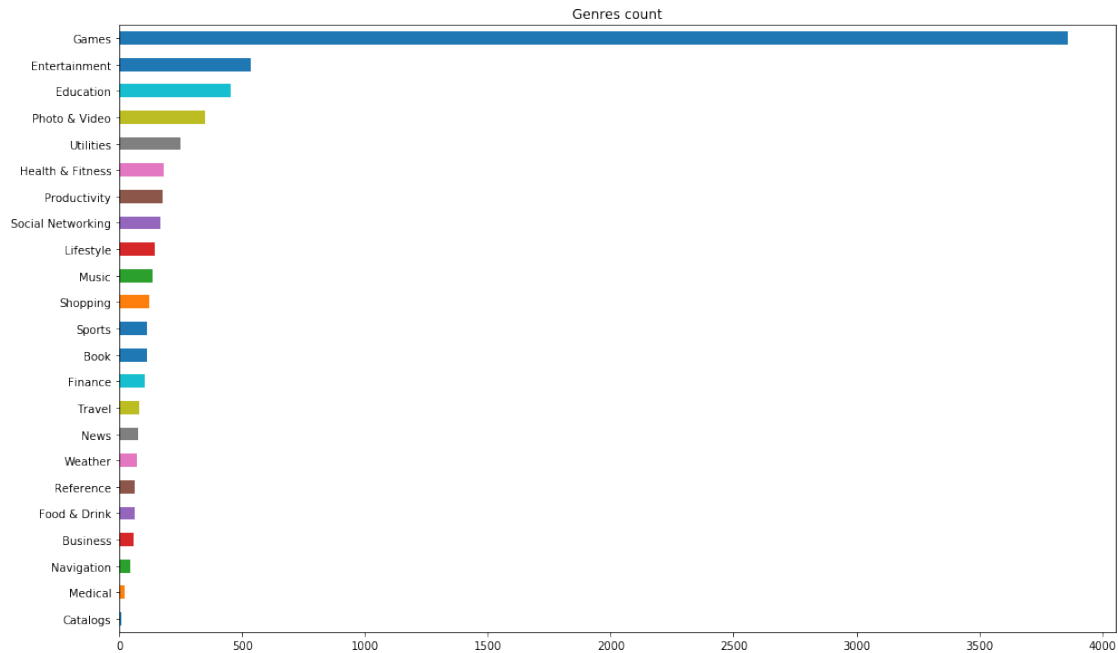
```
Out[8]:
```

	id	app_desc
0	281656475	SAVE 20%, now only \$3.99 for a limited time!\n...
1	281796108	Let Evernote change the way you organize your ...
2	281940292	Download the most popular free weather app pow...
3	282614216	The eBay app is the best way to find anything ...
4	282935706	On more than 250 million devices around the wo...

## 0.1 Análisis de categorías

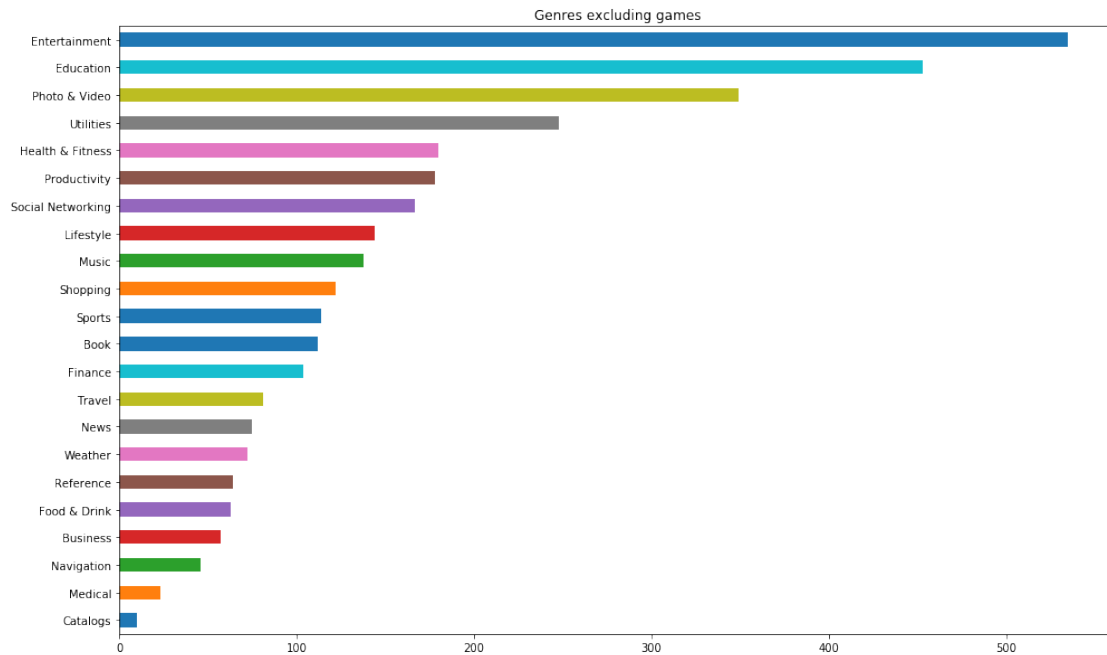
```
In [9]: apps.prime_genre.value_counts(ascending=True).plot(kind='barh', figsize=(16,10)).set_title
```

```
Out[9]: Text(0.5, 1.0, 'Genres count')
```



```
In [10]: #mismo plot filtrando games
apps[apps['prime_genre'] != 'Games'].prime_genre.value_counts(ascending=True).plot(kind='barh')
```

```
Out[10]: Text(0.5, 1.0, 'Genres excluding games')
```



## 0.2 Analisis de precios

```
In [11]: apps.currency.value_counts()
```

```
Out[11]: USD      7197
         Name: currency, dtype: int64
```

Como todos los precios estan en USD, se puede descartar esta columna.

```
In [12]: apps.drop('currency', axis=1, inplace=True)
```

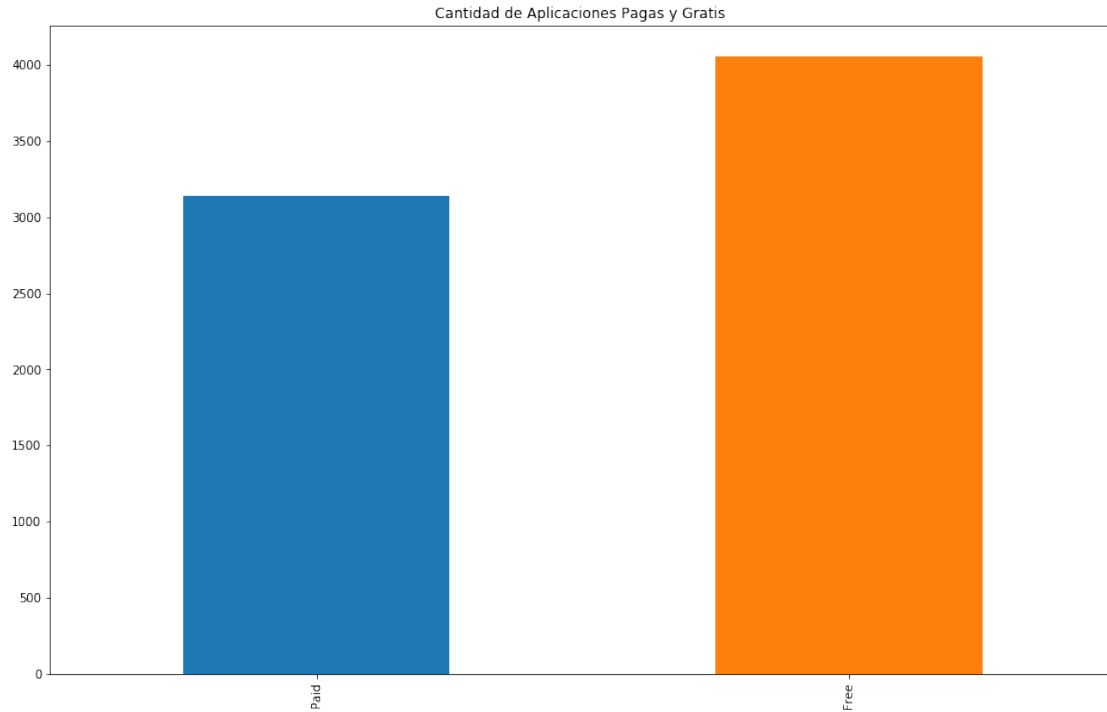
## 0.3 Apps pagas vs gratuitas

```
In [13]: def paid(x):
         if x>0:
             return 'Paid'
         else :
             return 'Free'
```

```
apps['category'] = apps.price.apply(lambda x : paid(x))
```

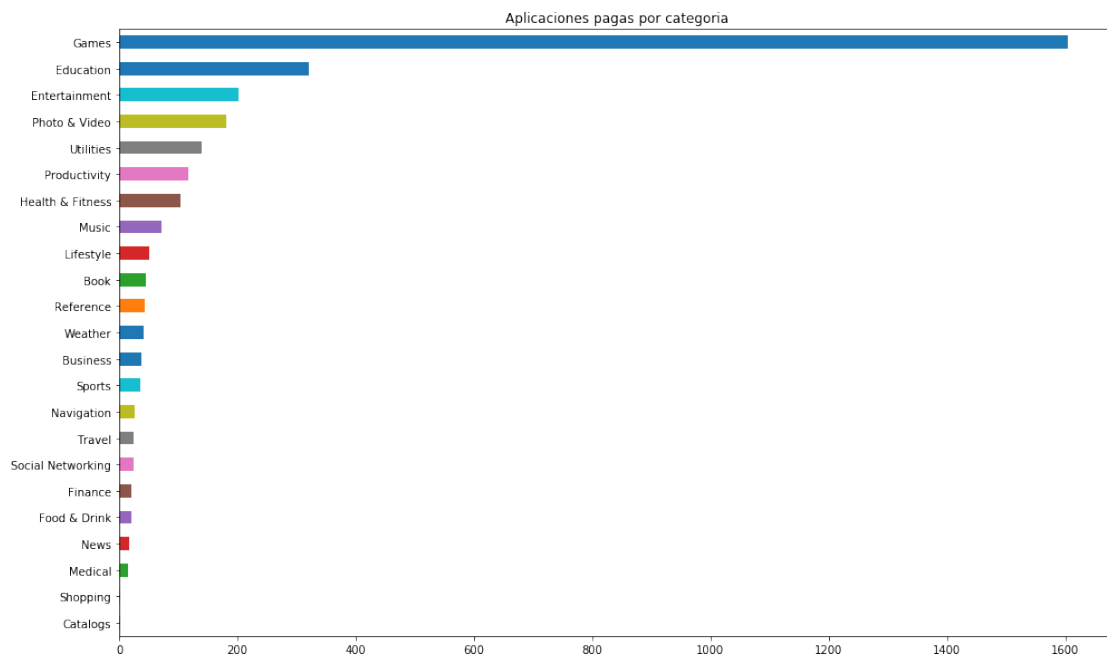
```
apps['category'].value_counts(ascending=True).plot(kind='bar', figsize=(16,10)).set_title
```

```
Out[13]: Text(0.5, 1.0, 'Cantidad de Aplicaciones Pagas y Gratis ')
```



```
In [14]: # plot generos de apps pagas
apps[apps['price'] > 0].prime_genre.value_counts(ascending=True).plot(kind='barh', figsize=(10, 10))
```

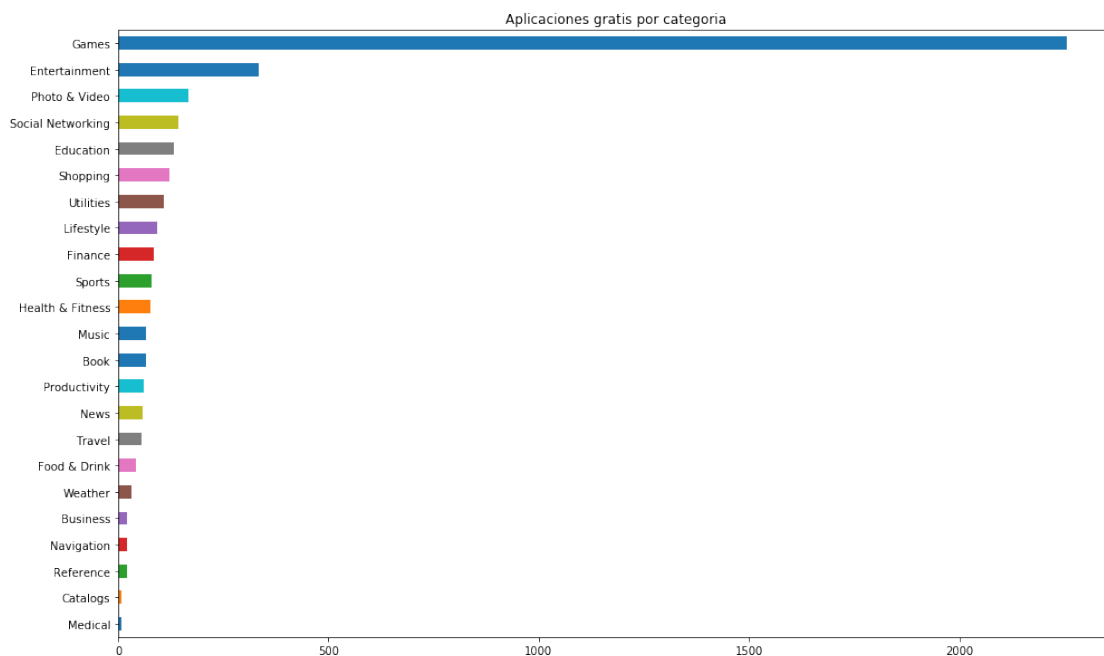
```
Out[14]: Text(0.5, 1.0, 'Aplicaciones pagas por categoria')
```



### Cantidad de aplicaciones pagas por categoría

```
In [15]: # plot generos de apps gratis
apps[apps['price'] == 0].prime_genre.value_counts(ascending=True).plot(kind='barh', fig

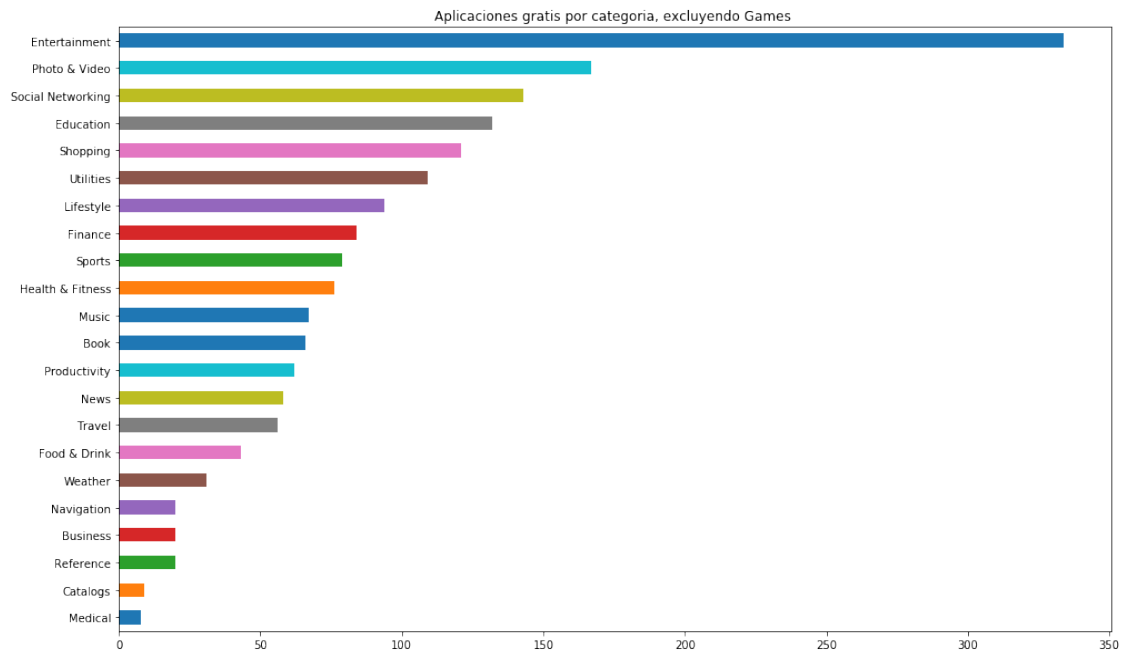
Out[15]: Text(0.5, 1.0, 'Aplicaciones gratis por categoria')
```



### Cantidad de aplicaciones gratis por categoría

```
In [16]: # mismo plot filtrando games
apps[(apps['price'] == 0) & (apps['prime_genre'] != 'Games')].prime_genre.value_counts(

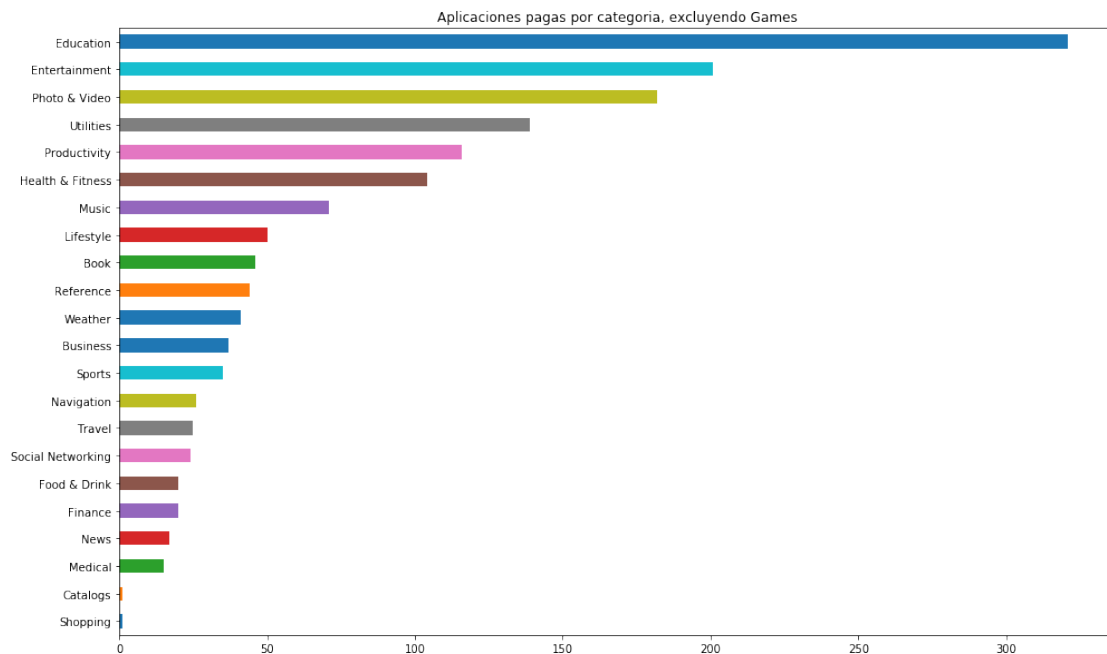
Out[16]: Text(0.5, 1.0, 'Aplicaciones gratis por categoria, excluyendo Games ')
```



Cantidad de aplicaciones gratis por categoría filtrando games

```
In [17]: # mismo plot filtrando games
apps[(apps['price'] > 0) & (apps['prime_genre'] != 'Games')].prime_genre.value_counts(a

Out[17]: Text(0.5, 1.0, 'Aplicaciones pagas por categoria, excluyendo Games')
```





Cantidad de aplicaciones pagas por categoria filtrando games

```
In [18]: s = ['Games', 'Entertainment', 'Education', 'Photo & Video']

def categ(x):
    if x in s:
        return x
    else :
        return "Others"

apps['broad_genre']= apps.prime_genre.apply(lambda x : categ(x))

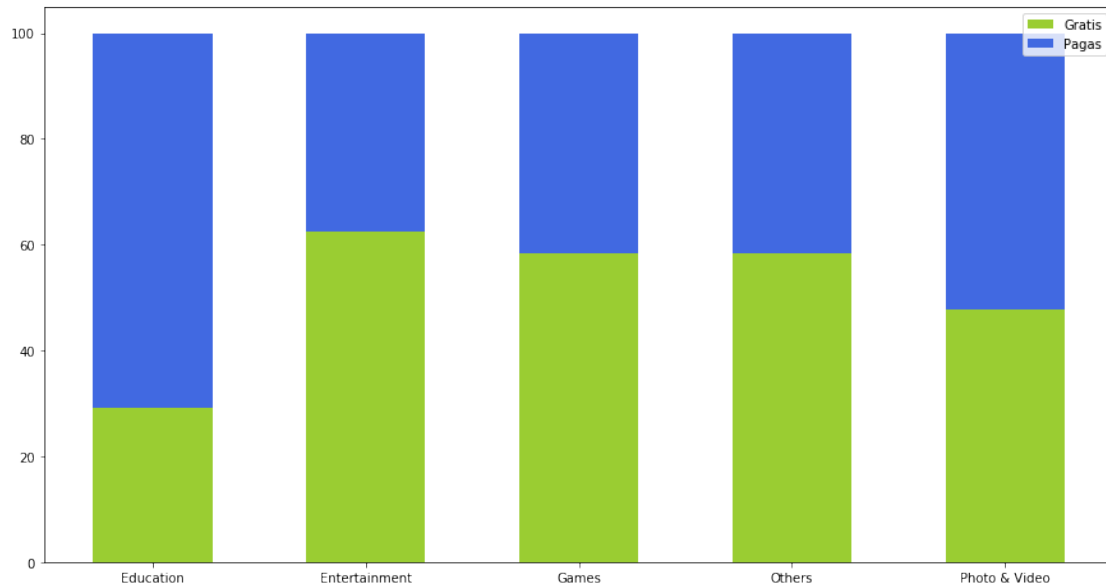
In [19]: free = apps[apps.price==0].broad_genre.value_counts().sort_index().to_frame()
paid = apps[apps.price>0].broad_genre.value_counts().sort_index().to_frame()
total = apps.broad_genre.value_counts().sort_index().to_frame()
free.columns=['Gratis']
paid.columns=['Pagas']
total.columns=['Total']
dist = free.join(paid).join(total)
dist ['Porcentaje Pagas %'] = dist.Pagas*100/dist.Total
dist ['Porcentaje Gratis %'] = dist.Gratias*100/dist.Total
dist

Out[19]:
```

	Gratis	Pagas	Total	Porcentaje Pagas %	Porcentaje Gratis %
Education	132	321	453	70.860927	29.139073
Entertainment	334	201	535	37.570093	62.429907
Games	2257	1605	3862	41.558778	58.441222
Others	1166	832	1998	41.641642	58.358358
Photo & Video	167	182	349	52.148997	47.851003

```
In [20]: list_free= dist['Porcentaje Gratis %'].tolist()
tuple_free = tuple(list_free)
tuple_paidapps = tuple(dist['Porcentaje Pagas %'].tolist())
plt.figure(figsize=(15,8))
N=5
ind = np.arange(N)
width =0.56
p1 = plt.bar(ind, tuple_free, width, color='#9ACD32')
p2 = plt.bar(ind, tuple_paidapps, width,bottom=tuple_free,color='#4169E1')
plt.xticks(ind,tuple(dist.index.tolist() ))
plt.legend((p1[0], p2[0]), ('Gratis', 'Pagas'))
plt.show()

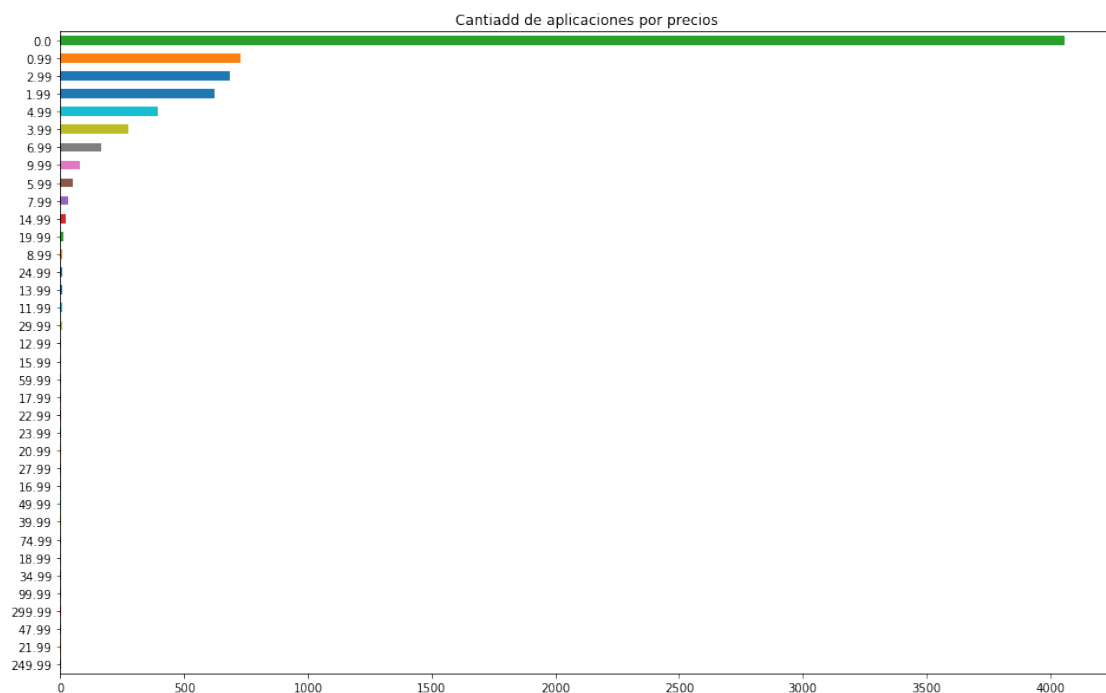
pies = dist[['Porcentaje Gratis %','Porcentaje Pagas %']]
pies.columns=['free %','paid %']
plt.show()
```



Vemos que para la única categoría que la cantidad de aplicaciones pagas supera a la cantidad de aplicaciones no pagas es Educación

```
In [21]: apps.price.value_counts(ascending=True).plot(kind='barh', figsize=(16,10)).set_title('Cantiadd de aplicaciones por precios')
```

```
Out[21]: Text(0.5, 1.0, 'Cantiadd de aplicaciones por precios')
```



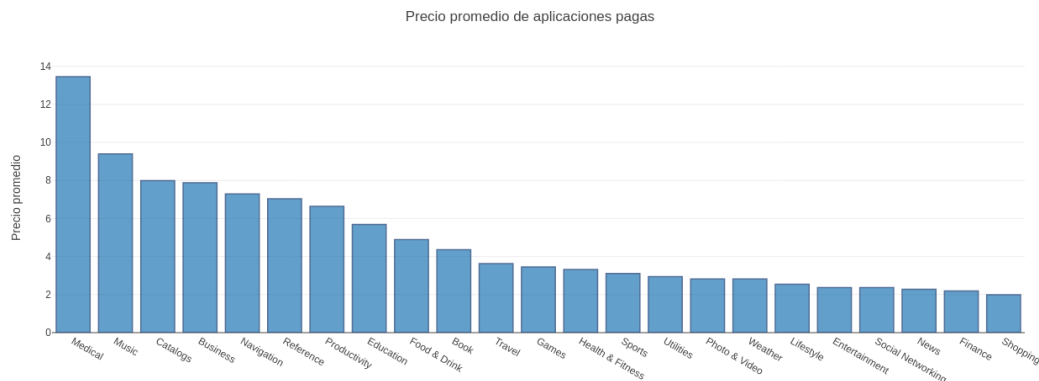
Como se puede ver, la gran mayoría de apps son gratis; de las pagas los precios van hasta los USD 10, a partir de ahí ya hay muy pocos casos como para generalizar.

```
In [22]: apps['isNotFree'] = apps['price'].apply(lambda x: 1 if x > 0 else 0)
df_app_notfree = apps[apps['isNotFree'] == 1]
df_app_free = apps[apps['isNotFree'] == 0]
cnt_srs = df_app_notfree[['prime_genre', 'price']].groupby('prime_genre').mean()['price']
text = ['{:.2f}%'.format(100 * (value / cnt_srs.sum())) for value in cnt_srs.values]

trace = go.Bar(
    x = cnt_srs.index,
    y = cnt_srs.values,
    text = text,
    marker = dict(
        line = dict(color='rgb(8, 48, 107)',
                    width = 1.5)
    ),
    opacity = 0.7
)
data = [trace]

layout = go.Layout(
    title = 'Precio promedio de aplicaciones pagas',
    margin = dict(
        l = 100
    ),
    yaxis = dict(
        title = 'Precio promedio'
    ),
    width = 800,
    height = 500
)

fig = go.Figure(data=data, layout=layout)
py.iplot(fig)
```



Dentro de las aplicaciones pagas, las aplicaciones Medicas son las mas caras, con un promedio de casi 14 dolares. Y si analizamos aquellas categorías con mayor cantidad de aplicaciones en el store mantienen precios menores a 6 dólares en promedio, como lo son Games, Entertainment, Education y Photo & Video

## 0.4 ## User ratings

Una vez analizadas la cantidad de aplicaciones pagas y gratis por categoría nos preguntamos si las aplicaciones pagas son realmente buenas. Esto lo vamos a analizar siguiendo la opinión de los usuarios.

El campo que define la opinion de los usuarios es USER RATING, que tiene valores entre 0 y 5, siendo 5 la mejor puntuacion.

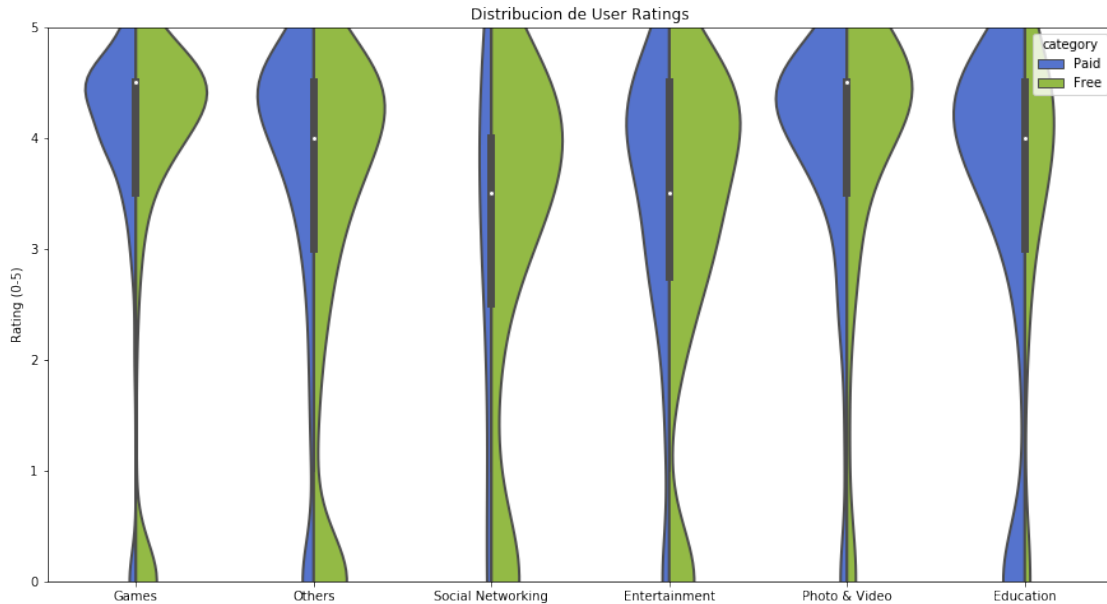
```
In [23]: s = ['Games', 'Entertainment', 'Education', 'Photo & Video', 'Social Networking']
```

```
def categ(x):
    if x in s:
        return x
    else :
        return "Others"
```

```
apps['broad_genre']= apps.prime_genre.apply(lambda x : categ(x))
```

```
In [24]: plt.figure(figsize=(15,8))
plt.style.use('fast')
plt.ylim([0,5])
plt.title("Distribucion de User Ratings")
sns.violinplot(data=apps, y='user_rating',x='broad_genre',hue='category',
               vertical=True,kde=False,split=True ,linewidth=2,
               scale='count', palette=['#4169E1','#9ACD32'])
plt.xlabel(" ")
plt.ylabel("Rating (0-5)")

plt.show()
```



Los resultados varían parecido en el caso de las apps pagas y de las gratuitas. En general vemos que la distribución de las puntuaciones de usuarios son parecidas en todas las categorías.

Se puede destacar que para el caso de entretenimiento y otros sí se aprecian puntuaciones entre 1 y 2, mientras que en el resto de las categorías las puntuaciones más presentes son 0 y luego entre 3 y 5, generalmente los valores entre 1 y 2 son poco usados. De todos modos las distribuciones son parecidas tanto para pagas como no pagas.

Se puede notar que en las apps pagas, en el género *Education* hay mayor concentración en la puntuación 4 para las pagas, mientras que para las no pagas, entre los valores 3 y 5, la distribución es más pareja.

La mayoría de apps relacionadas a Redes sociales por amplia diferencia es gratis. No sería popular tener que pagar por una red social; además las redes sociales generan ingresos mediante publicidades, por lo que conviene tener una base amplia de usuarios, por más que eso signifique que ellos estén 'gratis'.

No perder de vista que todas las apps también pueden generar ingresos mediante *in app purchases*.

```
In [25]: cnt_srs = apps[['prime_genre', 'user_rating']].groupby('prime_genre').mean()['user_rating']
```

```
trace = go.Bar(
    x = cnt_srs.index,
    y = cnt_srs.values,
    marker = dict(
        line = dict(color='rgb(8, 48, 107)',
                    width = 1.5)
    ),
    opacity = 0.7
)
data = [trace]
```

```

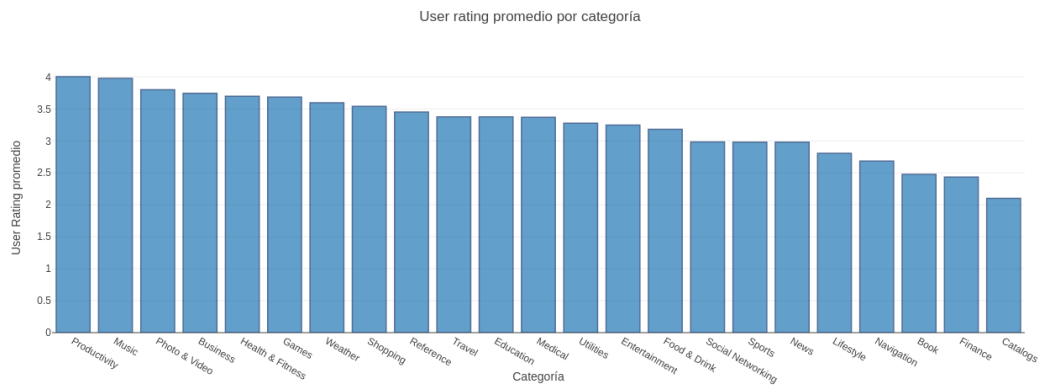
layout = go.Layout(
    title = 'User rating promedio por categoría',
    margin = dict(
        l = 100
    ),
    xaxis = dict(
        title = 'Categoría'
    ),
    yaxis = dict(
        title = 'User Rating promedio'
    ),
    width = 800,
    height = 500
)

```

```

fig = go.Figure(data=data, layout=layout)
py.iplot(fig)

```



```

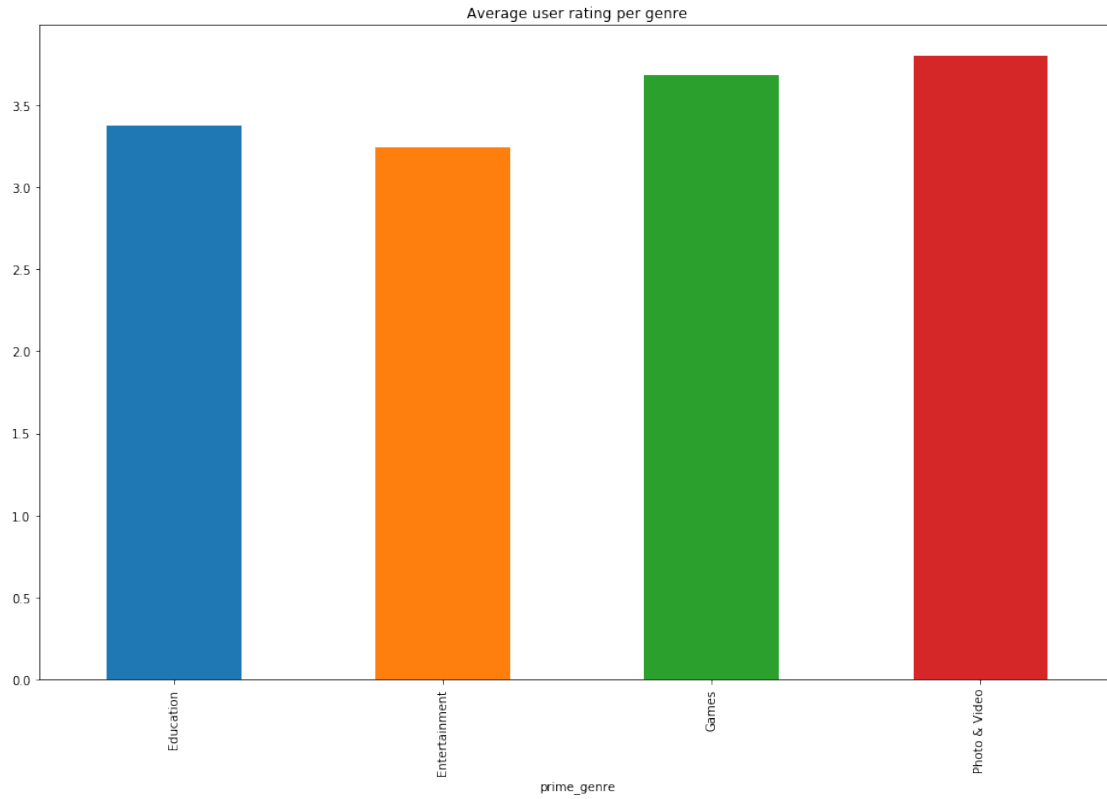
In [26]: interest_areas = ['Games', 'Entertainment', 'Education', 'Photo & Video']
         apps[apps.prime_genre.isin(interest_areas)].groupby('prime_genre')['user_rating'].mean()

```

```

Out[26]: Text(0.5, 1.0, 'Average user rating per genre')

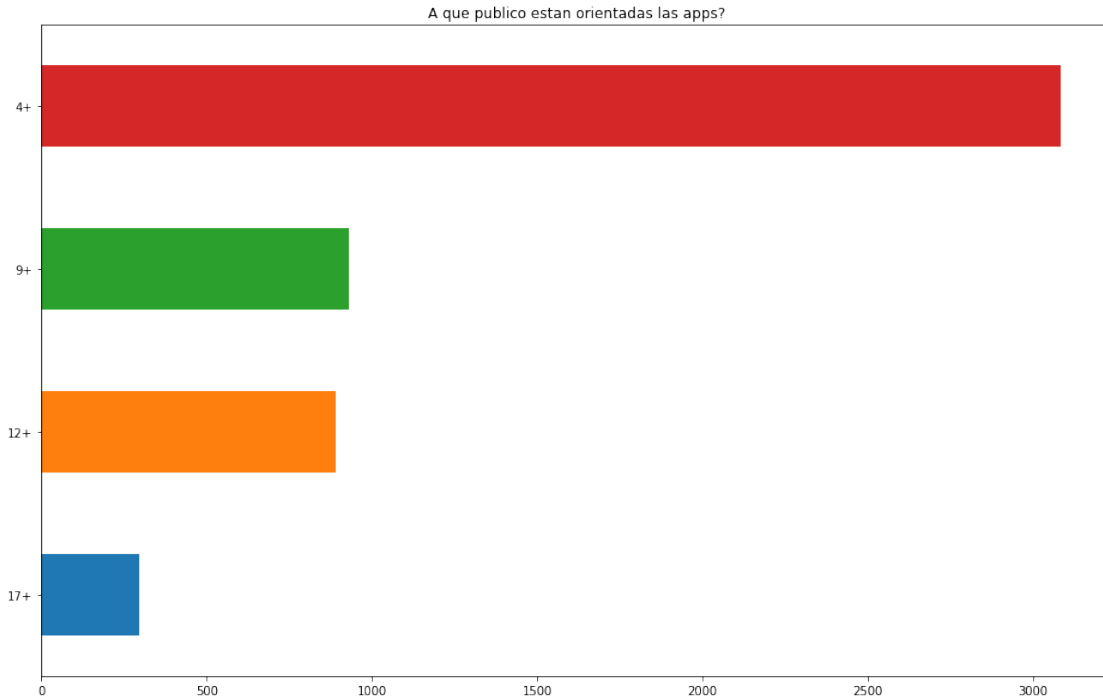
```



#### 0.4.1 cont\_rating

```
In [27]: # veamos los ratings de contenido de las areas de interes  
apps[apps['prime_genre'].isin(interest_areas)].cont_rating.value_counts(ascending=True)
```

```
Out[27]: Text(0.5, 1.0, 'A que publico estan orientadas las apps?')
```



La columna de rating edad se transforma en feature numérico, ya que no tiene sentido que sea del tipo *object*.

```
In [28]: apps.cont_rating = apps.cont_rating.apply(lambda x: int(x.split('+')[0]))
```

#### 0.4.2 track\_name

```
In [29]: apps.track_name = apps.track_name.apply(lambda x: x.lower())
```

#### 0.4.3 ver

Nos quedamos con la *major version* de las apps.

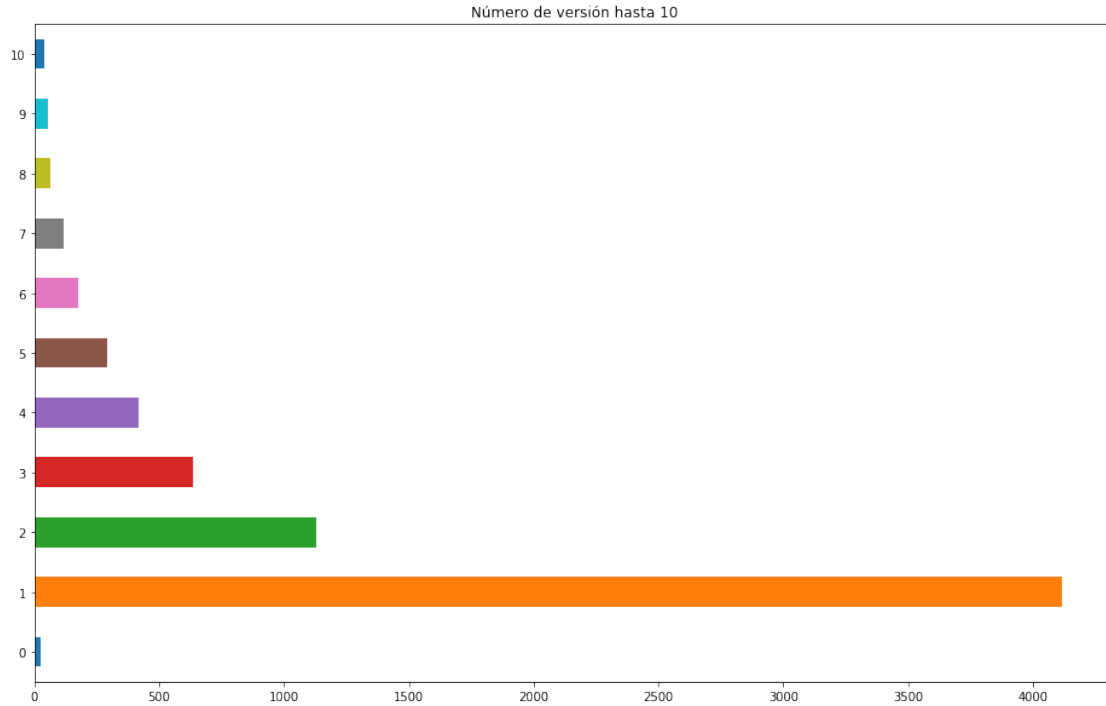
```
In [30]: # for Apple versioning criteria, see: https://en.wikipedia.org/wiki/Software_versioning
apps['major_version'] = apps.ver.apply(lambda x: x.split('.')[0])
```

```
In [31]: apps.major_version.value_counts(ascending=True).sort_index().plot(kind='barh', figsize=
```

```
Out[31]: Text(0.5, 1.0, 'version numbers')
```







## 1 Merge datasets

In [34]: *# se hace left join porque importan solamente los registros que estan en apps df*  
`m = apps.merge(desc, how='left')`

In [35]: `m.head()`

Out[35]:

	id	track_name	size_bytes	\
0	281656475	pac-man premium	100788224	
1	281796108	evernote - stay organized	158578688	
2	281940292	weatherbug - local weather, radar, maps, alerts	100524032	
3	282614216	ebay: best app to buy, sell, save! online shop...	128512000	
4	282935706	bible	92774400	

	price	rating_count_tot	rating_count_ver	user_rating	user_rating_ver	\
0	3.99	21292	26	4.0	4.5	
1	0.00	161065	26	4.0	3.5	
2	0.00	188583	2822	3.5	4.5	
3	0.00	262241	649	4.0	4.5	
4	0.00	985920	5320	4.5	5.0	

	ver	cont_rating	prime_genre	sup_devices.num	ipadSc_urls.num	\
0	6.3.5	4	Games	38	5	
1	8.2.2	4	Productivity	37	5	

2	5.0.0	4	Weather	37	5
3	5.10.0	12	Shopping	37	5
4	7.5.1	4	Reference	37	5

	lang.num	vpp_lic	category	broad_genre	isNotFree	major_version	\
0	10	1	Paid	Games	1	6	
1	23	1	Free	Others	0	8	
2	3	1	Free	Others	0	5	
3	9	1	Free	Others	0	5	
4	45	1	Free	Others	0	7	

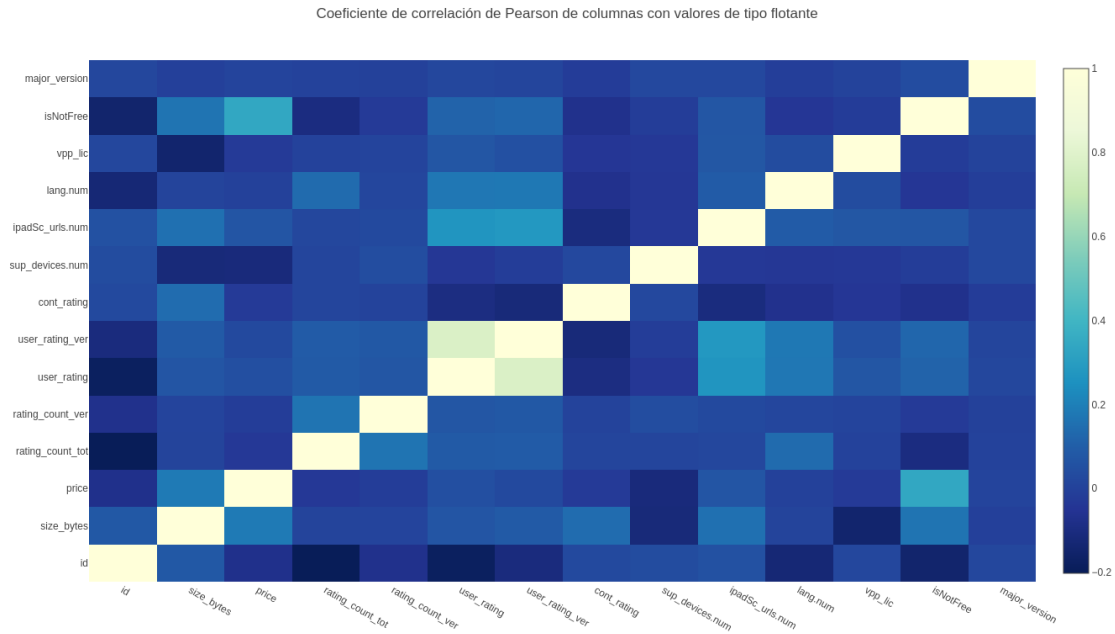
	app_desc
0	SAVE 20%, now only \$3.99 for a limited time!\n...
1	Let Evernote change the way you organize your ...
2	Download the most popular free weather app pow...
3	The eBay app is the best way to find anything ...
4	On more than 250 million devices around the wo...

Con esto se obtienen datos adicionales: track name, tamaño de la app en bytes y la descripción.

```
In [36]: data = [
    go.Heatmap(
        z = m.corr().values,
        x = m.corr().columns.values,
        y = m.corr().columns.values,
        colorscale='YlGnBu',
        reversescale=False,
    )
]

layout = go.Layout(
    title='Coeficiente de correlación de Pearson de columnas con valores de tipo flotante',
    xaxis = dict(ticks=''),
    yaxis = dict(ticks=''),
    width = 800, height = 800,
    margin = dict(
        l = 100
    )
)

fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='labelled-heatmap')
```



El coeficiente de correlación de Pearson es la estadística de prueba que mide la relación estadística, o asociación, entre dos variables continuas. Es conocido como el mejor método para medir la asociación entre variables de interés porque se basa en el método de covarianza. Da información sobre la magnitud de la asociación, o correlación, así como la dirección de la relación

### 1.0.1 Análisis de la descripción de las apps

Se agregan tres columnas con las tres palabras mas frecuentes en la descripción de las apps, omitiendo stopwords.

```
In [37]: desc = m['app_desc'][0].split(' ')
```

```
In [38]: import nltk
         from nltk.corpus import stopwords
         nltk.download('punkt')
         nltk.download('stopwords')
```

```
[nltk_data] Downloading package punkt to /home/rozanecm/nltk_data...
[nltk_data] Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data] /home/rozanecm/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
```

```
Out[38]: True
```

```
In [39]: %%time
         for i in range(m.shape[0]):
```

```

temp_desc = m['app_desc'][i]
temp_word_list = nltk.word_tokenize(temp_desc)
temp_word_list = [word.lower() for word in temp_word_list if word not in stopwords.]
for char in " {}()#&[]^`~_-@|£?¡'!'+*\""?./;:<>¿%, ":
    for ele in temp_word_list:
        if char in ele:
            temp_word_list.remove(ele)
fdist = nltk.FreqDist(temp_word_list)
temp_srs = pd.Series(fdist).sort_values(ascending=False)
try:
    m.loc[i, 'most_freq_word_1'] = temp_srs.index[0]
    m.loc[i, 'most_freq_word_2'] = temp_srs.index[1]
    m.loc[i, 'most_freq_word_3'] = temp_srs.index[2]
except:
    m.loc[i, 'most_freq_word_1'] = temp_srs.index[0]

```

CPU times: user 4min 52s, sys: 17.7 s, total: 5min 10s  
Wall time: 5min 10s

In [40]: m.tail()

```

Out[40]:

```

	id	track_name	size_bytes	\
7184	1187617475	kubik	126644224	
7185	1187682390	vr roller-coaster	120760320	
7186	1187779532	bret michaels emojis + lyric keyboard	111322112	
7187	1187838770	vr roller coaster world - virtual reality	97235968	
7188	1188375727	escape the sweet shop series	90898432	

	price	rating_count_tot	rating_count_ver	user_rating	user_rating_ver	\
7184	0.00	142	75	4.5	4.5	
7185	0.00	30	30	4.5	4.5	
7186	1.99	15	0	4.5	0.0	
7187	0.00	85	32	4.5	4.5	
7188	0.00	3	3	5.0	5.0	

	ver	cont_rating	...	lang.num	vpp_lic	category	\
7184	1.3	4	...	1	1	Free	
7185	0.9	4	...	1	1	Free	
7186	1.0.2	9	...	1	1	Paid	
7187	1.0.15	12	...	2	1	Free	
7188	1.0	4	...	2	1	Free	

	broad_genre	isNotFree	major_version	\
7184	Games	0	1	
7185	Games	0	0	
7186	Others	1	1	
7187	Games	0	1	

7188	Games	0	1	
------	-------	---	---	--

	app_desc	most_freq_word_1	\
7184	Place the falling blocks correctly in order to...	blocks	
7185	A thrilling virtual reality roller coaster exp...	vox	
7186	Rock star Bret Michaels, winner of Celebrity A...	bret	
7187	VR Roller Coaster World is an app for Google C...	vr	
7188	5 previous escape games plus 1 new game in one...	game	

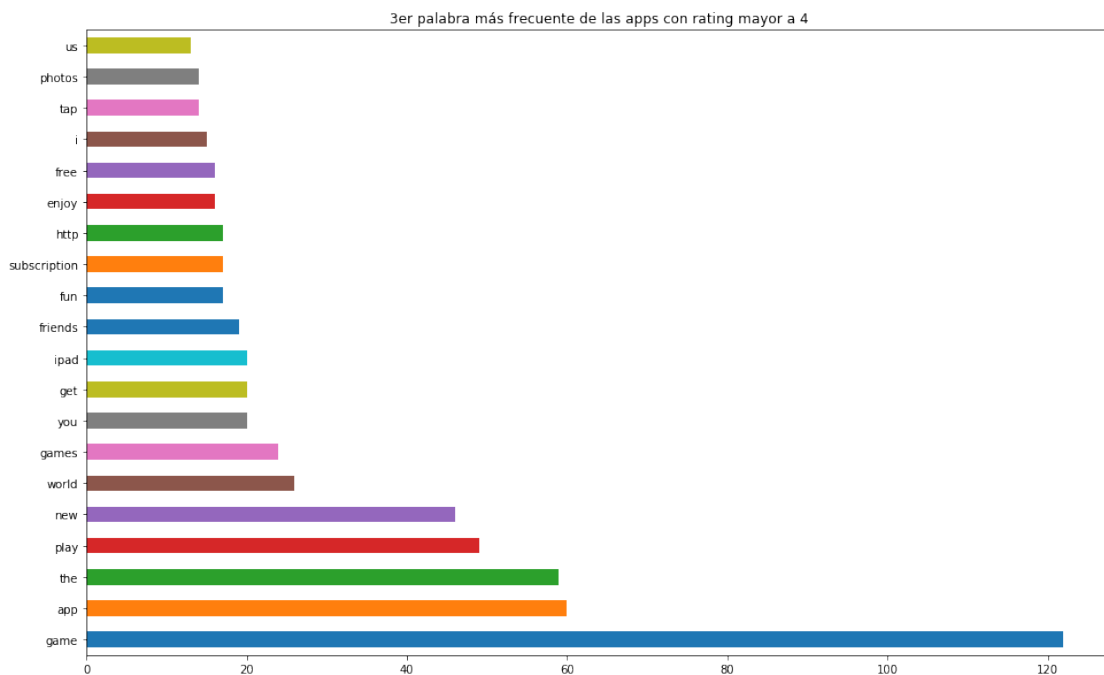
  

	most_freq_word_2	most_freq_word_3
7184	falling	layers
7185	virtual	3d
7186	rock	lyrics
7187	world	coaster
7188	escape	shop

[5 rows x 23 columns]

```
In [41]: m.loc[m['user_rating'] > 4, 'most_freq_word_3'].value_counts().head(20).plot(kind='barh')
```

```
Out[41]: Text(0.5, 1.0, '3er palabra más frecuente de las apps con rating mayor a 4')
```



## 1.1 Preparación de datos

```
In [42]: from sklearn.metrics import confusion_matrix
         from sklearn.preprocessing import OneHotEncoder
         from sklearn.model_selection import train_test_split
```

Vamos a definir una columna que clasifique como **aplicaciones exitosas** aquellas con **user rating mayor o igual a 4**.

```
In [43]: m['succesful'] = apps['user_rating'].apply(lambda x: 1 if x > 3 else 0)
m.tail(10)
```

```
Out[43]:
```

	id	track_name	size_bytes	\
7179	1186126548	escape game: illumination	52342784	
7180	1186384912	demolition derby virtual reality (vr) racing	168774656	
7181	1187128255	-pk 537462784		
7182	1187279979	add-ons studio for minecraft	22999040	
7183	1187282363	plead the fifth - the game	27853824	
7184	1187617475	kubik	126644224	
7185	1187682390	vr roller-coaster	120760320	
7186	1187779532	bret michael's emojis + lyric keyboard	111322112	
7187	1187838770	vr roller coaster world - virtual reality	97235968	
7188	1188375727	escape the sweet shop series	90898432	

	price	rating_count_tot	rating_count_ver	user_rating	user_rating_ver	\
7179	0.00	23	23	4.5	4.5	
7180	0.00	18	18	4.0	4.0	
7181	0.99	0	0	0.0	0.0	
7182	2.99	97	97	3.0	3.0	
7183	2.99	11	0	4.0	0.0	
7184	0.00	142	75	4.5	4.5	
7185	0.00	30	30	4.5	4.5	
7186	1.99	15	0	4.5	0.0	
7187	0.00	85	32	4.5	4.5	
7188	0.00	3	3	5.0	5.0	

	ver	cont_rating	...	vpp_lic	category	broad_genre	isNotFree	\
7179	1.0	4	...	1	Free	Games	0	
7180	1.0.0	12	...	1	Free	Games	0	
7181	2.1.0	9	...	1	Paid	Games	1	
7182	1.0	4	...	1	Paid	Games	1	
7183	1.1.1	17	...	1	Paid	Games	1	
7184	1.3	4	...	1	Free	Games	0	
7185	0.9	4	...	1	Free	Games	0	
7186	1.0.2	9	...	1	Paid	Others	1	
7187	1.0.15	12	...	1	Free	Games	0	
7188	1.0	4	...	1	Free	Games	0	

	major_version	app_desc	\
7179	1	Escape from here! \n\nTap on the objects in th...	
7180	1	Multiplayer Demolition Derby goes Virtual Real...	
7181	2	ARPGPK...	
7182	1	The makers of the official Minecraft Skin Stud...	
7183	1	It's the cheeky, provocative, late-night telev...	

```

7184      1 Place the falling blocks correctly in order to...
7185      0 A thrilling virtual reality roller coaster exp...
7186      1 Rock star Bret Michaels, winner of Celebrity A...
7187      1 VR Roller Coaster World is an app for Google C...
7188      1 5 previous escape games plus 1 new game in one...

```

	most_freq_word_1	most_freq_word_2	most_freq_word_3	sucesful
7179	items	look	closer	1.0
7180	vr	racing	car	1.0
7181				0.0
7182	minecraft	horse	rabbit	0.0
7183	round	game	scoop	1.0
7184	blocks	falling	layers	0.0
7185	vox	virtual	3d	0.0
7186	bret	rock	lyrics	0.0
7187	vr	world	coaster	1.0
7188	game	escape	shop	1.0

[10 rows x 24 columns]

Agregamos la columna que va a definir si es una aplicación exitosa. Como mencionamos antes, son aplicaciones exitosas aquellas con user rating mayor o igual a 4.

---

Eliminamos las columnas ID y category.

Esta decisión fue tomada porque, para el caso de ID, como se ve en el plot del coeficiente de Perason, la correlación con el resto de los atributos es 0 o menor a 0.

Y para el caso de category, la columna isNotFree representa lo mismo.

```

In [44]: m = m.drop(['id', 'category'], axis=1)
         m.tail()

```

```

Out[44]:
           track_name  size_bytes  price  \
7184              kubik    126644224    0.00
7185      vr roller-coaster    120760320    0.00
7186  bret michael's emojis + lyric keyboard    111322112    1.99
7187  vr roller coaster world - virtual reality    97235968    0.00
7188  escape the sweet shop series    90898432    0.00

           rating_count_tot  rating_count_ver  user_rating  user_rating_ver  \
7184              142              75              4.5              4.5
7185              30              30              4.5              4.5
7186              15              0              4.5              0.0
7187              85              32              4.5              4.5
7188              3              3              5.0              5.0

           ver  cont_rating  prime_genre  ...  lang.num  vpp_lic  \
7184      1.3              4          Games  ...          1          1

```



7185	0.9	4	Games	...	1	1
7186	1.0.2	9	Utilities	...	1	1
7187	1.0.15	12	Games	...	2	1
7188	1.0	4	Games	...	2	1

	broad_genre	isNotFree	major_version	\
7184	Games	0	1	
7185	Games	0	0	
7186	Others	1	1	
7187	Games	0	1	
7188	Games	0	1	

	app_desc	most_freq_word_1	\
7184	Place the falling blocks correctly in order to...	blocks	
7185	A thrilling virtual reality roller coaster exp...	vox	
7186	Rock star Bret Michaels, winner of Celebrity A...	bret	
7187	VR Roller Coaster World is an app for Google C...	vr	
7188	5 previous escape games plus 1 new game in one...	game	

	most_freq_word_2	most_freq_word_3	successful
7184	falling	layers	0.0
7185	virtual	3d	0.0
7186	rock	lyrics	0.0
7187	world	coaster	1.0
7188	escape	shop	1.0

[5 rows x 22 columns]

In [45]: m.isnull().any()

```
Out[45]: track_name      False
size_bytes      False
price           False
rating_count_tot False
rating_count_ver False
user_rating     False
user_rating_ver False
ver            False
cont_rating     False
prime_genre     False
sup_devices.num False
ipadSc_urls.num False
lang.num        False
vpp_lic         False
broad_genre     False
isNotFree       False
major_version   False
app_desc        False
```

```

most_freq_word_1    False
most_freq_word_2     True
most_freq_word_3     True
sucesful             True
dtype: bool

```

Vemos que tenemos valores nulos en: \* most\_freq\_word\_2 True \* most\_freq\_word\_3 True \* sucesful True

Vamos a analizar cuántos registros de cada uno son los que cuentan con estos valores nulos

```
In [46]: m.sucesful.isnull().sum()
```

```
Out[46]: 8
```

```
In [47]: nan_rows = m[m['sucesful'].isnull()]
nan_rows
```

```
Out[47]:
```

	track_name	size_bytes	price	\
224	the impossible quiz!	44652544	0.00	
1133	abrsm aural trainer grades 1-5	329866240	7.99	
3092	todo number matrix: brain teasers, logic puzzl...	41566208	0.99	
3224	- 85620736	0.00		
3581	green riding hood	316589056	0.00	
3668	immortal legends - td	273789952	0.00	
4121	jcnews - anime & game culture	25467904	0.00	
4176	292899840	0.00		

	rating_count_tot	rating_count_ver	user_rating	user_rating_ver	ver	\
224	18884	451	4.0	4.5	1.62	
1133	0	0	0.0	0.0	2.5	
3092	15	5	4.5	4.0	1.1.1	
3224	0	0	0.0	0.0	4.7.0	
3581	392	2	4.0	5.0	1.2.1	
3668	26	26	3.0	3.0	2.0.0	
4121	0	0	0.0	0.0	2.0.5	
4176	0	0	0.0	0.0	2.1.6	

	cont_rating	prime_genre	...	lang.num	vpp_lic	broad_genre	\
224	9	Entertainment	...	1	1	Entertainment	
1133	4	Education	...	1	1	Education	
3092	4	Education	...	8	1	Education	
3224	4	Shopping	...	2	1	Others	
3581	4	Book	...	12	1	Others	
3668	9	Games	...	3	1	Games	
4121	17	News	...	31	1	Others	
4176	17	Games	...	1	1	Games	

	isNotFree	major_version	\
224	0	1	

1133	1	2
3092	1	1
3224	0	4
3581	0	1
3668	0	2
4121	0	2
4176	0	2

	app_desc	most_freq_word_1	\
224	Its not the "difficult quiz". Its not the "r...	quiz	
1133	The OFFICIAL ABRSM Aural Trainer contains inte...	music	
3092	4.5 stars! "Todo Number Matrix is a unique mat...	todo	
3224	\n20153...		
3581	* "Free App of the Week" in 2017\n* iPad App o...	app	
3668	Defend your spirit master in epic battles, evo...	heroes	
4121	We'll update the latest news of Japanese anima...	news	
4176	200\n...	--	

	most_freq_word_2	most_freq_word_3	sucesful
224	impossible	it	NaN
1133	aural	abrsn	NaN
3092	number	children	NaN
3224		NaN	
3581	riding	green	NaN
3668	journey	across	NaN
4121		you	NaN
4176			NaN

[8 rows x 22 columns]

Para el caso de *sucesful* son solo 8 registros. Al ser tan pocos determinamos directamente eliminar dichos registros

```
In [48]: m.most_freq_word_2.isnull().sum()
```

```
Out[48]: 7
```

```
In [49]: nan_rows = m[m['most_freq_word_2'].isnull()]
nan_rows
```

```
Out[49]:
```

	track_name	size_bytes	price	rating_count_tot	\
4899		97892352	0.00	0	
5890		267673600	0.99	0	
5982		67259392	0.00	0	
6440		27525120	0.00	0	
6765	83985408	0.00		0	
7044	- 106102784	0.00	5		
7112	js	1841152	0.00	0	

	rating_count_ver	user_rating	user_rating_ver	ver	cont_rating	\
4899	0	0.0	0.0	2.2.1	17	
5890	0	0.0	0.0	10.99	4	
5982	0	0.0	0.0	1.7	17	
6440	0	0.0	0.0	1.0.6	4	
6765	0	0.0	0.0	1.6	12	
7044	0	3.5	0.0	0.16.3	4	
7112	0	0.0	0.0	1.0	17	

	prime_genre	...	lang.num	vpp_lic	broad_genre	isNotFree	\
4899	Lifestyle	...	2	1	Others	0	
5890	Games	...	1	1	Games	1	
5982	Games	...	1	1	Games	0	
6440	Entertainment	...	1	1	Entertainment	0	
6765	Games	...	1	1	Games	0	
7044	Games	...	2	1	Games	0	
7112	Entertainment	...	1	1	Entertainment	0	

	major_version	app_desc	\
4899	2 ...		
5890	10 MMORPGMMORPG...		
5982	1		
6440	1 ...		
6765	1 ...		
7044	0 3D...		
7112	1		

	most_freq_word_1	most_freq_word_2	\
4899	...	NaN	
5890	mmorpgqmmorpg...	NaN	
5982		NaN	
6440	...	NaN	
6765	...	NaN	
7044	3d...	NaN	
7112		NaN	

	most_freq_word_3	sucesful
4899	NaN	1.0
5890	NaN	0.0
5982	NaN	1.0
6440	NaN	0.0
6765	NaN	1.0
7044	NaN	1.0
7112	NaN	1.0

[7 rows x 22 columns]

Para el caso de *most\_freq\_word\_2* son solo 7 registros. Al ser tan pocos determinamos direc-

tamente eliminar dichos registros

```
In [50]: m.most_freq_word_3.isnull().sum()
```

```
Out[50]: 14
```

```
In [51]: nan_rows = m[m['most_freq_word_3'].isnull()]
nan_rows
```

```
Out[51]:
```

		track_name	size_bytes	price	rating_count_tot	\
560	hd	68668416	0.00	990		
1267		61895680	0.00		22	
1285	-	98640896	0.00		9	
4899		97892352	0.00		0	
4912		20328448	0.00		0	
5503		44026880	0.00		0	
5890		267673600	0.99		0	
5982		67259392	0.00		0	
6440		27525120	0.00		0	
6765		83985408	0.00	0		
6962		gogogo	7212032	0.00		0
7019	777-2017	102120448	0.00		0	
7044	-	106102784	0.00	5		
7112		js	1841152	0.00		0

	rating_count_ver	user_rating	user_rating_ver	ver	cont_rating	\
560	4	3.0	2.0	5.5.2	12	
1267	0	3.0	0.0	4.1.8	4	
1285	0	1.5	0.0	6.1.2	17	
4899	0	0.0	0.0	2.2.1	17	
4912	0	0.0	0.0	2.0	4	
5503	0	0.0	0.0	1.1	12	
5890	0	0.0	0.0	10.99	4	
5982	0	0.0	0.0	1.7	17	
6440	0	0.0	0.0	1.0.6	4	
6765	0	0.0	0.0	1.6	12	
6962	0	0.0	0.0	1.0	4	
7019	0	0.0	0.0	1.1.0	17	
7044	0	3.5	0.0	0.16.3	4	
7112	0	0.0	0.0	1.0	17	

	prime_genre	...	lang.num	vpp_lic	broad_genre	isNotFree	\
560	Entertainment	...	1	1	Entertainment	0	
1267	Lifestyle	...	2	1	Others	0	
1285	Finance	...	1	1	Others	0	
4899	Lifestyle	...	2	1	Others	0	
4912	Games	...	2	1	Games	0	
5503	Games	...	1	1	Games	0	
5890	Games	...	1	1	Games	1	

5982	Games	...	1	1	Games	0
6440	Entertainment	...	1	1	Entertainment	0
6765	Games	...	1	1	Games	0
6962	Shopping	...	2	1	Others	0
7019	Games	...	1	1	Games	0
7044	Games	...	2	1	Games	0
7112	Entertainment	...	1	1	Entertainment	0

	major_version		app_desc	\
560	5	...		
1267	4	...		
1285	6	...		
4899	2	...		
4912	2		HEY!HEY!HEY!!\n	
5503	1	\n		
5890	10	MMORPGQMMORPG...		
5982	1			
6440	1	...		
6765	1	...		
6962	1		gogogo APP	
7019	1	777\n...		
7044	0	3D...		
7112	1			

	most_freq_word_1	\
560	...	
1267		
1285		
4899	...	
4912		hey
5503		
5890	mmorpgqmmorpg...	
5982		
6440	...	
6765	...	
6962		gogogo
7019	77...	
7044	3d...	
7112		

	app	most_freq_word_2	most_freq_word_3	\
560		NaN		
1267	...	NaN		
1285	...	NaN		
4899			NaN	NaN
4912			NaN	
5503		NaN		
5890			NaN	NaN

5982		NaN	NaN
6440		NaN	NaN
6765		NaN	NaN
6962	app		NaN
7019	777		NaN
7044		NaN	NaN
7112		NaN	NaN

succesful	
560	1.0
1267	1.0
1285	1.0
4899	1.0
4912	0.0
5503	0.0
5890	0.0
5982	1.0
6440	0.0
6765	1.0
6962	1.0
7019	0.0
7044	1.0
7112	1.0

[14 rows x 22 columns]

Para el caso de *most\_freq\_word\_3* son solo 14 registros. Al ser tan pocos determinamos directamente eliminar dichos registros

```
In [52]: m.dropna(inplace=True)
         m.isnull().any()
```

```
Out[52]: track_name      False
         size_bytes      False
         price           False
         rating_count_tot False
         rating_count_ver False
         user_rating      False
         user_rating_ver  False
         ver             False
         cont_rating      False
         prime_genre      False
         sup_devices.num  False
         ipadSc_urls.num  False
         lang.num         False
         vpp_lic          False
         broad_genre      False
         isNotFree        False
```

```
major_version      False
app_desc            False
most_freq_word_1    False
most_freq_word_2    False
most_freq_word_3    False
succesful           False
dtype: bool
```

---

```
In [53]: m['rating_count_previo'] = m['rating_count_tot'] - m['rating_count_ver']

df_train = m[['size_bytes', 'isNotFree', 'price', 'rating_count_previo', 'sup_devices.n
target = m['user_rating']

df_train = pd.get_dummies(df_train)

target = target.apply(lambda x: 1 if x>3 else 0)

X_train, X_test, y_train, y_test = train_test_split(df_train.values, target, test_size=

print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
```

```
X_train shape: (5733, 31)
X_test shape: (1434, 31)
```

## 2 Predicciones

Para el presente caso de estudio se eligió utilizar la métrica *Accuracy score*. De la documentación de sklearn:

*Accuracy classification score. In multilabel classification, this function computes subset accuracy: the set of labels predicted for a sample must exactly match the corresponding set of labels in y\_true.*

```
In [54]: from sklearn.metrics import accuracy_score
         from sklearn.model_selection import KFold
         from sklearn.model_selection import cross_val_score, cross_validate

         from sklearn.ensemble import RandomForestClassifier
         from lightgbm import LGBMClassifier
         from xgboost import XGBClassifier
         from keras.models import Sequential
```

Using TensorFlow backend.

```
In [55]: from keras.layers import Dense
         from keras.wrappers.scikit_learn import KerasClassifier
```



```

# Function to create model, required for KerasClassifier
def create_model():
    # create model
    model = Sequential()
    model.add(Dense(12, activation='relu'))
    model.add(Dense(8, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))

    # Compile model
    model.compile(optimizer='rmsprop',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model

```

```

In [56]: models = [RandomForestClassifier(), LGBMClassifier(), XGBClassifier(), KerasClassifier(

kfold = KFold(n_splits=5, random_state=1234)

model_comparison = pd.DataFrame(columns=['Classifier_name', 'train_score', 'test_score'])

for i, model in enumerate(models):
    clf = model
    cv_result = cross_validate(model, X_train, y_train, cv=kfold, scoring='accuracy')
    model_comparison.loc[i, 'Classifier_name'] = model.__class__.__name__
    model_comparison.loc[i, 'train_score'] = cv_result['train_score'].mean()
    model_comparison.loc[i, 'test_score'] = cv_result['test_score'].mean()

model_comparison

```

```

Out[56]:
   Classifier_name  train_score  test_score
0  RandomForestClassifier    0.989403    0.830283
1      LGBMClassifier    0.917931    0.848944
2      XGBClassifier    0.868176    0.852085
3      KerasClassifier    0.658177    0.65824

```

### 3 Pred basadas en descripciones

```

In [57]: m.loc[:, 'isGame'] = m['app_desc'].apply(lambda x: 1 if 'game' in x.lower() else 0)
         m.loc[:, 'descLen'] = m['app_desc'].apply(lambda x: len(x.lower()))

df_train = m[['size_bytes', 'isNotFree', 'price', 'rating_count_previo', 'sup_devices.m
target = m['user_rating']

df_train = pd.get_dummies(df_train)

target = target.apply(lambda x: 1 if x > 3 else 0)

```

```

X_train, X_test, y_train, y_test = train_test_split(df_train.values, target, test_size=

print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)

```

```

X_train shape: (5733, 33)
X_test shape: (1434, 33)

```

```

In [58]: model_comparison = pd.DataFrame(columns=['Classifier_name', 'train_score', 'test_score'])

for i, model in enumerate(models):
    clf = model
    cv_result = cross_validate(model, X_train, y_train, cv=kfold, scoring='accuracy')
    model_comparison.loc[i, 'Classifier_name'] = model.__class__.__name__
    model_comparison.loc[i, 'train_score'] = cv_result['train_score'].mean()
    model_comparison.loc[i, 'test_score'] = cv_result['test_score'].mean()

```

```

model_comparison

```

```

Out[58]:
   Classifier_name  train_score  test_score
0  RandomForestClassifier    0.991104    0.843886
1          LGBMClassifier    0.934284    0.853304
2          XGBClassifier    0.877333    0.861329
3          KerasClassifier    0.446402    0.450742

```

```

In [59]: # play a sound when whole notebook finished executing
import os
duration = 1 # second
freq = 1500 # Hz
os.system('play --no-show-progress --null --channels 1 synth %s sine %f' % (duration, f

```

```

Out[59]: 0

```