

# TaskRabbit Dataset Analysis ¶

In [2]:

```
import pandas as pd
import warnings
from IPython.display import display
warnings.filterwarnings('ignore')
df = pd.read_csv("sample.csv")
df.head()
```

Out[2]:

	recommendation_id	created_at	tasker_id	position	hourly_rate	num_completed_
0	0-0-70cf97d7-37af-4834-901c-ce3ad4893b8c	2017-09-01 00:32:25	1009185352	1	38	151
1	0-0-70cf97d7-37af-4834-901c-ce3ad4893b8c	2017-09-01 00:32:25	1006892359	2	40	193
2	0-0-70cf97d7-37af-4834-901c-ce3ad4893b8c	2017-09-01 00:32:25	1012023956	3	28	0
3	0-0-70cf97d7-37af-4834-901c-ce3ad4893b8c	2017-09-01 00:32:25	1009733517	4	43	303
4	0-0-70cf97d7-37af-4834-901c-ce3ad4893b8c	2017-09-01 00:32:25	1013579273	5	29	39

**1. How many recommendation sets are in this data sample?**

**2100**

In [3]:

```
len(df.recommendation_id.unique())
```

Out[3]:

2100

**2. Each recommendation set shows from 1 to 15 Taskers, what is:**

**- average number of Taskers shown :**

**14.28**

**- median number of Taskers shown :**

**15.00**

In [4]:

```
df2 = df.groupby('recommendation_id')['position'].count().reset_index() \
        .rename(columns={'recommendation_id': 'recommendation_id', 'position': 'no_of_taskers'})
print("mean of taskers per recommendation set")
display(df2['no_of_taskers'].mean()) #mean
print("median of taskers per recommendation set")
display(df2['no_of_taskers'].median()) #median
```

mean of taskers per recommendation set

14.285714285714286

median of taskers per recommendation set

15.0

**3. How many total unique Taskers are there in this data sample?**

**830**

In [5]:

```
len(df.tasker_id.unique())
```

Out[5]:

830

**4. Which Tasker has been shown the most?**

**Tasker with id 1014508755 with 608 times**

**Which Tasker has been shown the least?**

**There are 68 taskers who showed up a minimum of 1 time**

In [6]:

```
df3 = df.groupby('tasker_id')['recommendation_id'].count().reset_index() \
        .rename(columns={'tasker_id': 'tasker_id', 'recommendation_id': 'no_of_times_shown'})
print("taskers who are shown maximum number of times")
display(df3[df3['no_of_times_shown'] == df3['no_of_times_shown'].max()])
print("taskers who are shown minimum number of times")
display(df3[df3['no_of_times_shown'] == df3['no_of_times_shown'].min()])
```

taskers who are shown maximum number of times

	tasker_id	no_of_times_shown
780	1014508755	608

taskers who are shown minimum number of times

	tasker_id	no_of_times_shown
3	1006690425	1
12	1006853970	1
14	1006899551	1
31	1007246122	1
34	1007295623	1
42	1007383273	1
46	1007472083	1
49	1007480912	1
63	1007638825	1
85	1007923586	1
102	1008033678	1
134	1008368716	1
138	1008469117	1
141	1008474216	1
153	1008604368	1
170	1008828652	1
179	1008870833	1
190	1008919567	1
229	1009112003	1
270	1009461190	1
285	1009547227	1
300	1009603880	1
305	1009612428	1
311	1009618500	1
319	1009641175	1

<b>341</b>	1009702351	1
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	<b>tasker_id</b>	<b>no_of_times_shown</b>
<b>346</b>	1009712638	1
<b>350</b>	1009754999	1
<b>352</b>	1009772528	1
<b>364</b>	1009871933	1
...	...	...
<b>472</b>	1011949117	1
<b>474</b>	1011952623	1
<b>477</b>	1011957940	1
<b>480</b>	1011968845	1
<b>482</b>	1011972750	1
<b>486</b>	1011985968	1
<b>507</b>	1012071620	1
<b>516</b>	1012151299	1
<b>522</b>	1012166729	1
<b>537</b>	1012289475	1
<b>546</b>	1012348656	1
<b>551</b>	1012364558	1
<b>557</b>	1012386513	1
<b>564</b>	1012678504	1
<b>583</b>	1012805440	1
<b>645</b>	1013362004	1
<b>673</b>	1013573125	1
<b>674</b>	1013573988	1
<b>693</b>	1013656032	1
<b>701</b>	1013731883	1
<b>721</b>	1013830691	1
<b>725</b>	1013854788	1
<b>733</b>	1013934937	1
<b>739</b>	1014086818	1
<b>763</b>	1014310300	1
<b>773</b>	1014439502	1
<b>775</b>	1014478773	1
<b>783</b>	1014547884	1
<b>788</b>	1014593279	1

816	1014926743	1
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68 rows × 2 columns

**5. Which Tasker has been hired the most?**

Tasker 1012043028 was hired 59 times which is highest

**Which Tasker has been hired the least?**

There are 518 taskers who are hired 0 times. List is below

In [7]:

```
df4 = df.groupby('tasker_id')['hired'].sum().reset_index() \
        .rename(columns={'tasker_id': 'tasker_id', 'hired': 'no_of_times_hired'})
print("taskers who are hired minimum number of times")
display(df4[df4['no_of_times_hired'] == df4['no_of_times_hired'].max()])## Max hired
print("taskers who are hired minimum number of times")
display(df4[df4['no_of_times_hired'] == df4['no_of_times_hired'].min()]) ## Min hired
```

taskers who are hired minimum number of times

	tasker_id	no_of_times_hired
502	1012043028	59

taskers who are hired minimum number of times

	tasker_id	no_of_times_hired
0	1006646767	0
2	1006655883	0
3	1006690425	0
4	1006702141	0
7	1006720473	0
8	1006751673	0
9	1006771484	0
10	1006797028	0
11	1006808958	0
12	1006853970	0
14	1006899551	0
15	1006912729	0
17	1006997279	0
18	1007007551	0
19	1007030973	0
20	1007062502	0
22	1007079569	0
24	1007084219	0
25	1007099706	0
28	1007184581	0
30	1007227664	0
31	1007246122	0
32	1007281889	0
34	1007295623	0
35	1007298334	0

<b>37</b>	1007306634	0
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	<b>tasker_id</b>	<b>no_of_times_hired</b>
<b>38</b>	1007330127	0
<b>40</b>	1007341779	0
<b>41</b>	1007359134	0
<b>42</b>	1007383273	0
...	...	...
<b>781</b>	1014532398	0
<b>782</b>	1014539109	0
<b>783</b>	1014547884	0
<b>784</b>	1014551627	0
<b>785</b>	1014571994	0
<b>786</b>	1014578899	0
<b>787</b>	1014586046	0
<b>788</b>	1014593279	0
<b>790</b>	1014632169	0
<b>791</b>	1014640927	0
<b>792</b>	1014657461	0
<b>793</b>	1014659781	0
<b>794</b>	1014667352	0
<b>796</b>	1014697426	0
<b>798</b>	1014710322	0
<b>803</b>	1014753188	0
<b>804</b>	1014753677	0
<b>806</b>	1014788707	0
<b>807</b>	1014790265	0
<b>808</b>	1014820493	0
<b>810</b>	1014860648	0
<b>811</b>	1014866421	0
<b>813</b>	1014881086	0
<b>814</b>	1014901856	0
<b>815</b>	1014917205	0
<b>816</b>	1014926743	0
<b>817</b>	1014928212	0
<b>822</b>	1014983247	0
<b>823</b>	1015000099	0

824	1015000442	0
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518 rows × 2 columns

**6. If we define the "Tasker conversion rate" as the number of times a Tasker has been hired, out of the number of times the Tasker has been shown, how many Taskers have a conversion rate of 100%**

There are 6 taskers who had 100 % conversion rate

In [8]:

```
df5 = pd.merge(df3, df4, on='tasker_id', how='inner')
df5['conversion_rate'] = df5['no_of_times_hired']*100/df5['no_of_times_shown']
df5[df5['conversion_rate']==100]
```

Out[8]:

	tasker_id	no_of_times_shown	no_of_times_hired	conversion_rate
49	1007480912	1	1	100.0
110	1008094420	2	2	100.0
175	1008861741	9	9	100.0
486	1011985968	1	1	100.0
553	1012369686	2	2	100.0
775	1014478773	1	1	100.0

**7. Would it be possible for all Taskers to have a conversion rate of 100%. Please explain your reasoning.**

For every recommendation\_id, the company is showing on an average 15 taskers out of which only one person is hired. So the probability of hiring of a person for single recommendation is just 1/15. Since only one tasker is hired for every recommendation id, the remaining 14 taskers did not get hired atleast one time they showed which counters the possibility of conversion rate of 100 as we have found atleast one tasker who cannot have 100 % conversion rate. This means we cannot have 100% conversion rate for all the taskers.

From the above table we see that all the taskers who have lesser number of appearances have 100 % conversion rate. Which means as the number of times he is shown is less , more the conversion rate of tasker even if he is hired lesser number of times.

Also, From the above results, some of the recommendations were having 0 hiring. The only way to get 100 % conversion rate is to show single tasker for each recommendation and have him hired. But this adversely affects the business as the clients would have lesser opportunities to chose and the taskers would believe they are getting less opportunities.

There is a intermediate option of reducing the number of recommendations for each task a little low to 10 which would increase the probability of hiring from 1/15 to 1/10 but this needs to be considered only if does not impact the business negatively.



In [9]:

```
df6 = df.groupby('recommendation_id')['hired'].sum().reset_index().reset_index() \
        .rename(columns={'recommendation_id': 'recommendation_id', 'hired': 'hired_not_hired'})
df6.head()
```

Out[9]:

	index	recommendation_id	hired_not_hired
0	0	0-0-00033225-3f89-47dd-b4f1-5d1feb359a76	1
1	1	0-0-000ea7f0-2ad9-48ee-bc79-899ee439be82	1
2	2	0-0-0027ac52-1983-4130-8a65-5048dda560c9	1
3	3	0-0-003a3672-3c80-4134-b409-b80baee0e082	1
4	4	0-0-0045d200-f7c0-4fe6-94df-b89a4cde3ee7	1

In [10]:

```
df6[df6['hired_not_hired'] ==0].count()
```

Out[10]:

```
index          395
recommendation_id  395
hired_not_hired  395
dtype: int64
```

**8. For each category, what is the average position of the Tasker who is hired?**

**9. For each category, what is the average hourly rate and average number of completed tasks for the Taskers who are hired?**

In [11]:

```
df7 = df[df['hired'] ==1]
print("Please see the table below for answers")
display(df7.groupby('category')['position','hourly_rate','num_completed_tasks'].mean().reset_index()
        .rename(columns={'category': 'category', 'position': 'average_position', 'hourly_rate': 'average_hourly_rate',
                          'num_completed_tasks': 'average_num_completed_tasks'}))
```

Please see the table below for answers

	category	average_position	average_hourly_rate	average_num_completed_tasks
0	Furniture Assembly	3.611888	38.701049	249.020979
1	Mounting	4.596085	50.154804	284.096085
2	Moving Help	4.145359	63.012259	273.882662

**10. Based on the previous, how would you approach the question of:**

How can we use market data to suggest hourly rates to Taskers that would maximize their opportunity to be hired? Please describe in detail, with code and formulas that support your model.

In [12]:

```
## Statistics of people who are not hired
df8 = df[df['hired'] ==0]
df8.groupby('category')['position','hourly_rate','num_completed_tasks'].agg({'median','mean',
    .rename(columns={'category': 'category', 'position': 'position_stats_not_hired', \
        'hourly_rate':'hourly_rate_stats_not_hired', 'num_completed_tasks':'num_completed_tasks_stats_not_hired'})})
```

Out[12]:

	category	position_stats_not_hired				hourly_rate_stats_not_hired				num_completed_tasks_stats_not_hired		
		min	max	mean	median	min	max	mean	median	min	max	mean
0	Furniture Assembly	1	15	8.139054	8	19	290	39.463301	38	0	1396	13.44
1	Mounting	1	15	8.065586	8	18	120	50.493961	50	0	1406	28.11
2	Moving Help	1	15	8.095662	8	18	250	83.736345	65	0	1243	27.11

In [13]:

```
#Statistics of people who are hired
df7 = df[df['hired'] ==1]
df7.groupby('category')['position','hourly_rate','num_completed_tasks'].agg({'median','mean',
    .rename(columns={'category': 'category', 'position': 'position_stats_hired', 'hourly_rate':'hourly_rate_stats_hired', 'num_completed_tasks':'num_completed_tasks_stats_hired'})})
```

Out[13]:

	category	position_stats_hired				hourly_rate_stats_hired				num_completed_tasks_stats_hired		
		min	max	mean	median	min	max	mean	median	min	max	mean
0	Furniture Assembly	1	15	3.611888	2	22	180	38.701049	38	0	988	24.44
1	Mounting	1	15	4.596085	3	26	95	50.154804	50	0	1397	28.11
2	Moving Help	1	15	4.145359	3	18	190	63.012259	49	0	1178	27.11

In [14]:

```
#Overall statistics on the entire dataset
df.groupby('category')['position', 'hourly_rate', 'num_completed_tasks'].agg({'median', 'mean', 'min', 'max'})
.rename(columns={'category': 'category', 'position': 'position_stats_overall', 'hourly_rate': 'hourly_rate_stats_overall',
                  'num_completed_tasks': 'num_completed_tasks_stats_overall'})
```

Out[14]:

	category	position_stats_overall				hourly_rate_stats_overall				num_completed_tasks_stats_overall		
		min	max	mean	median	min	max	mean	median	min	max	mean
0	Furniture Assembly	1	15	7.8801	8	19	290	39.4197	38	0	1396	185.83
1	Mounting	1	15	7.8706	8	18	120	50.4749	50	0	1406	220.27
2	Moving Help	1	15	7.8701	8	18	250	82.5530	65	0	1243	257.60

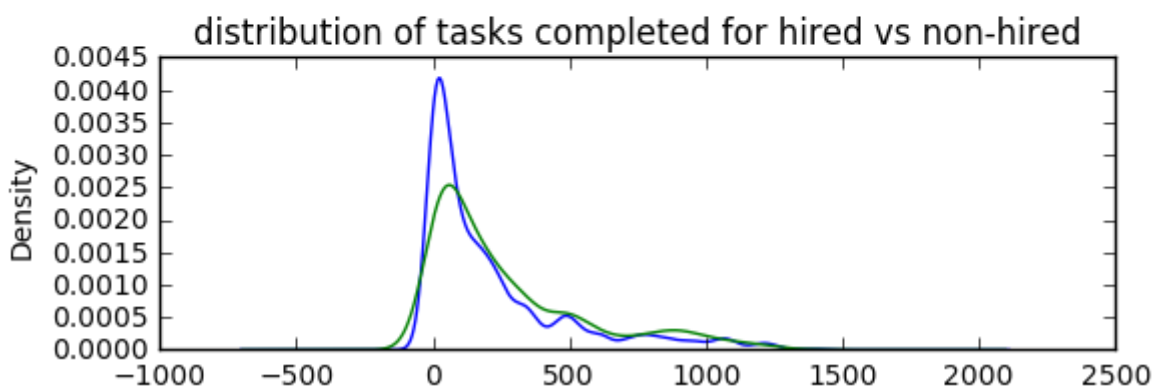
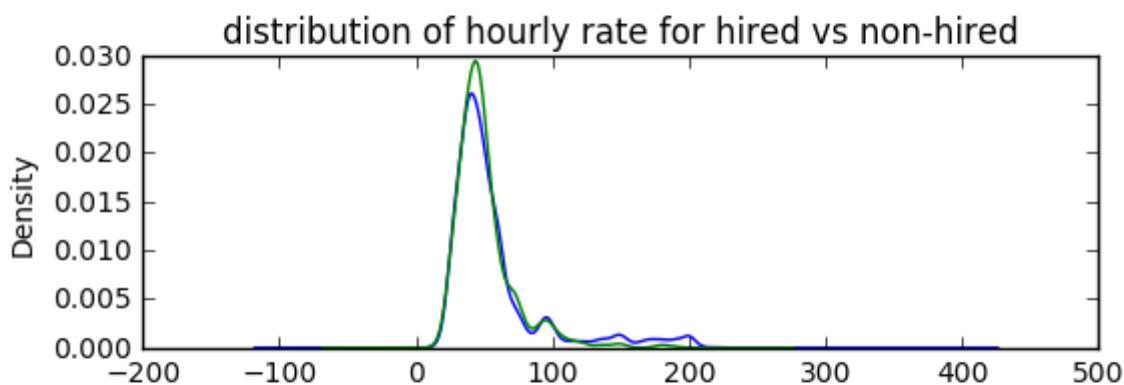
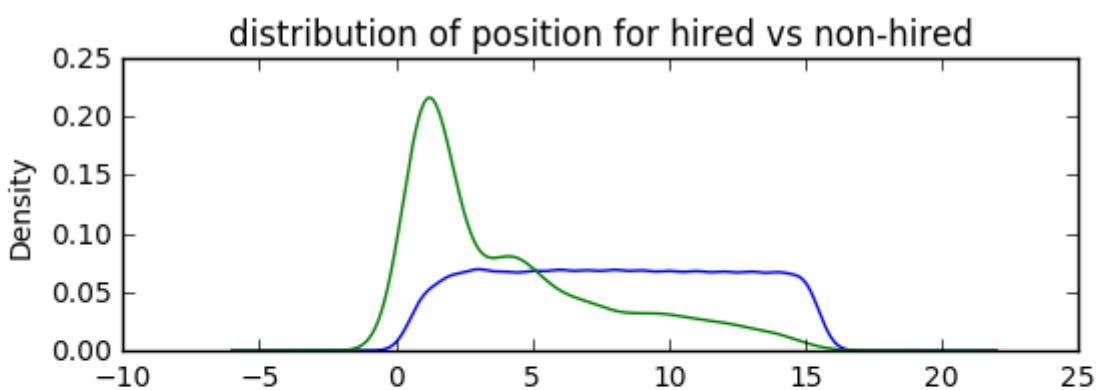


- From the above tables we see a clear difference in the position of people who are hired. They are having a mean in the range of 3-5 while the non-hired people have a mean around 8
- Also if we see the average hourly rate of hired vs non-hired vs overall dataset, they almost remain the same. Also people who are hired are having higher average of previous number of tasks than non-hired
- From this we can consider that position would surely affect the probability of getting hired, but the hourly rate and number of previously completed tasks also should be considered. Generally clients prefer the ones with lesser hourly rate and higher number of previous tasks completed in the same category
- The probability of hiring is inversely proportional to position and hourly rate and directly proportional to number of previously completed tasks
- With this in mind, since we are handling a case of probability of hiring which is a binomial distribution, we can model this data with binomial logistic regression

In [16]:

```
#Plott of distributions for hired vs non hired for all the variables
import matplotlib.pyplot as plt
fig, axes = plt.subplots(nrows=3)
pc12 = df8['position'].plot(kind='density',ax = axes[0],title= "distribution of position for hired vs non-hired")
pc11 = df7['position'].plot(kind='density', ax = axes[0])
pc22 = df8['hourly_rate'].plot(kind='density',ax= axes[1],title= "distribution of hourly rate for hired vs non-hired")
pc21 = df7['hourly_rate'].plot(kind='density',ax = axes[1])
pc32 = df8['num_completed_tasks'].plot(kind='density', ax = axes[2],title= "distribution of tasks completed for hired vs non-hired")
pc31 = df7['num_completed_tasks'].plot(kind='density',ax = axes[2])
fig.tight_layout()

fig.set_figheight(8)
fig.set_figwidth(6)
plt.show()
```



- Logistic regression model calculates the log of odds ratio which would make it easy for us to estimate the probability of change in success for change in the independent variable. Formula we use for logistic regression is  

$$\log(p/1-p) = a + b_{position} + c_{hourly\_rate} + d_{num\_completed\_tasks}$$
- Since logistic regression does not have assumptions of data normalization, preprocessing the data is not needed as of now

In [17]:

```
## code for running logistic regression with the above formula
import statsmodels.api as sm
X = df[['position', 'num_completed_tasks', 'hourly_rate']]
X['intercept'] = 1
Y = df[['hired']]
logit = sm.Logit(Y, X)
result = logit.fit()
result.summary()
```

Optimization terminated successfully.  
 Current function value: 0.190719  
 Iterations 8

Out[17]:

Logit Regression Results

<b>Dep. Variable:</b>	hired	<b>No. Observations:</b>	30000
<b>Model:</b>	Logit	<b>Df Residuals:</b>	29996
<b>Method:</b>	MLE	<b>Df Model:</b>	3
<b>Date:</b>	Mon, 06 Nov 2017	<b>Pseudo R-squ.:</b>	0.1258
<b>Time:</b>	00:42:42	<b>Log-Likelihood:</b>	-5721.6
<b>converged:</b>	True	<b>LL-Null:</b>	-6544.9
		<b>LLR p-value:</b>	0.000

	coef	std err	z	P> z	[95.0% Conf. Int.]
<b>position</b>	-0.2656	0.008	-32.733	0.000	-0.281 -0.250
<b>num_completed_tasks</b>	0.0010	9e-05	11.338	0.000	0.001 0.001
<b>hourly_rate</b>	-0.0056	0.001	-5.180	0.000	-0.008 -0.003
<b>intercept</b>	-1.1885	0.064	-18.708	0.000	-1.313 -1.064

- All the three variables are significant in the model. Let us now consider the coefficients of model and find their impact on probability of getting hired.
- Impact of position on probability of getting hired :  

$$(\exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value}) - \exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value} + 1)) / 100 / \exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value} + 1)$$

We get this to be 34.82. This means that if the position value decreases by 1 keeping all the remaining variables constant, the probability of hiring goes up by 34.82 %

- Impact of position on hourly rate of getting hired :

$$\frac{(\exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value}) - \exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value} + 5))}{\exp(\text{intercept} + \text{coefficient\_position} \times \text{position\_value} + 5)} \times 100$$

We get this to be 4.86. This means that if the hourly rate decreases by 5\$ keeping all the remaining variables constant, the probability of hiring goes up by 4.86 %

- So the hourly price can be reduced slightly than the actual hourly rate of the person if as tasker's position is >5 to fancier the chances of tasker getting hired. If the tasker is in the top 5 positions, then you can go by suggesting the hourly rate of that person.