TalkingData

Predicting consumer demographics

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Problem

- Businesses need to be smart to survive in the competitive business world
- Have to, at the bare minimum, be mindful of:
  - Knowing what their clients need
  - Being able to meet that demand
  - Attracting new clients
- Need to properly interpret and make use of the data

Project Description

- TalkingData
  - China's largest data intelligence solution provider
  - Founded in 2011

- Using their data, predict a mobile user's demographic group (gender & age group)

TalkingData
Mobile·Data·Value

Data Acquisition

- Data acquired from a Kaggle competition
- Data source comprised of 8 separate CSV files:
  - app_events.csv
  - app_labels.csv
  - events.csv
  - gender_age_test.csv
  - gender_age_train.csv
  - label_categories.csv
  - phone_brand_device_model.csv
  - sample_submission.csv

Data Wrangling

- Most of the datasets were too large to process on a single machine
- Dask
  - Large datasets spread over multiple nodes
  - Enables parallel computation
  - Full support for Python (unlike Spark, a popular alternative)

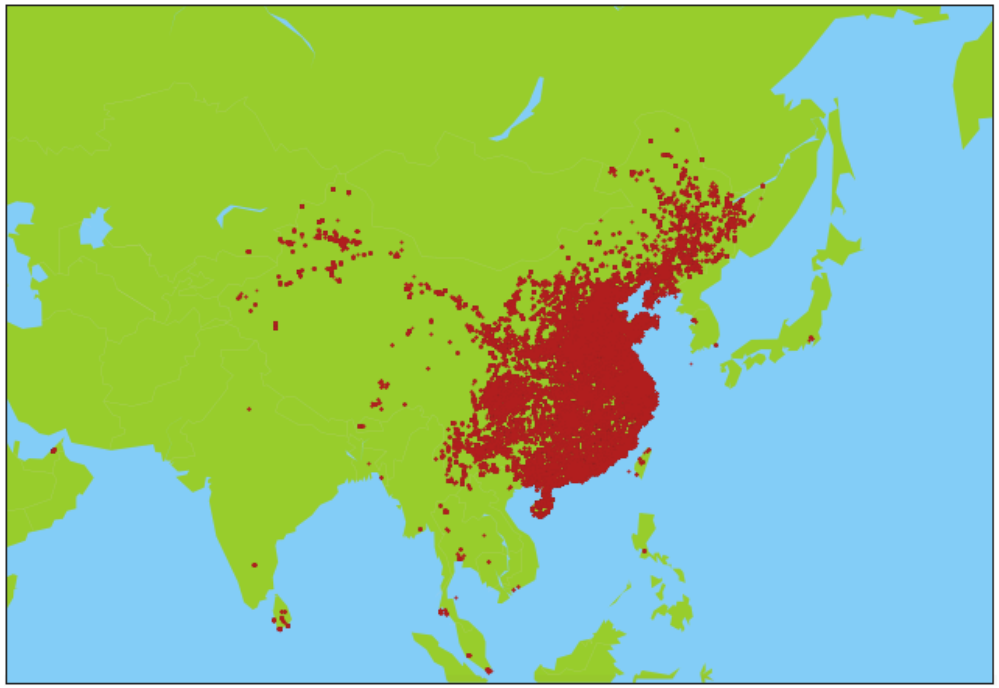
```
app_events = dd.read_csv('talkingdata/app_events.csv')
app_labels = dd.read_csv('talkingdata/app_labels.csv')
events = dd.read_csv('talkingdata/events.csv')
train = dd.read_csv('talkingdata/gender_age_train.csv')
label_categories = dd.read_csv('talkingdata/label_categories.csv')
phone_brand_model = dd.read_csv('talkingdata/phone_brand_device_model.csv')
```

Data Wrangling

- No missing values
- Create new column: "app_count"
  - Only attainable through merging multiple tables
  - Grouped by "device_id" after each merge to remove duplicates and get app count

	device_id	gender	age	group	app_count	phone_brand	device_model
0	-8260683887967679142	M	35	M32-38	53	小米	MI 2
1	7477216237379271436	F	37	F33-42	26	华为	荣耀6 plus
2	6352067998666467520	M	32	M32-38	19	华为	荣耀畅玩4X
3	8026504930081700361	M	25	M23-26	31	小米	MI 4
4	-7271319853104672050	M	27	M27-28	34	三星	Galaxy Note 3

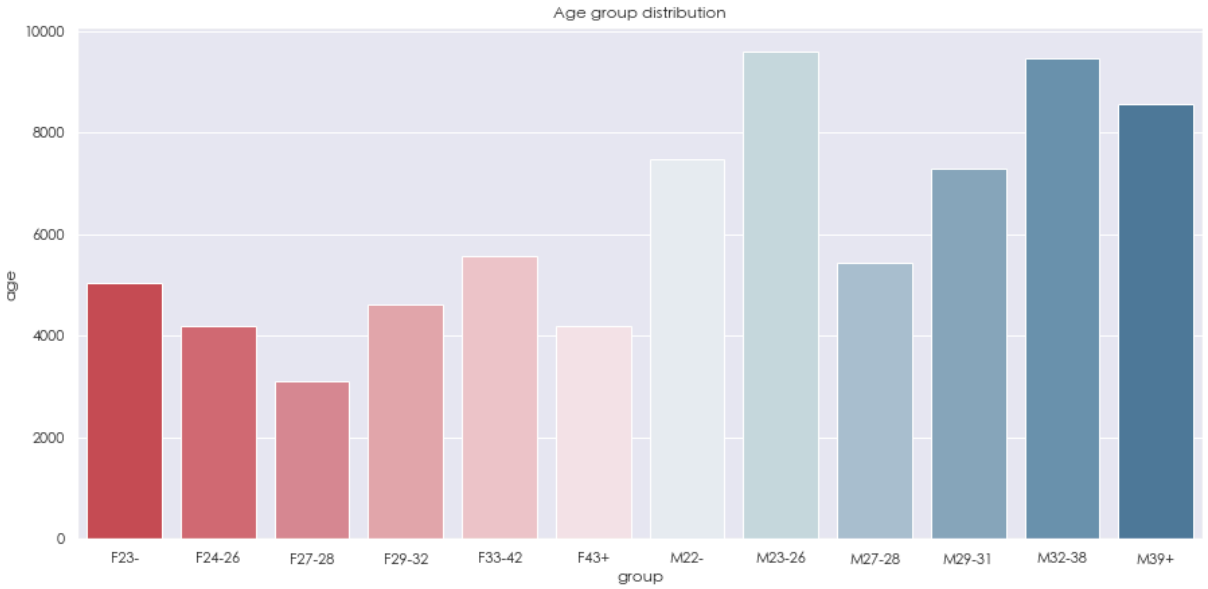
Exploratory Data Analysis



- Majority of data gathered from eastern region of China
  - 5 most populous cities (Shanghai, Beijing, Tianjin, Shenzhen, Guangzhou) are located in eastern China

Exploratory Data Analysis

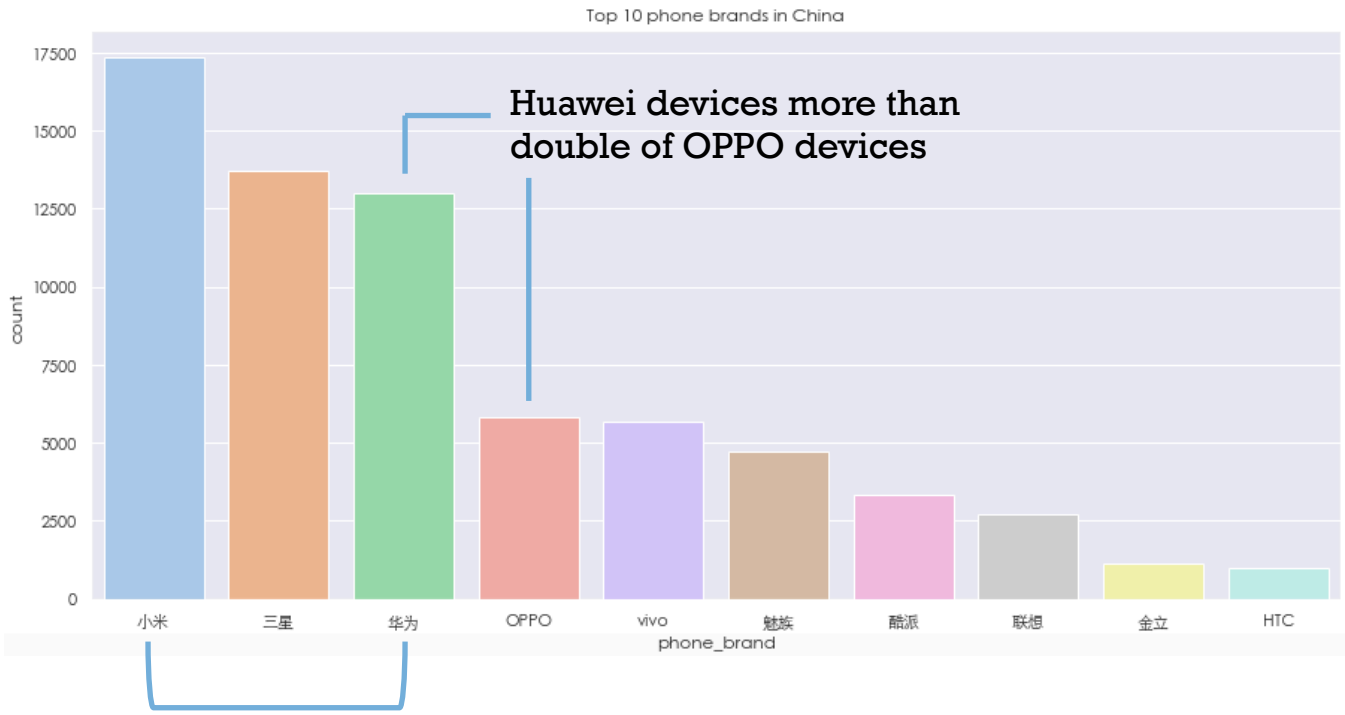
Bar chart of age group distribution



- Top two age group (female): under 23 and 33-42
- Top two age group (male): 23-26 and 32-38
- Gender imbalance in dataset, but *is* representative of the Chinese population because male population outnumbers female population by at least 30 million

Exploratory Data Analysis

- Top 10 mobile phone brands in China

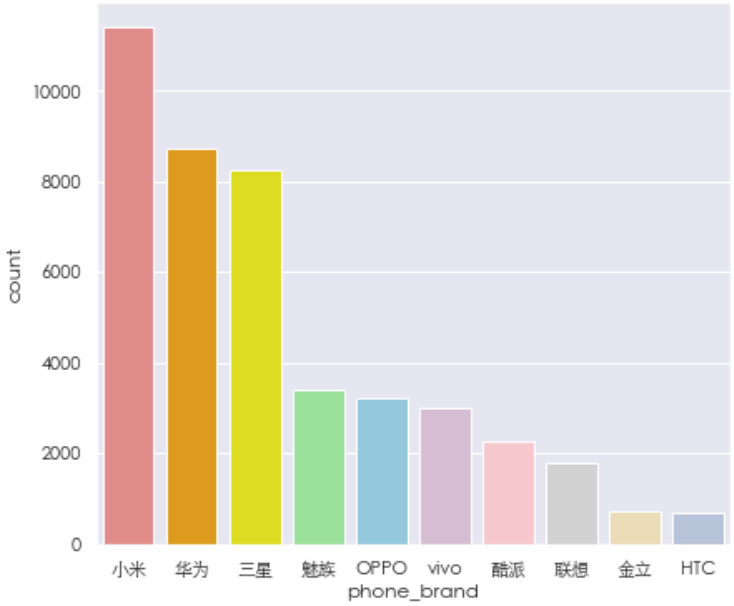


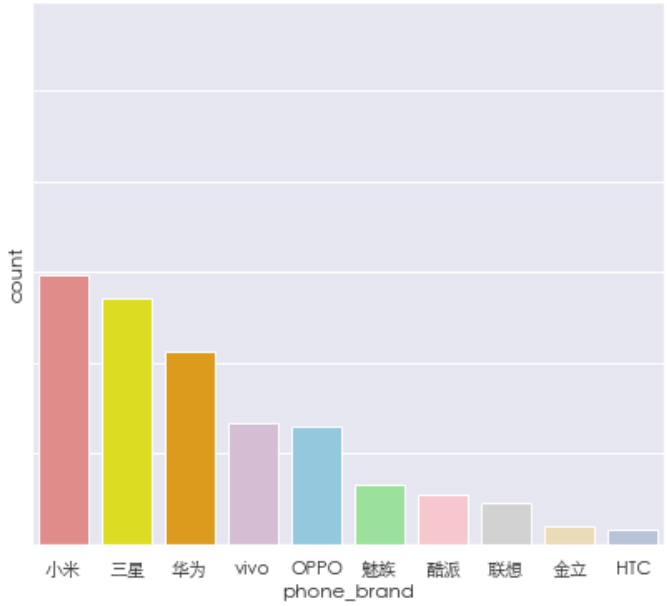
	phone_brand	count
47	Xiaomi	17336
14	Samsung	13706
29	Huawei	13001
6	OPPO	5802
12	vivo	5658
117	Meizu	4710
106	Coolpad	3349
91	Lenovo	2695
109	Gionee	1124
1	HTC	1015

Leading by a staggering amount

Exploratory Data Analysis

- Chinese men and women have slightly different preferences when it comes to mobile devices

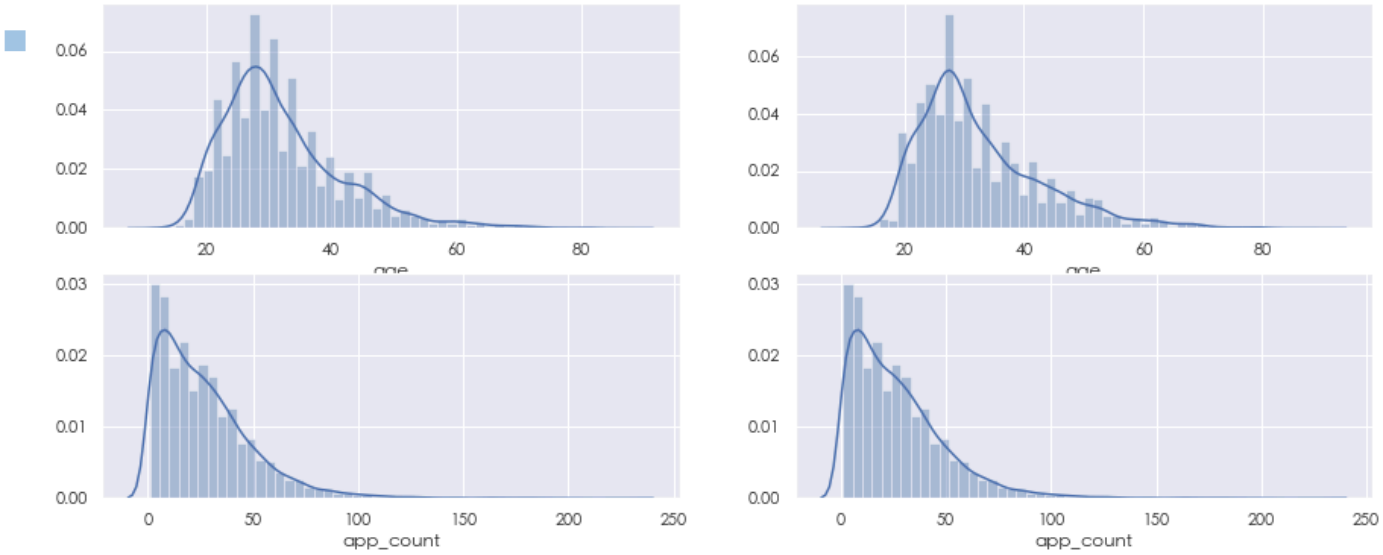




- Huawei & Meizu devices more popular to men
- Chinese women more likely to get a Samsung over Huawei

Inferential Statistics

- Most, if not all, features in this dataset have skewed distributions



- Mann-Whitney U test
  - Tests whether two samples are likely to derive from the same population

Inferential Statistics

- Null hypotheses:
  - The distributions of age between genders are the same
  - The distributions of number of apps per device by gender are the same
- Significance level: 0.05

```
Mann Whitney U p-value (age): 0.053658866312685l8
```

1. Distributions of age between genders are the same
   - P-value is slightly larger than 0.05
   - Fail to reject null hypothesis

```
Mann Whitney U p-value (number of apps): 1.41087243517370 35e-13
```

2. Distributions of number of apps are *not* the same
   - P-value is significantly smaller than 0.05
   - Reject null hypothesis

Machine Learning

- Random Forest Classifier
- Combine brand and model into one column

phone_brand	device_model
小米	MI 2
华为	荣耀6 plus
华为	荣耀畅玩4X
小米	MI 4
三星	Galaxy Note 3

phone
小米 MI 2
华为 荣耀6 plus
华为 荣耀畅玩4X
小米 MI 4
三星 Galaxy Note 3

  - Men and women seem to have slightly different preferences in mobile phone brands
  - Use phone to predict demographic group

Machine Learning

- Machine learning algorithms have difficulty working with categorical data
  - Use a method called Feature Hashing to convert each unique phone value to a hash value

	app_count	0	1	2	3	4	5	6	7	8	...	880	881	882	883	884	885	886	887	888	889
0	53	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	26	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	31	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	34	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Machine Learning

- Result of model performance

```
RANDOM FOREST CLASSIFIER
------------------------
F1 score: 0.1044042469524184
```

- F1 score is a metric that measures accuracy
  - F1 score close to 1 indicates predictions are quite accurate
  - Looking at just the kind of phone and number of apps is not enough

Conclusion

- Poor model performance
- Ideas to improve performance (NEXT STEPS):
  - Utilize text mining and/or Natural Language Processing (NLP) techniques to analyze mobile app label categories
    - 900+ unique label categories in dataset
    - Different gender/age group possibly interested in different kinds of mobile apps
    - App categories should improve model performance
  - Analyze app usage based on time of day