Classified

Team members:
Jordi Beernink
Gerdriaan Mulder
Thijs Werrij
Jeffrey Luppes
Roel Bouman

Machine Learning in Practice, 2017

Outline

- 1. Introduction
- 2. Approach
- 3. Results
- 4. Other Ideas
- 5. Future
- 6. Conclusion

Introduction: Team members and roles

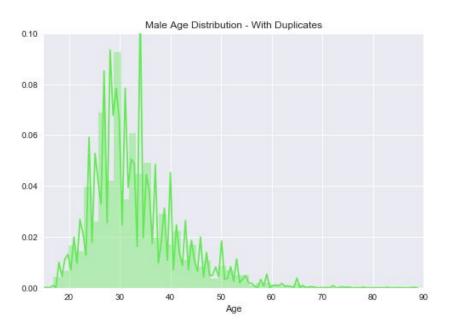
- Jordi Beernink
 - Coordination, pre-processing, XGBoost implementation
- Gerdriaan Mulder
 - Pre-processing, repository manager
- Thijs Werrij
 - Deep learning
- Jeffrey Luppes
 - Classification
- Roel Bouman
 - Pipeline and classification

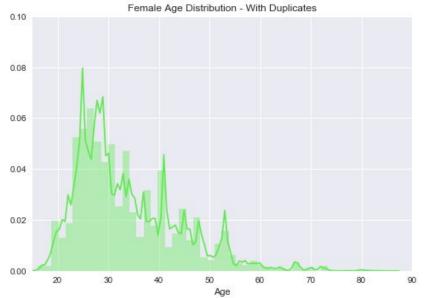
Introduction: Problem description

- TalkingData is the largest third-party mobile data platform
- Seeking to leverage behavioral data for more than 70% of the 500 million mobile devices active daily in China to help its clients better understand
 - "Nothing is more comforting than being greeted by your favorite drink just as you walk through the door of the corner café." TalkingData competition page
- Predict user demographic based on:
 - application usage, phone brand and location
- Demographic to predict given a device:
 - Gender (male, female)
 - Age class (6 categories per gender, e.g.: 23-, 29-33, 43+ etc.)

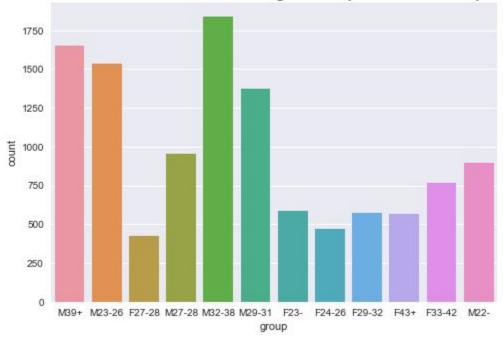
Introduction: Dataset

- About 1,2GB of CSV files
- Structure per CSV file:
 - App_events (event_id/app_id/is_installed/is_active)
 - App labels (app id/label id)
 - Events (event_id/device_id/timestamp/coordinates)
 - Gender_age_train (device_id/gender/age/group)
 - Gender_age_test (device_id)
 - Phone_brand_device_model (device_id/phone_brand/device_model)

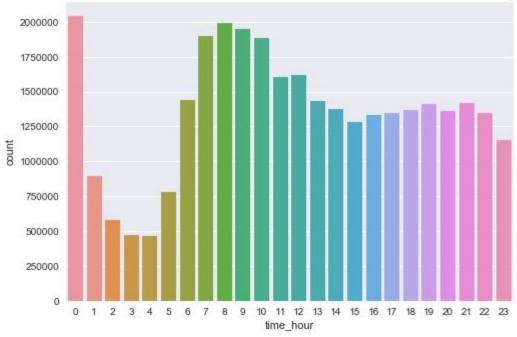




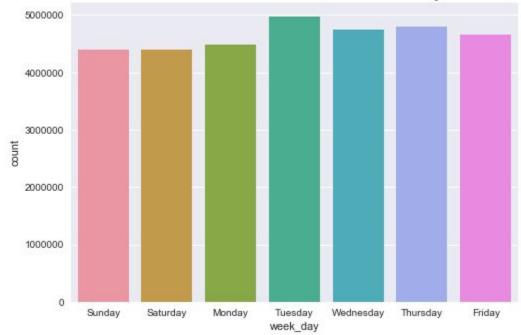
Universal Total Information - Age Group - Without Duplicates



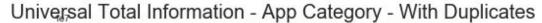
Universal Total Information - Event Count Hour - With Duplicates

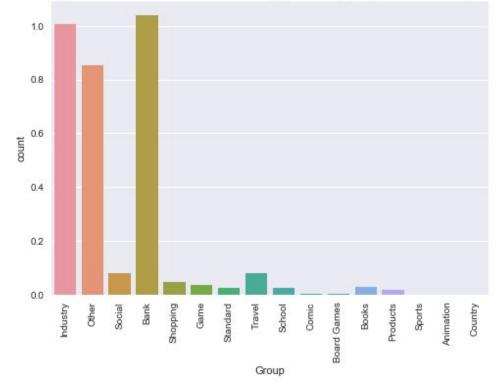


Universal Total Information - Event Count Weekday - With Duplicates



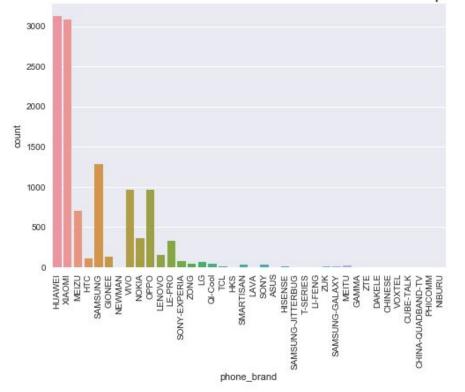
- 1. Bank
- 2. Industry
- 3. (Other)
- 4. Travel
- 5. Social





- 1. Huawei
- 2. Xiaomi
- 3. Samsung
- 4. Vivo / Oppo
- 5. Meizu

Universal Total Information - Phone Brand - Without Duplicates



- Predictors
 - Apps
 - App Category
 - Brands
 - Models

- Problems
 - Missing data
 - Geographic coordinates did not make sense
 - Class imbalance
 - 40% of device users were male older than 32
 - 15% of device users were female

Approach: Pre-processing

- First situation
 - All the CSV files were combined (resulting in 4,2GB dataset)
 - Sparse data
 - Missing properties of the mobile devices (owner, brand...)
 - About 66% of the devices did not participate in any event

- Second situation
 - Combing .csv files based on device properties and installed apps
 - Creating sparse csr matrix for the features

Approach: Feature Extraction

- First situation
 - Creating normalized co-occurrence matrices of possible combinations
 - Timestamp
 - Brands
 - Device
 - Location
 - Apps
- Second situation
 - One Hot Encoding the different device properties
 - Apps installed
 - Phone brand
 - Phone device model

Approach: Classifiers

- Random Forests/Logistic Regression
- XGBoost
- Deep learning
 - Keras (library for Theano and Tensorflow)
 - Three layers (Dense, Dropout and PReLU)
 - Dense: standard densely-connected neural network
 - Dropout: compensation for overfitting
 - PReLU: Parametric Rectified Linear Unit; adaptively learns the parameters of the rectifiers and improves accuracy

Results: Kaggle Rankings

Random Forest

Score: 3.2 Rank: 1667/1689

LogisticRegression

Score: 2.265 Rank: 666/1689

XGBoost

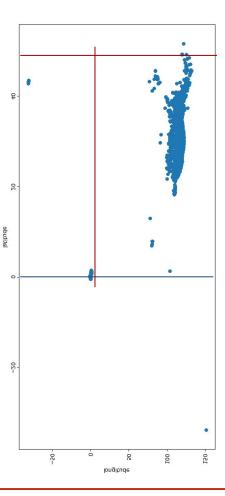
Score: 2.26853 Rank: 777/1689

Deep learning

Score: 2.25992 Rank: 645/1689

Other Ideas

- Geolocation (distance travelled, travel patterns)
 - No guarantees on accuracy of lat/long data
 - Odd points (e.g. 0,00N 0,00E)
 - Distance travelled varied from 0 to 160km / day
 - Reverse geocoding (i.e. extract addresses)
- Weighted categories



For the next competition

- Focus on pre-processing
- Optimalization of parameters
- Exploring the possibilities of XGBoost and DeepLearning

Conclusion

Thanks for listening!