Kobe Bryant Shot Selection

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Introduction

This report analysed the Kaggle playground challenge Kobe Bryant's shot selection. Various models were run for this project:

1. XGBOOST in Python
2. XGBOOST in R
3. TensorFLOW DNN in Python
4. sklearn (random forest, logistic regression, linear discriminant analysis, K-NN, decision tree, naive bayes, extra tree, adaboost, and gbm) in Python

The final result was 0.60126 on LB (99th position).

Main scripts

The script that was used to generate the final score was xgboost_final.ipynb.

Other scripts:

- xgboost.R (ran locally) – basic xgboost in R.
- show-me-your-best-model.ipynb (ran on Kaggle kernel) – a forked public notebook containing exploratory data analysis, feature selection, and various sklearn models.
- models_war.py (ran on Kaggle kernel) – various sklearn models (made into a script from "show-me-your-best-model.ipynb").
- tensorflow.ipynb (ran using GCP docker) – tensorflow deep neural network classifier.
- temporal_spatial_eda.ipynb (ran on Kaggle kernel) – a forked public notebook containing exploratory data analysis results related to Kobe's psychology into the game.

Feature selection

Based on insights gleaned from the exploratory analysis of the data, I decided that the following features should be dropped:

- shot_id (used as index, not included as a feature)
- team_name (only one category)
- team_id (only one category)
- game_event_id (unique within a game, not related to shots made)
- game_id (redundant information already contained in matchup/opponent)
- lon (correlated with loc_x)
- lat (correlated with loc_y)

In all instances of the models (sk-learn, xgboost, and tensorflow), the following (raw) categorical variables are converted to columns of 0/1 with one-hot encoding:

1. action_type
2. combined_shot_type
3. period
4. shot_type

5. shot_zone_area
6. shot_zone_basic
7. shot_zone_range
8. opponent

Model selection

For model selection, I built on a public script that explored multiple models in scikit-learn including Logistic Regression, Linear Discriminant Analysis, K-Nearest-Neighbor, Decision Tree, Naive Bayes, Random Forest, Extra Trees, Adaboost, and GBM. Interestingly, the models performed quite well on cross-validation (~0.6xx), but when I submitted the output, the results were very poor (~1.0 logloss).

At first, I thought it was the feature selection process that introduced the overfitting (as it involved selecting top 20 features according to Random Forest Classifier and Recursive Feature Elimination using Logistic Regression Classifier), but it became evident that this overfitting had to do with the data leakage after I reproduced a similar score even after removing the automated feature selection process.

Therefore, I had to use another strategy for this challenge: XGBOOST was the best next thing to do. Using this starter script: XGBOOST in Ras a starting template, I modified the feature selection and used one-hot-encoding to handle the categorical variables (c.f. xgboost.R) and managed to get ~0.607 logloss (local CV and LB). Furthermore, doing my own feature selection and using one-hot encoding for the categorical variables (the starter script simply converted the categorical variables to ordered integers) gave me 0.606 on LB!

Using tensorflow in Python (c.f. tensorflow.ipynb), I also managed to achieve ~0.66 logloss on LB, but the training time was too expensive as it exceeded Kaggle's kernel limit with only 4 hidden layers (~50 neurons each) so I had to use GCP docker on my laptop.

Due to the accuracy and efficiency of XGBOOST, I concluded that the best strategy for this competition would be to do some advanced feature engineering and feed the engineered features to XGBOOST. Using this strategy, I managed to improve my LB score from 0.606 (basic XGBOOST) to ~0.604 then ~0.603 with progressively more features added...

Figure 1: Leaderboard score comparison between XGBOOST in Python, Random Forest (sklearn) and TensorFlow)

Feature Engineering

Time remaining

I combined seconds_remaining and minutes_remaining into a single variable time_remaining. Furthermore, I created a flag of whether it's last 5 seconds of the period (it has been shown that Kobe's last-minute shots tend to be more desperate). Two additional variables (seconds_from_period_start and seconds_from_game_start) were also created from combination of the variable time_remaining and the variable period.

Home game vs Away game

I also created a flag of whether it's home game for LA Lakers, using the information from matchup (it's home game if it is written like "LA vs X", away if it's like "LA @ X").

Extraction of temporal features

I extracted the year and month of game date because this may provide some seasonal information on Kobe's performance. In addition, the day of the week and the day of the year may also be of some importance. As day of week and time of year are cyclical, I converted them to radian and take the sine/cosine values (c.f. last_shot_feature.ipynb – not included in the final xgboost model because this radial transformation did not improve xgboost's performance).

Level reduction of categorical variables

The 20 least-common action types were replaced with 'Other'.

One-hot encoding

Each unique level of categorical variables was converted into a column of binary (0/1).

Shot location clusters

Another exploration was to use Gaussian mixture models to cluster the locations of shot attempts. Following temporal_spatial_eda.ipynb, I specified 13 clusters based on loc_x and loc_y. However, this shot location cluster was not included in the final XGBOOST model because it did not improve the final score.

Last shot status

A flag on whether the last shot that Kobe attempted was made or missed (cf last_shot_feature.ipynb). This feature did not improved the final score of xgboost.

Future work

Aside from hyperparameter tuning of the xgboost model (due to time constraint I had to skip the grid search process and resort to hand-tuning), there were other potential things to try:

- feature interaction using tensorflow's cross_column
- hyperparameter tuning of tensorflow's deep NN
- ensemble of xgboost and DNNclassifier
- exploring the data leak

Conclusion

A single model xgboost without much feature engineering performed very well. XGBOOST is really efficient in identifying non-linear interactions between features that not much feature engineering was required to get a good score (in fact several features that I generated ended up not used because they did not improve the final score by XGBoost).

References

I would like to credit the discussion forums and public kernels in this competition; some notebooks in the public kernels would take significant effort to produce – without them it wouldn't be possible for me to produce the results in this report within such a short time.