Outline

- Data Introduction
- Evaluation Criterion
- Possible Directions
- Practical Issue
Data Introduction

The data sets origin from our validation set blending process in the track 2 of KDDCUP2012.

The track 2 of KDDCUP2012

- Task: predict click-through rate of ads on search engine.
- Data: 155,750,158 training instances, over 10 GB data sets.
- Goal: Maximize AUC among those instances.
- Difficulties: Huge data sets and feature extraction.
- Key to our success:
  - Explore useful features from the data.
  - Exploit diverse set of model.
  - Use blending to enhance the diversity, and boost the performance.
Validation set blending

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3. Split V into sub-training(V1) and sub-testing(V2) sets.

4. Use models in step 2 to get predictions on both V and test set.
5. Create features of V1, V2 and testing data sets for validation set blending, including the predictions of models in step 2 and some optional extra features.
6. Treat V1 as the new training data and V2 as the new validation data, then do training to predict on the test set.
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Validation set blending (cont.)

Benefits:
- Validation set blending works when single models have enough diversity.
- The training size is much smaller than training for single models, we can try more complicated algorithms and feature engineering.
- We get about 1% improvement in the last week of the competition.

Data sets of final project

- 40,000 training examples, and 50,000 test ones.
- Binary label and each example contains 71 features.
- All training and testing examples are sampled from our validation set (V) of track2 of KDDCUP2012.
- The features including 45 single model predictions and 26 numerical features we extract from the raw data.
The ROC Curve
Receiver Operating Characteristic

- **True Positive Rate** = \( \frac{TP}{P} \)
- **False Positive Rate** = \( \frac{FP}{N} \)
The ROC Curve
Receiver Operating Characteristic

- Each point on the curve correspond to an (TP, FP) pair.
- Imagine as we incline to report more positive instances, both TP and FP increases.
Typical Ranking Scenario & ROC Curve

![Graph showing True positive rate vs False positive rate with data points and an ROC curve]

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<th>Class</th>
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Area Under Curve (AUC)

- Defined as the area under ROC curve.
Area Under Curve (AUC)

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- Characteristics:
  - Equal to the $P(\text{Rank}(I^+) \leq \text{Rank}(I^-))$
  - Equal to the proportion of “corrected-ranked pair” among all pairs.
  - Measure how well your training model rank positive instances (higher), in a sense.
Calculation of AUC

- Equal to the proportion of “corrected-ranked pair” among all pairs.
- Given a sorted list, we can count the number of “corrected-ranked pair” in $O(n)$.
  - For each Negative item, (accumulately) count how many instances are before it.
The Challenges

What you know so far:
- How to do (binary) classification.
- How to do linear / logistic regression.

The challenge:
- Ranking: output is a sorted list.
  - Bipartite ranking: instance is either positive or negative.
- Missing values.
The Bipartite Ranking Problem

- “Ranking”: give “score” to each instance
  - Similar as in a regression problem.
  - But the binary label in training data could be a problem.
- Want to rank positive instance before negative ones.
  - Not that different with a classification problem.
- Thus, possible strategies:
  - “Score”: use regression techniques.
  - “Pairwise Comparison”: transform to the binary classification problem over pair of examples: $F : (x, x') \rightarrow y$, which measures if $x$ is “better” than $x'$.
  - Any way you can turn a classification prediction into a confidence measure.
Few things to note, though:

- Handle ties with caution. Try to break ties if possible.
- As typical bipartite ranking problems, the samples could be **unbalanced**.
- Be sure to use AUC to measure your performance. (that’s including your validation performance)
Handling Missing Data

- Random values.
- Average values.
- Special label ‘?’ ..?
- Most “likely” values.
  - Look for similar sample?
  - Predict the missing value?
- Use your imagination.
Practical Issue

1. Data Pre-Processing
   - Target normalization
   - Feature normalization
   - Feature engineering

2. Parameter Selection
   - Depends on your data
   - Overfitting and Under fitting
   - Model type selection
   - Tradeoff between training time and performance
   - Stopping criteria: error tolerance

3. Accelerate the whole training procedure
   - Training time v.s. Loading time
   - Local disk v.s. NFS
   - Parallelization
   - Parameter selection
Questions?