Karlsruhe Institute of Technology

SDQ Software Design and Quality

LAMA Presentation
Elo Merchant Category Recommendation

Team Members

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INSTITUT FÜR TECHNIK DER INFORMATIONSVERARBEITUNG

Outline

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1. Overview
   - Motivation and goals
   - Overview of data dictionary
   - Data Processing
2. Model Training
   - Methodology
   - Tools and Models
   - Further Improvement

Motivation and goals

Motivations

- Competition from Kaggle
- Recommendation System is one of the most typical commercial requests
- Many hands-on experience we can refer to
- Many challenges to overcome

Goals

- make a regression model to fit the loyalty of different card owner

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Overview of data dictionary

5 Datasets in all

- train, test datasets that contains features and target
- 3 additional datasets requires features engineering
- total size 3.1 GB
- one of the challenge in our project

Overview of data dictionary

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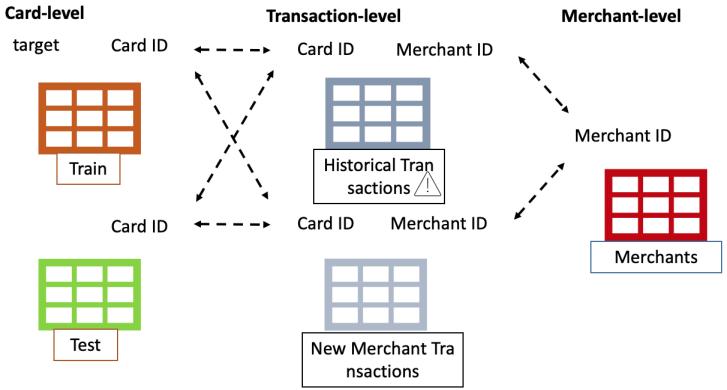

Solution to ease memory pressure

- read dataframe in chunk, process the collections of dataframes as stream pipeline

```
@experimental
class StreamerBuilder(t.Generic[T]):
    """      You, a month ago • fix standarize problem …

    def __init__(self, iterator: It[T]):
        if not isinstance(iterator, t.Iterable):
            raise Exception(
                "Streamer Builder must accept an instance from Iterable")
        self._iterator = iterator
        self._callbacks = []

    def __del__(self):
        # finalize stream
        if isinstance(self._iterator, IOBase) and not self._iterator.closed:
            self._iterator.close()
        del self._iterator

    @staticmethod
    def build(iterator: It[T]) -> StreamerBuilder:
        return StreamerBuilder(iterator)
```

Solution to leverage memory pressure

- python buildin mappings can't tackle with iterators with high dimensions in our case it is a two-dimensional streams

```
    def map(self, function: t.Callable[[T], U]) -> StreamerBuilder:
        """      You, a month ago • first commit …

        def _mapper(iterator: It[T]) -> It[U]:
            for data in iterator:
                yield function(data)

        self._register_callback(_mapper)
        return self

    def filter(self, f: t.Callable[[T], bool]) -> StreamerBuilder:

        def _filter(iterator: t.Iterable[T]):
            for data in iterator:
                if f(data):
                    yield data

        self._register_callback(_filter)
        return self
```

Example in Jupyter Notebook

- another merit is that we can postpone our dataset operations until the stream is consumed. which enables us to define behaviour before actual processing

```
lder = histories_builder() \
            .map(lambda df: reformat_dataframe(df, features, change_
            .map(lambda df: df.merge(df_merchant[cols], how='left',
            .map(convert_columns) \
            .map(add_datetime_index)


csv
lder.consume(lambda df: df.to_csv(transactions_path, mode='a', inc
```

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General operations to all tables

- check nans and drop or fill the rows
- change category to numbers with one-hot-encoder
- analyze features co-variance and visualize data
- write the result back into new csv files

Data distributions

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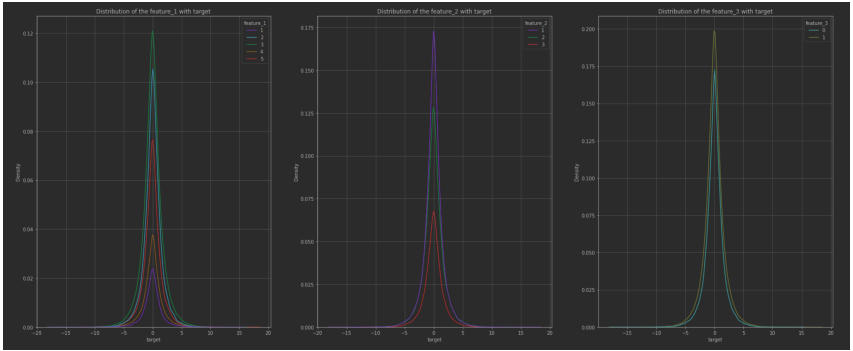

Merging each tables

Merge merchants table with transcations

- Relationships on merge
- Aggregator

Merging each tables

Merge merchants table with transcations

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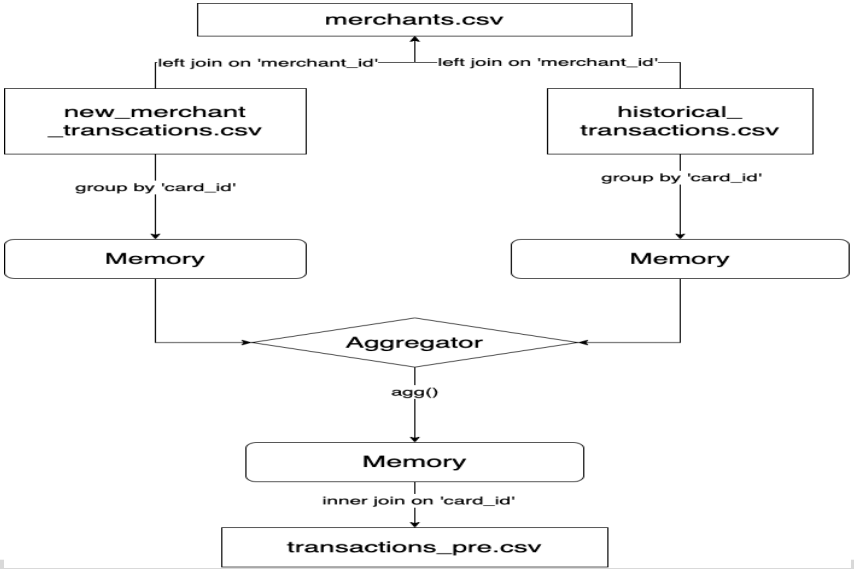
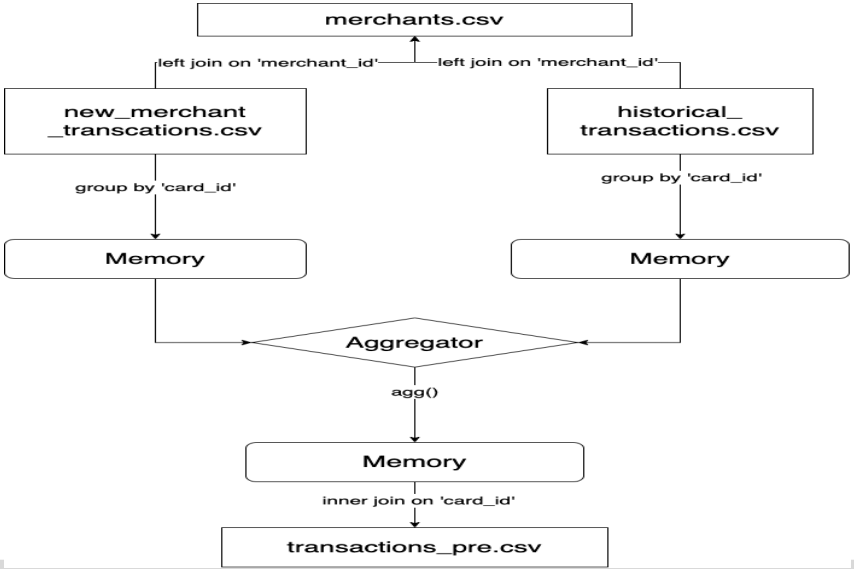
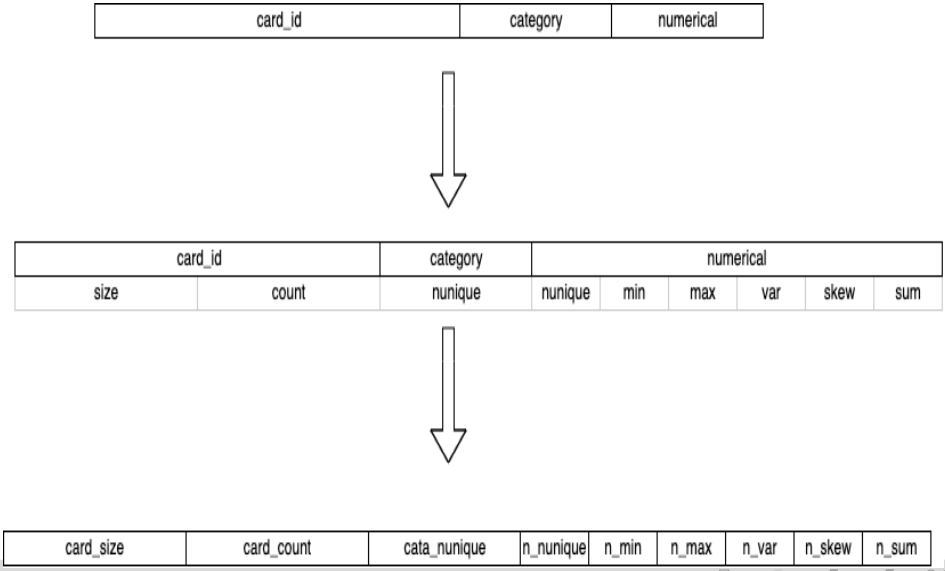
Merging each tables



Merging each tables



Aggregator


card_id
category
numerical
card_id
category
numerical
size
count
nunique
nunique
min
max
var
skew
sum
card_size
card_count
cata_nunique
n_nunique
n_min
n_max
n_var
n_skew
n_sum

Solution to challenge

- group rows with the same key into one
- Transactions table are too large to be read into memory
- Challenges here: How to split the chunk to ensure the rows with the same group by key are in the same table

```
>>> df = pd.DataFrame({'Animal': ['Falcon', 'Falcon',
...                               'Parrot', 'Parrot'],
...                    'Max Speed': [380., 370., 24., 26.]})
>>> df
   Animal  Max Speed
0  Falcon      380.0
1  Falcon      370.0
2  Parrot       24.0
3  Parrot       26.0
>>> df.groupby(['Animal']).mean()
        Max Speed
Animal
Falcon      375.0
Parrot       25.0
```

Stream Group by

- luckily key ids are sorted by name
- make fully usage of space locality, use greedy algorithms

```
authorized_flag,card_id,city_id,category_1,installments,category_3,merch
Y,C_ID_415bb3a509,107,N,1,B,307,M_ID_b0c793002c,1,-0.55757375,2018-03-11
Y,C_ID_415bb3a509,140,N,1,B,307,M_ID_88920c89e8,1,-0.56957993,2018-03-19
Y,C_ID_415bb3a509,330,N,1,B,507,M_ID_ad5237ef6b,2,-0.55103721,2018-04-26
Y,C_ID_415bb3a509,-1,Y,1,B,661,M_ID_9e84cda3b1,1,-0.67192550,2018-03-07
Y,C_ID_ef55cf8d4b,-1,Y,1,B,166,M_ID_3c86fa3831,1,-0.65990429,2018-03-22
Y,C_ID_ef55cf8d4b,231,N,1,B,367,M_ID_8874615e00,2,-0.63300684,2018-04-02
Y,C_ID_ef55cf8d4b,69,N,1,B,333,M_ID_6d061b5ddc,1,5.26369692,2018-03-28 1
Y,C_ID_ef55cf8d4b,231,N,1,B,307,M_ID_df1e022f41,2,-0.55378707,2018-04-05
Y,C_ID_ef55cf8d4b,69,N,1,B,278,M_ID_d15eae0468,2,-0.59664268,2018-04-07
Y,C_ID_ef55cf8d4b,69,N,1,B,437,M_ID_5f9bffd028,1,-0.60719129,2018-03-17
Y,C_ID_ef55cf8d4b,69,N,-1,,45,M_ID_3ffd43b4cd,1,4.45226529,2018-03-31 09
Y,C_ID_ef55cf8d4b,69,N,1,B,108,M_ID_e6f5213fbf,1,-0.60595911,2018-03-11
Y,C_ID_ef55cf8d4b,69,N,1,B,278,M_ID_aa97bc87f6,1,-0.63420896,2018-03-14
```

Stream Group by

- check last row with key of current stream
- yield all items to dataframe (we call it orphans) if key value equals last key values
- concate orphans to chunk at the beginning of each iteration

```python
def stream_groupby_csv(path: str, key: str, chunk_size: int = 10**6, dtype=None) ->
    """…

    with pd.read_csv(path, chunksize=chunk_size, dtype=dtype) as reader:
        orphans = pd.DataFrame()
        for chunk in reader:
            # Add the previous orphans to the chunk
            chunk = pd.concat([orphans, chunk])

            last_val = chunk[key].iloc[-1]
            is_orphan = chunk[key] == last_val

            orphans = chunk[is_orphan]
            yield chunk[~is_orphan]
        # yield orphans if not empty      You, seconds ago • Uncommitted changes
        if len(orphans):
            yield orphans
```

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Model Training

Tree Ensembled Methodology

- Bagging – RandomForestRegressor
- Gradient Boosting – LightGBM, XGBoost
- Stacking – We made our own

Model Training

Bagging

- Learn base learners in parallel, combine to reduce model variance
- Each base learner is trained on a bootstrap sample
- Combine learners by averaging the outputs (regression) or majority voting (classification)

Model Training

Boosting

- Learn weak learners sequentially, combine to reduce model bias
- At step t, repeat:
  - Evaluate the existing learners' errors
  - Train a weak learner f_t, focus on wrongly predicted examples
  - Train learner to predict errors
- Additively combining existing weak learners with f_t.

Stacking

- Combine multiple base learners to reduce variance

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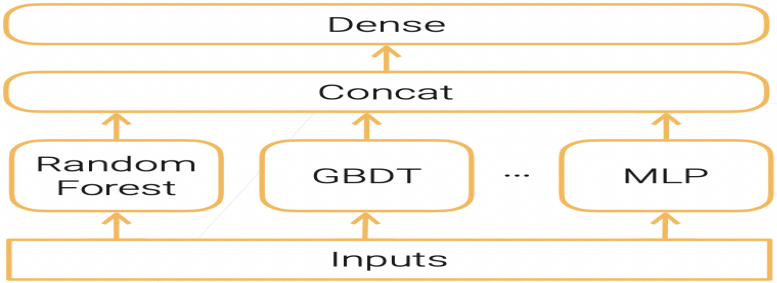
Stacking with one layer

Stacking

- bagging VS stacking
- Bagging: bootstrap samples to get diversity
- Stacking: different types of models extract different features



Tools and Models

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Tools

- sklearn
- lightgbm
- xgboost
- All models are trained with kfold
- plots are plotted with validation and train set

Result with validations random forest

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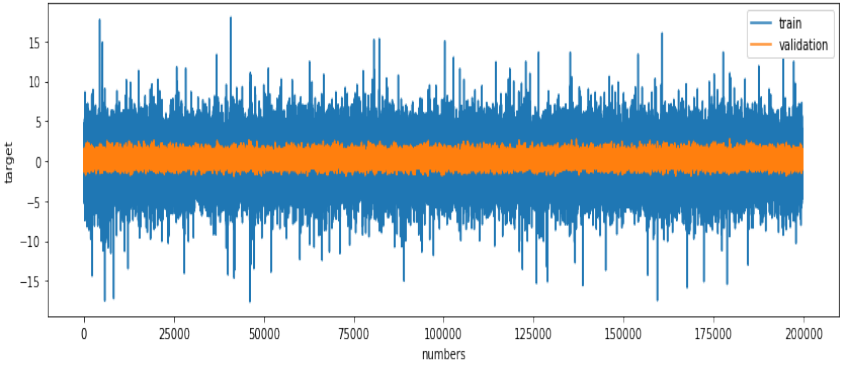

Result with validations lightGBM

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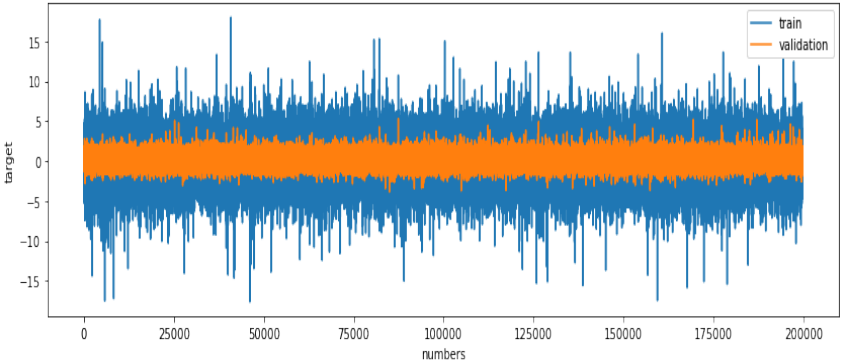

Result with validations xgboost

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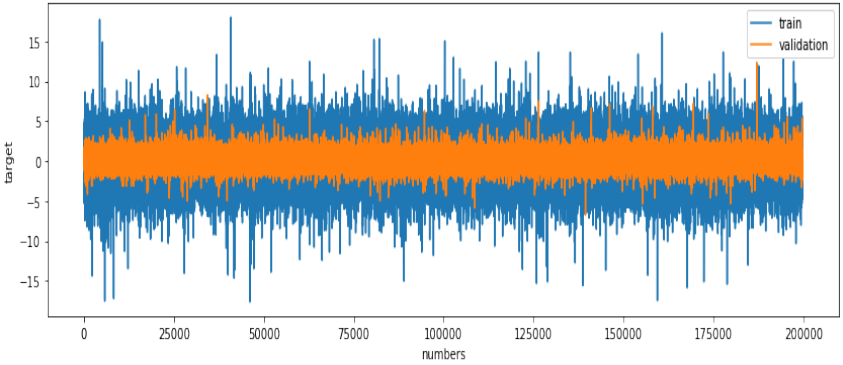

Result with validations xgboost

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submission_stacking_kfold.csv a day ago by Zeyu Li666 add submission details	4.29987	4.39653
submission_stacking.csv a day ago by Zeyu Li666 add submission details	4.47945	4.57733
submission_stacking.csv a day ago by Zeyu Li666 add submission details	4.18149	4.28077
submission_light_gbm_best_params.csv 3 days ago by Zeyu Li666 add submission details	3.78958	3.90831
submission_light_gbm_kfold.csv 3 days ago by Zeyu Li666 add submission details	3.78916	3.90822
submission_random_forest_kfold.csv 5 days ago by Zeyu Li666 kfold	3.81648	3.93563

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Further Improvement

Features Engineering

- Features Engineering improvement
- more visualization with models
- not 100 percent finish