Collaborative Embedding Features and Diversified Ensemble for E-Commerce Repeat Buyer Prediction

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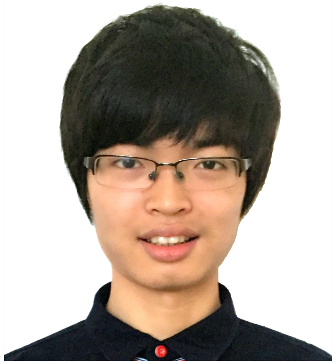
Results

- Team “FAndy&kimiyoung&Neo”
- 2nd place in stage 1
- 3rd place in stage 2
- The only team marching in top 3 of both stages

Team Members

- Zhanpeng Fang
  - Master student, Tsinghua Univ. & Carnegie Mellon Univ.



- Zhilin Yang
  - Bachelor E., Tsinghua Univ.

- Yutao Zhang
  - PhD student, Tsinghua Univ.

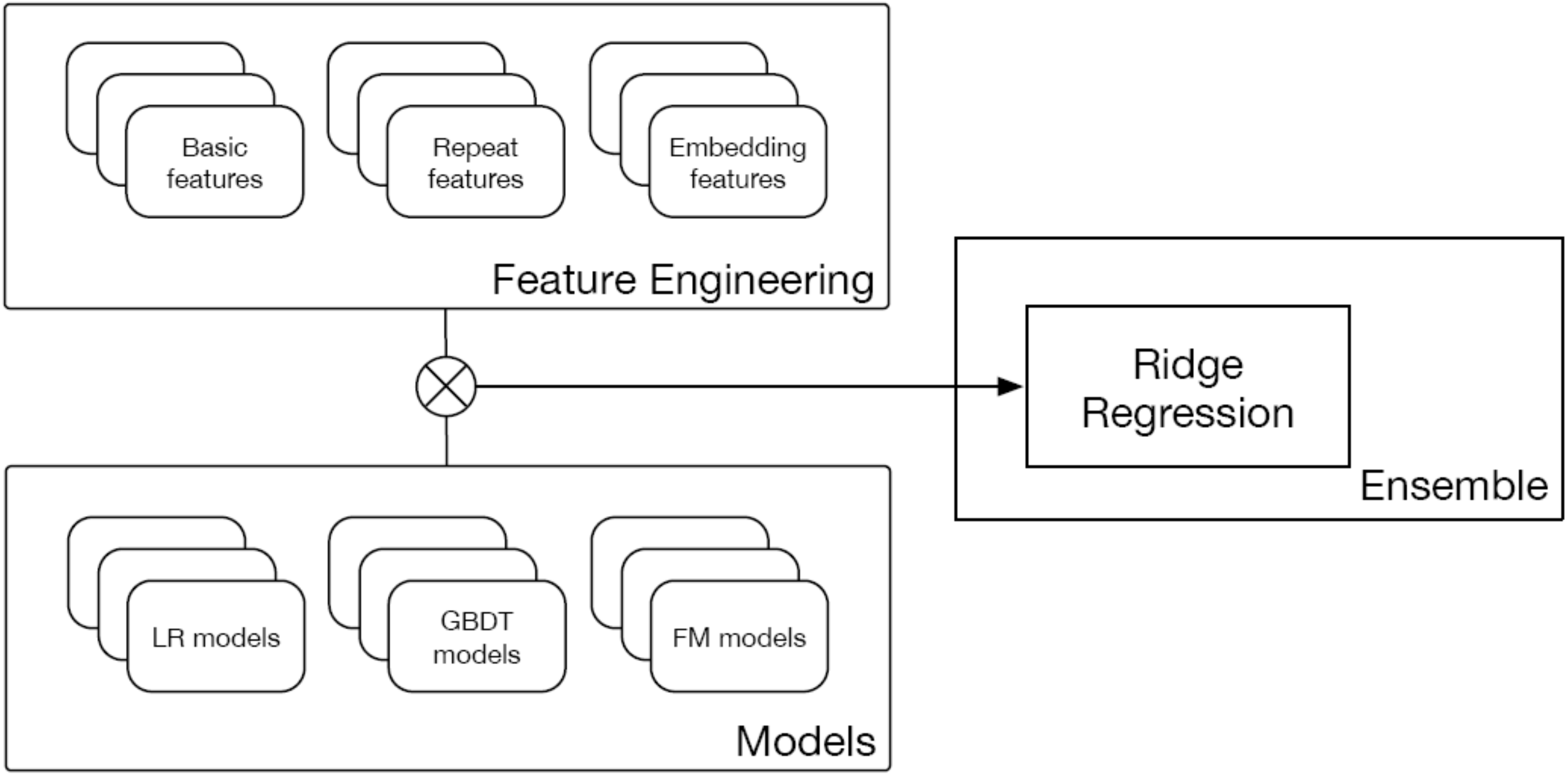
Task

- Input:
  - User behavior logs
    - user, item, category, merchant, brand, timestamp, action
  - User profile
    - age, gender.
- Output:
  - The probability that a new buyer of a merchant is a repeat buyer

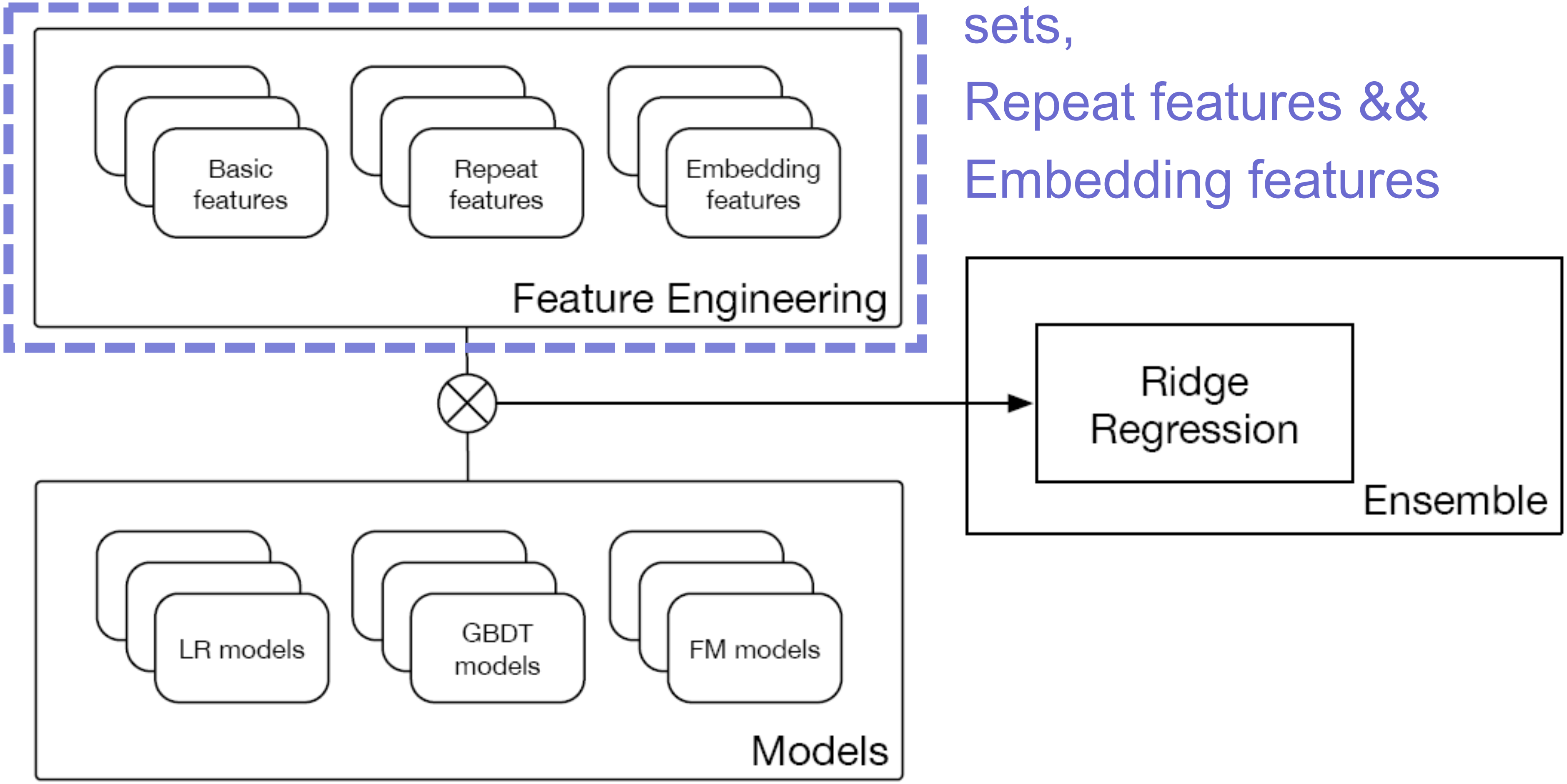
Challenges

- Heterogeneous data
  - User, merchant, category, brand, item
- Repeat buyer modeling
  - What are the characteristic features for modeling repeat buyer?
- Collaborative information
  - How to leverage the collaborative information between users and merchants [in a shared space]?

Framework


Basic features
Repeat features
Embedding features
Feature Engineering
Ridge Regression
Ensemble
LR models
GBDT models
FM models
Models

Framework

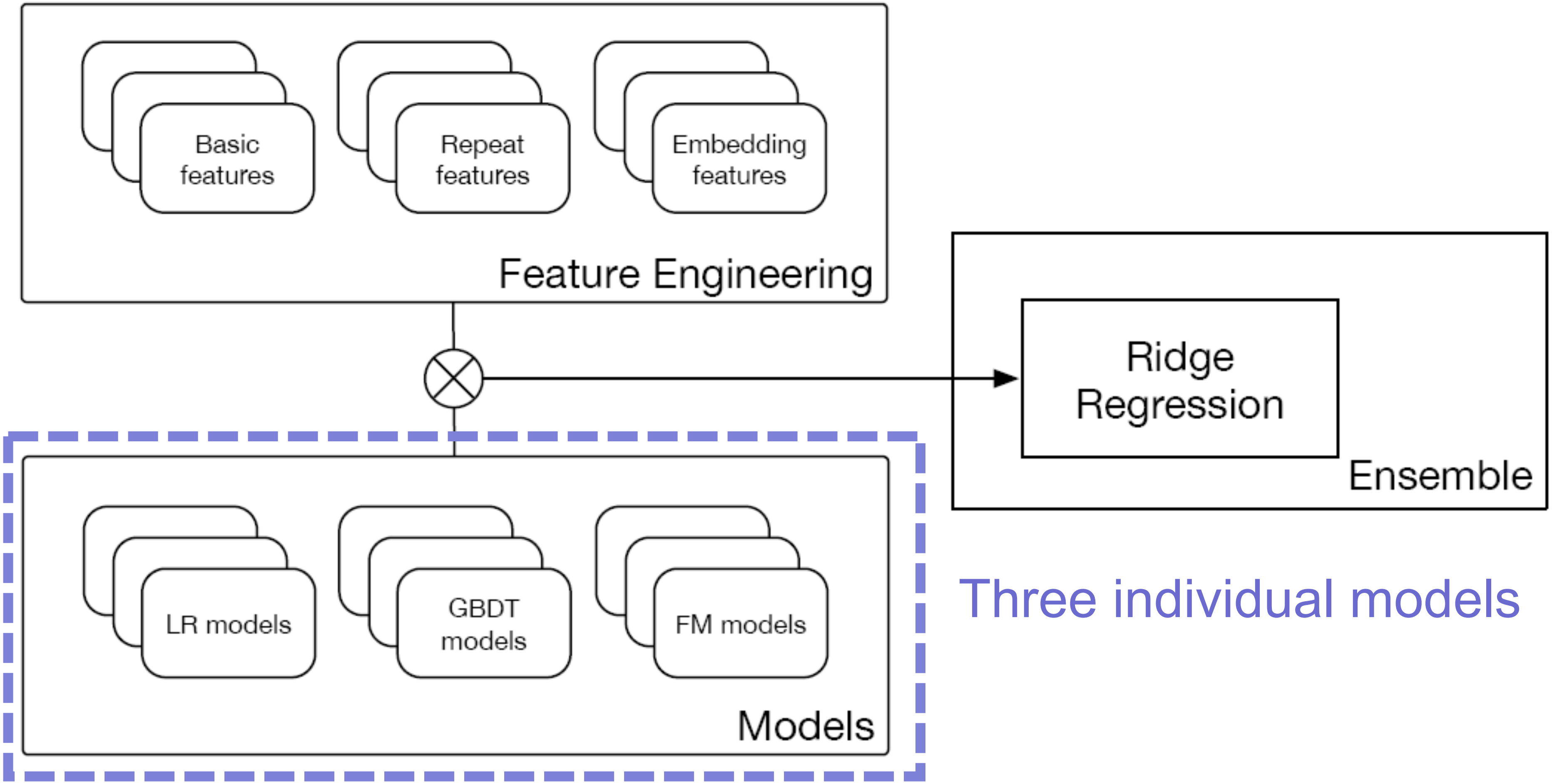


Two novel feature sets,

Repeat features &&

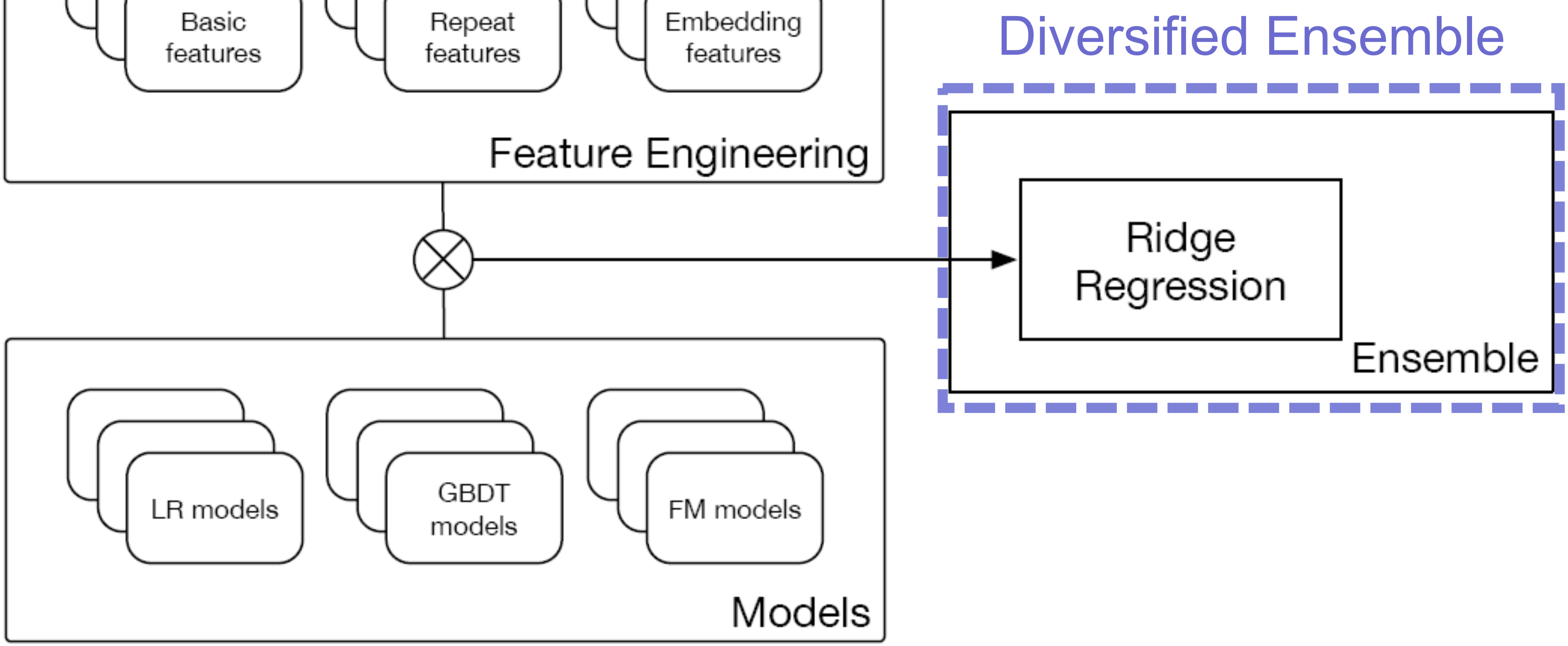
Embedding features

Framework



Three individual models

Framework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Diversified Ensemble
Ridge Regression
Ensemble

Feature Engineering – Basic Features

- User-Related Features
  - Age, gender, # of different actions
  - #items/merchants/… that clicked/purchased/favored
  - **Omitting add-to-cart in all actions related features increases performance (since almost identical to purchase)**
- Merchant-Related Features
  - Merchant ID
  - #actions and #distinct users that clicked/purchased/ favored (only in Stage 1)

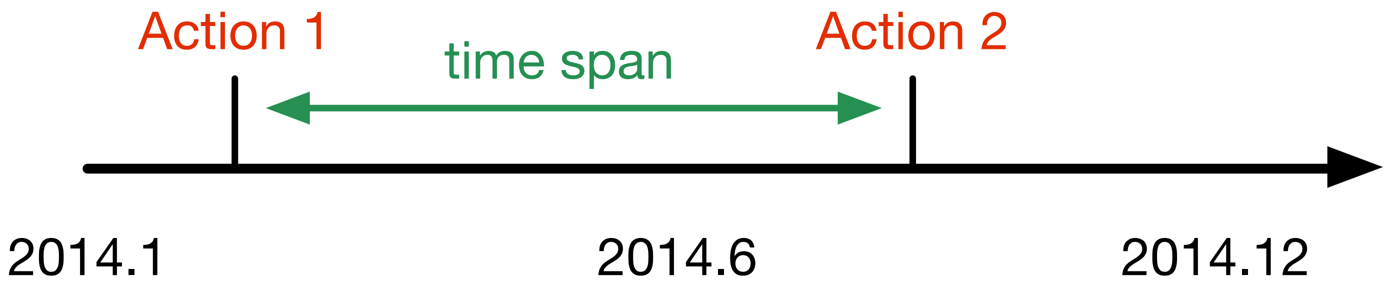
Feature Engineering – Basic Features

- User-Merchant Features
  - # different actions
  - Category IDs and brand IDs of the purchased items

- Post Processing
  - Feature binning in Stage 1
  - Log(1+x) conversion in Stage 2
  - **Perform similarly. Both much better than raw values.**

Repeat Features

- User Repeat Features
  - Average span between any two **actions**
  - Average span between two **purchases**
  - How many days since last **purchase**



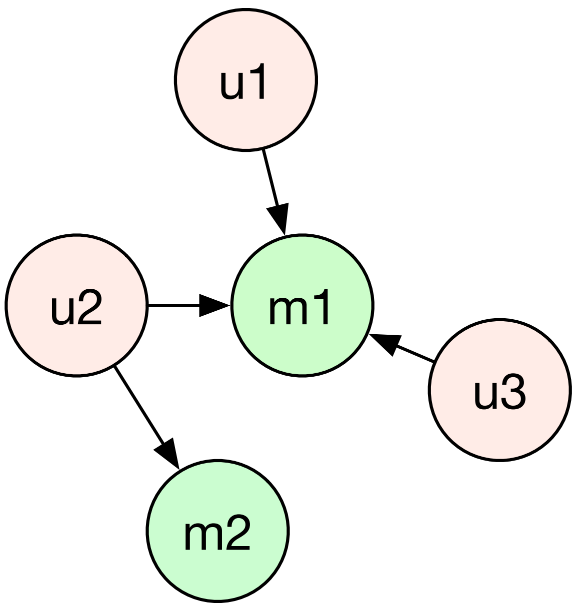
Repeat Features

- User-Merchant/Category/Brand/Item Repeat Features
  - **Average active days** for one merchant/ category/brand/item
  - **Maximum active days** for one merchant/ category/brand/item
  - **Average span** between any two actions for one merchant/category/brand/item
  - **Ratio** of merchants/categories/brands/items with **repeated actions**

Repeat Features

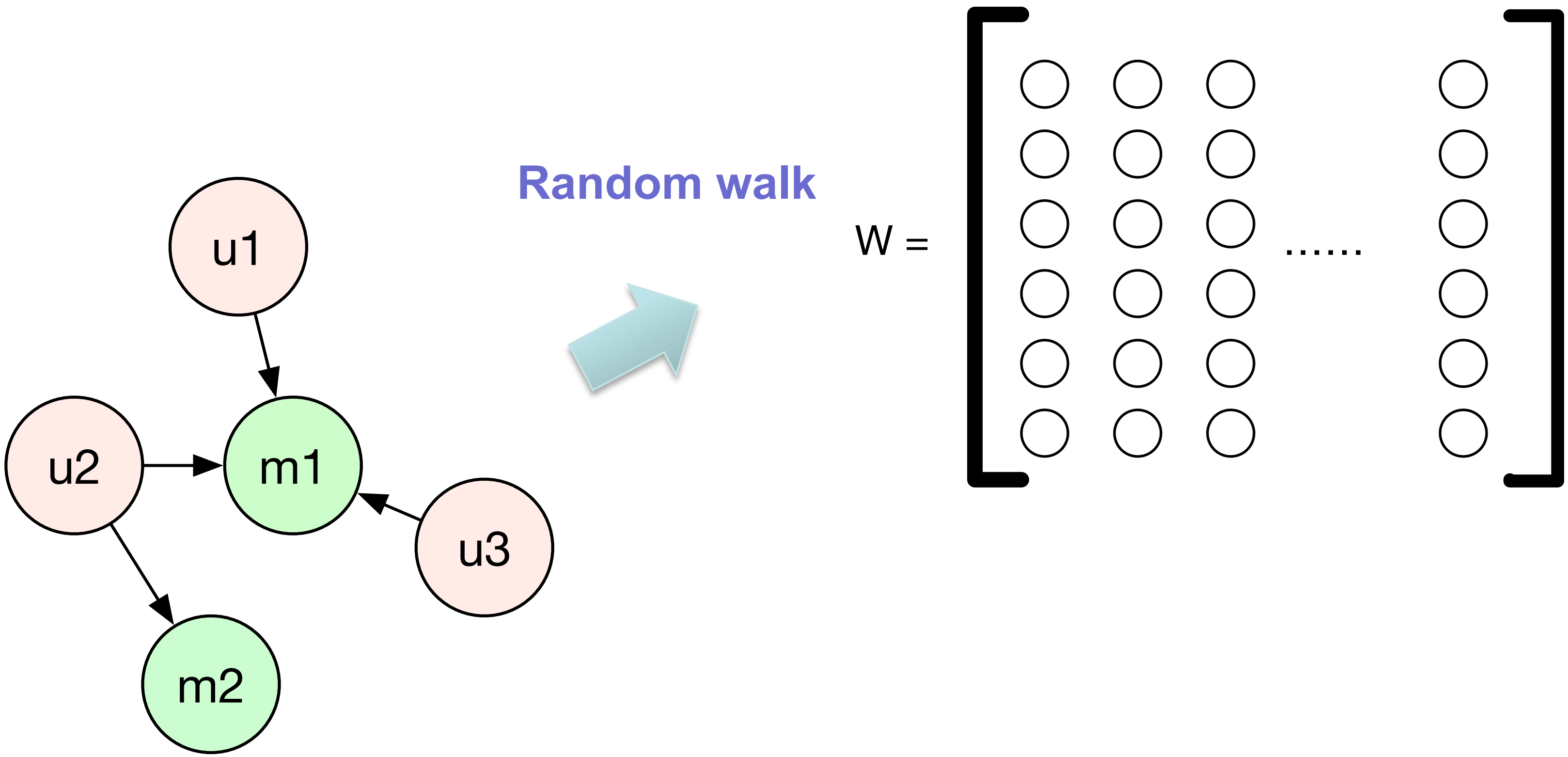
- Category/Brand/Item Repeat Features
  - **Average active days** on given category/category/brand/item of all users
  - **Ratio** of **repeated active users** on given category/brand/item
  - **Maximum active days** on given category/brand/item of all users
  - **Average days** of purchasing the given category/brand/item of all users
  - **Ratio** of users who purchase the given categories/brands/item **more then once**
  - **Maximum days** of purchasing the given category/brand/item of all users
  - **Average span** between two actions of purchasing the given category/brand/item of all users

Embedding Features



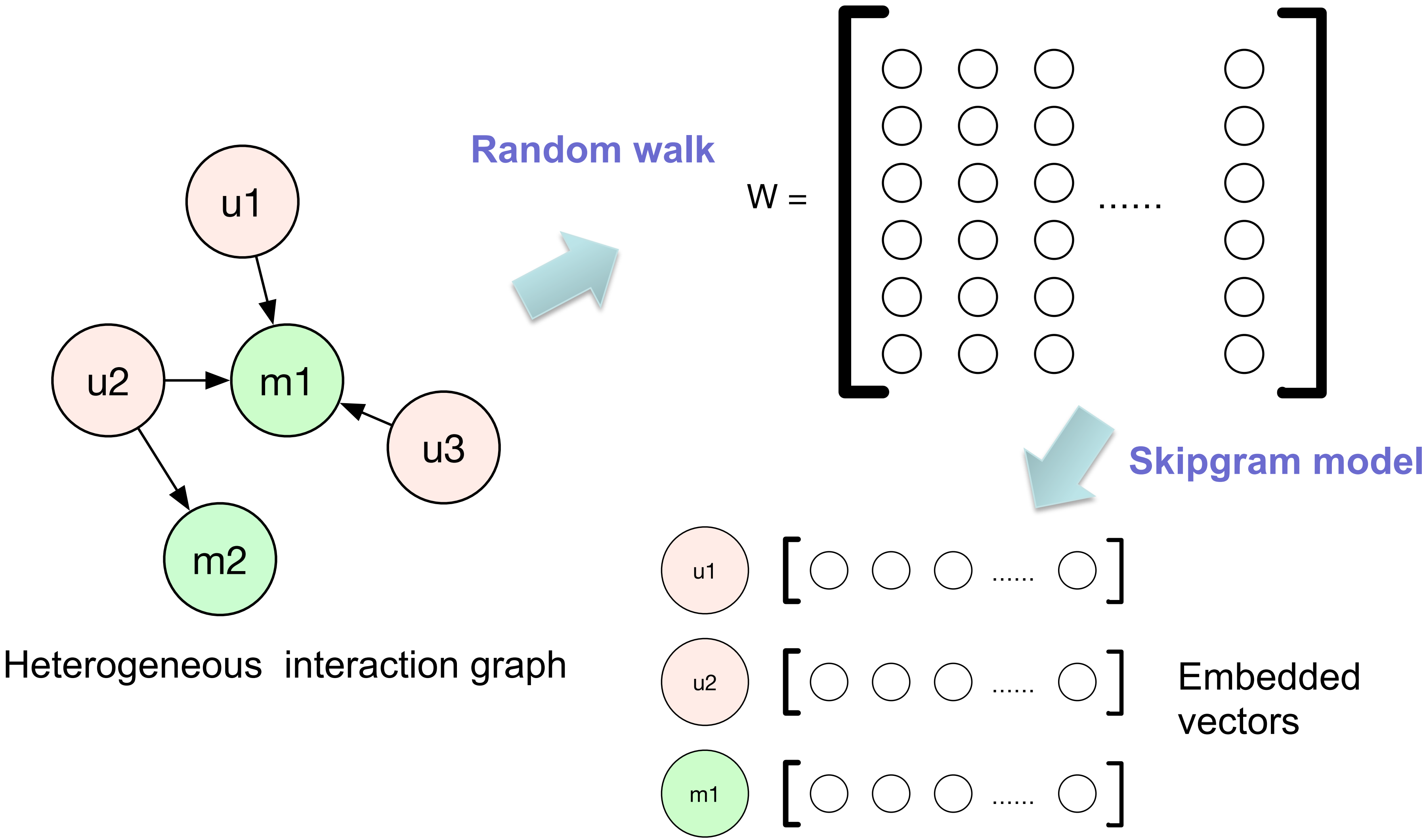
Heterogeneous interaction graph

Embedding Features

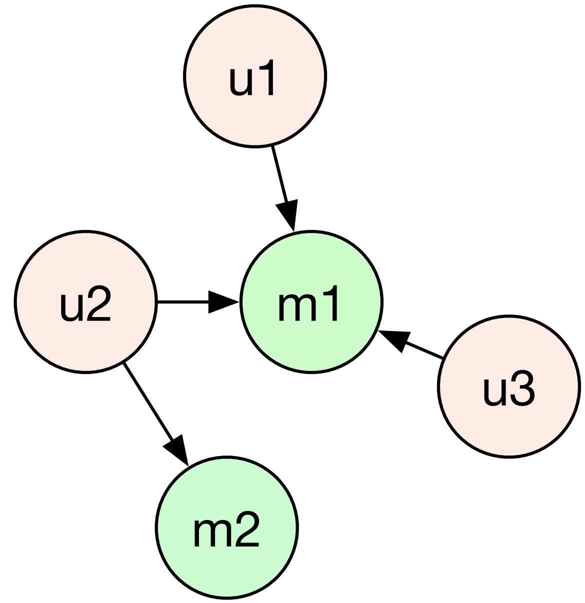


Heterogeneous interaction graph

Embedding Features



Embedding Features: Interaction Graph

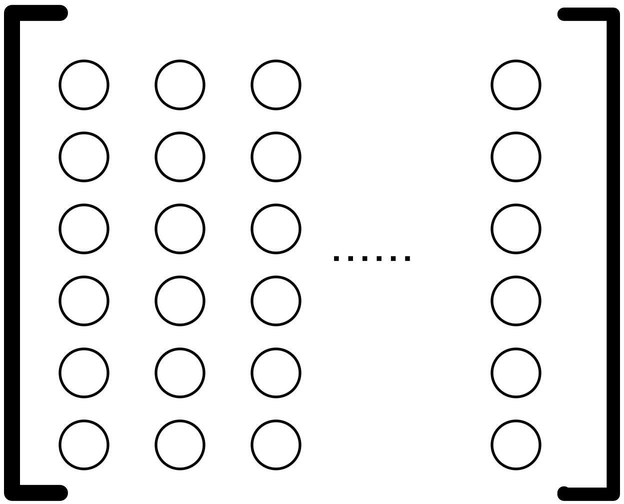


- Let the graph G = (V, E)
  - V is the vertex set
  - E is the edge set

- V contains all users and merchants
- If user u interacts with merchant m, then add an edge <u, m> into E

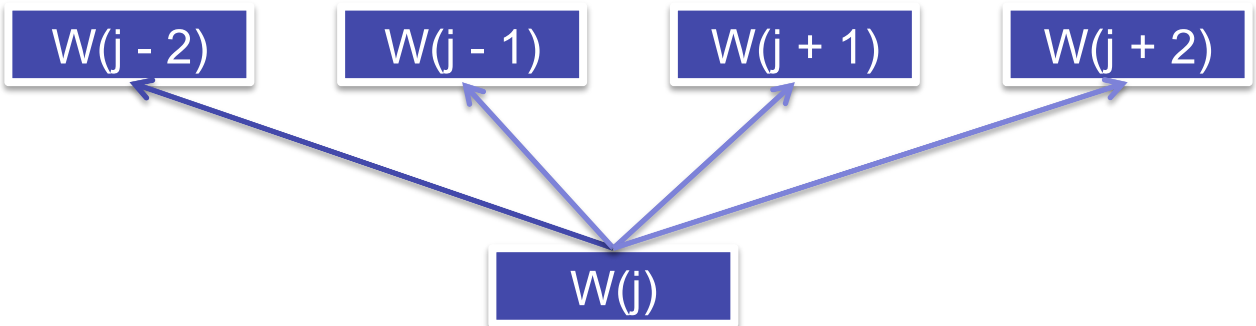
Embedding Features: Random Walk

- Repeat a given number of times
  - For each vertex v in V
    - Generate a sequence of random walk starting from v
    - Append the sequence to the corpus

W = 

Generate random walk corpus

Embedding Features: Skipgram



Use the current word W(j) to predict the context.

Objective function:

$$L = -\sum_{W \in \mathcal{W}} \frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \left({f'_{W_{t+j}}}^{\intercal} f_{W_t} - \sum_{w \in V} {f'_w}^{\intercal} f_{W_t} \right)$$

Use SGD to optimize the above objective and obtain embeddings for users and merchants.

Embedding Features: Dot Products

- Now we have embeddings of all users and merchants.
- Given a pair <u, m>, we derive a feature

$$f_u^{\top} f_m$$

- to represent the semantic similarity between u and m.
- f means embeddings.

Embedding Features: Diversification

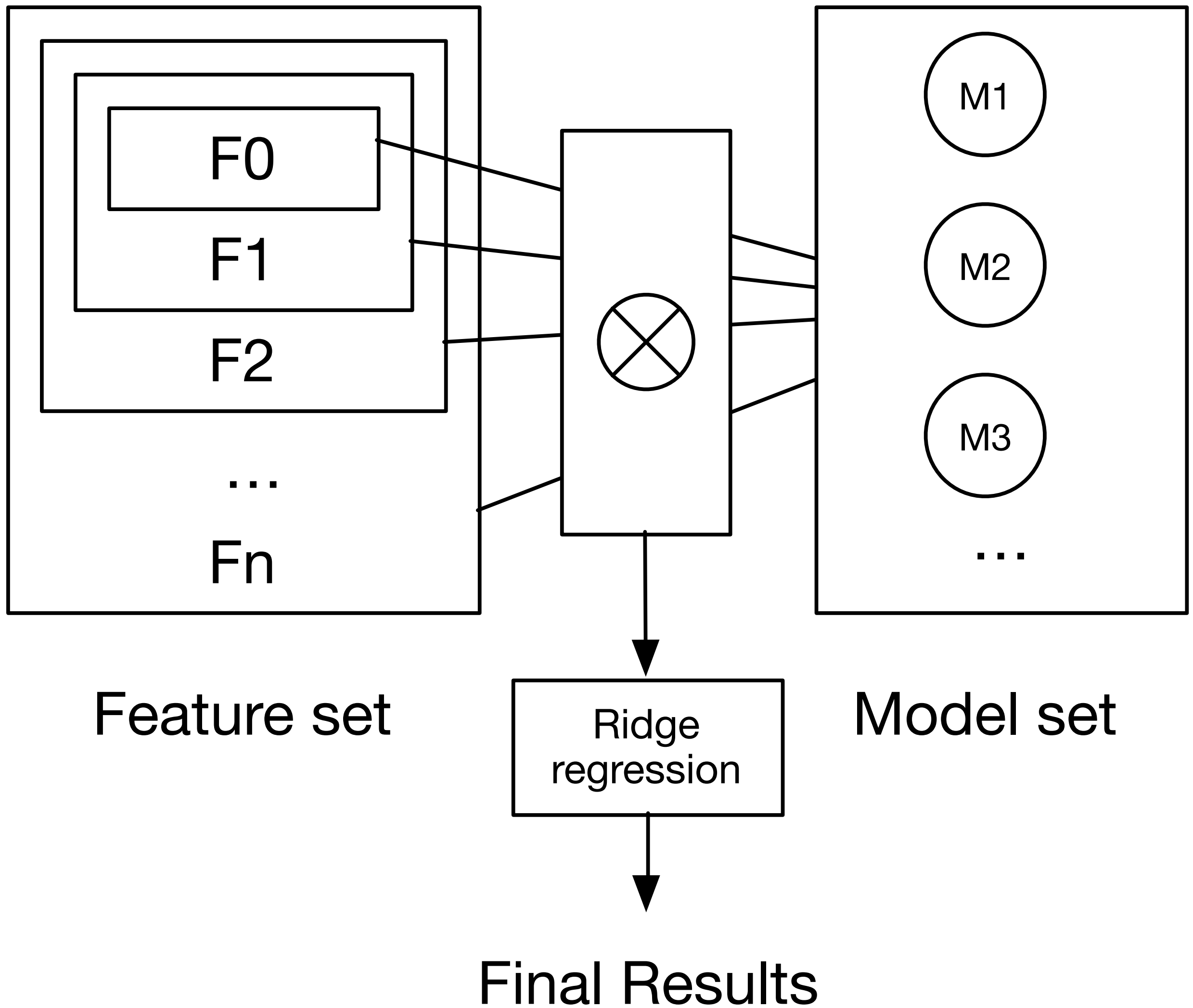
- Simply applying the dot product of embeddings is not powerful enough.
- Recall that we use SGD to learn the embeddings.
- We use embeddings at different iterations of SGD.
- An example
  - Run 100 iterations of SGD.
  - Read out embeddings at iteration 10, 20, …, 100.
  - Obtain a 10-dim feature vector of dot products
- **Intuition: similar to ensemble models with different regularization strengths**

Individual Models

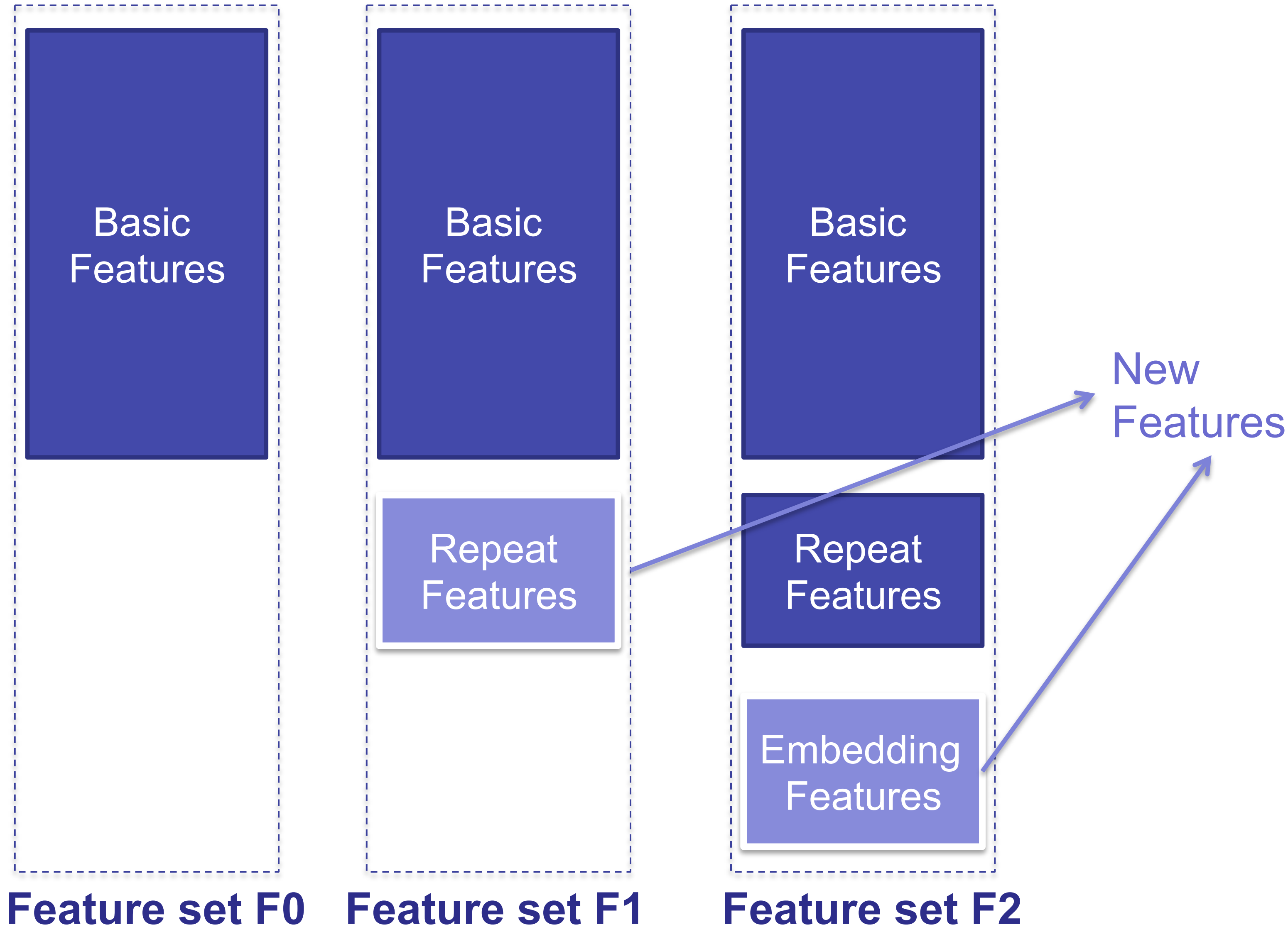
- Logistic regression
  - Use the implementation of Liblinear
- Factorization machine
  - Use the implementation of LibFM
- Gradient boosted decision trees
  - Use the implementation of XGBoost

Method	Implementation	Best AUC in Stage 1 (%)
Logistic Regression	Liblinear	69.782
Factorization Machine	LibFM	69.509
GBDT	XGBoost	69.196

Diversified Ensemble



Diversified Ensemble: Appending New Features



Diversified Ensemble: Cartesian Product

	LR	GBDT	FM
Feature Set F0	Ensemble 1	Ensemble 2	Ensemble 3
Feature Set F1	Ensemble 4	Ensemble 5	Ensemble 6
Feature Set F2	Ensemble 7	Ensemble 8	Ensemble 9

Diversified Ensemble Results

- Simple ensemble: Only ensemble the top 3 models
- Diversified ensemble outperforms simple ensemble

Method	Implementation	Best AUC in Stage 1 (%)
Logistic Regression	Liblinear	69.782
Factorization Machine	LibFM	69.509
GBDT	XGBoost	69.196
Simple Ensemble	Sklearn Ridge	70.329
Diversified Ensemble	Sklearn Ridge	**70.476**

Factor Contribution Analysis

- Clear performance increase after adding each feature set
- Both embedding features and repeat features provide **unique information** to help the prediction
- The results are based on Logistic Regression

No.	Feature Sets	Stage 1 AUC (%)	Gain
1	Basic features	69.369	-
2	1 + Embedding features	69.495	**0.126**
3	2 + Repeat features	69.782	**0.287**

Stage 2 Performance

- Repeat features are consistent in both stages
- **Data cleaning** is important
  - duplicated/inconsistent records exist in this stage
- The results are based on Logistic Regression

No.	Method	AUC (%)	Gain
1	Basic features	70.346	-
2	1 + Repeat features	70.589	0.243
3	2 + Data cleaning & more features	70.898	0.309
4	3 + Fine-tuning parameters	71.016	0.118

Summary

- “Tricks” on how to win top 3 in both stages
  - **Diversified ensemble**
  - **Novel embedding features**

Thank you!

Questions ?