Acquire Valued Shoppers Challenge

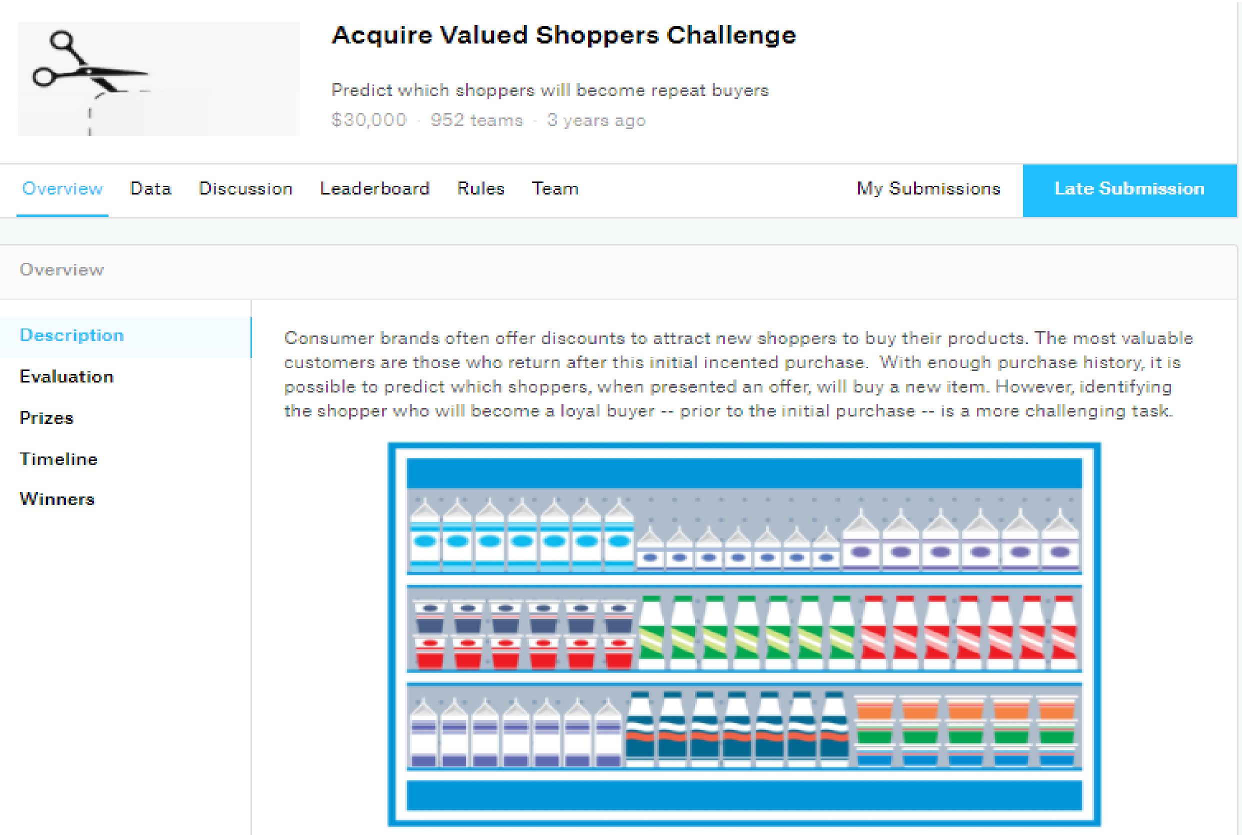
By Marios Michailidis

Background

- A recommenders' challenge
- Around 1,000 teams
- 1st place with Gert Jacobusse

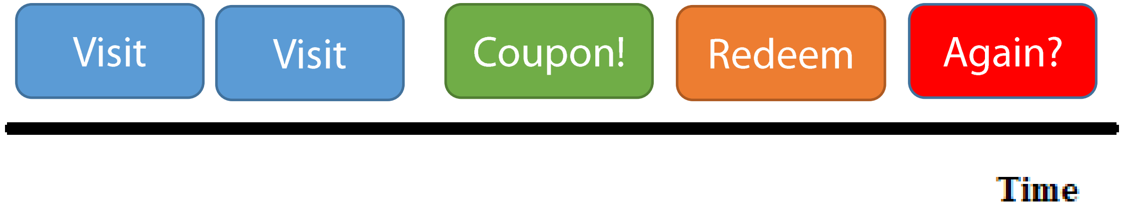
First Place:

- Marios Michailidis - London, United Kingdom
- Gert Jacobusse - Goes, The Netherlands



Problem to solve

- 310,000 shoppers (160K in train and 150K in test)
- 350,000,000 transactions (for 1 year+ for each shopper)
- 37 offers
- No exactly products , but could infer a product is a combination of:
  - The **brand** a product belongs to
  - The **category**
  - The **company** that produced it



- Optimize AUC for whether the shopper will buy again

“Challenges” of this challenge

- Datasets were big
- You had to create the features yourself.
- Irregular testing environment because:
  - Train and test data had different customers
  - Train and test data had in general different offers

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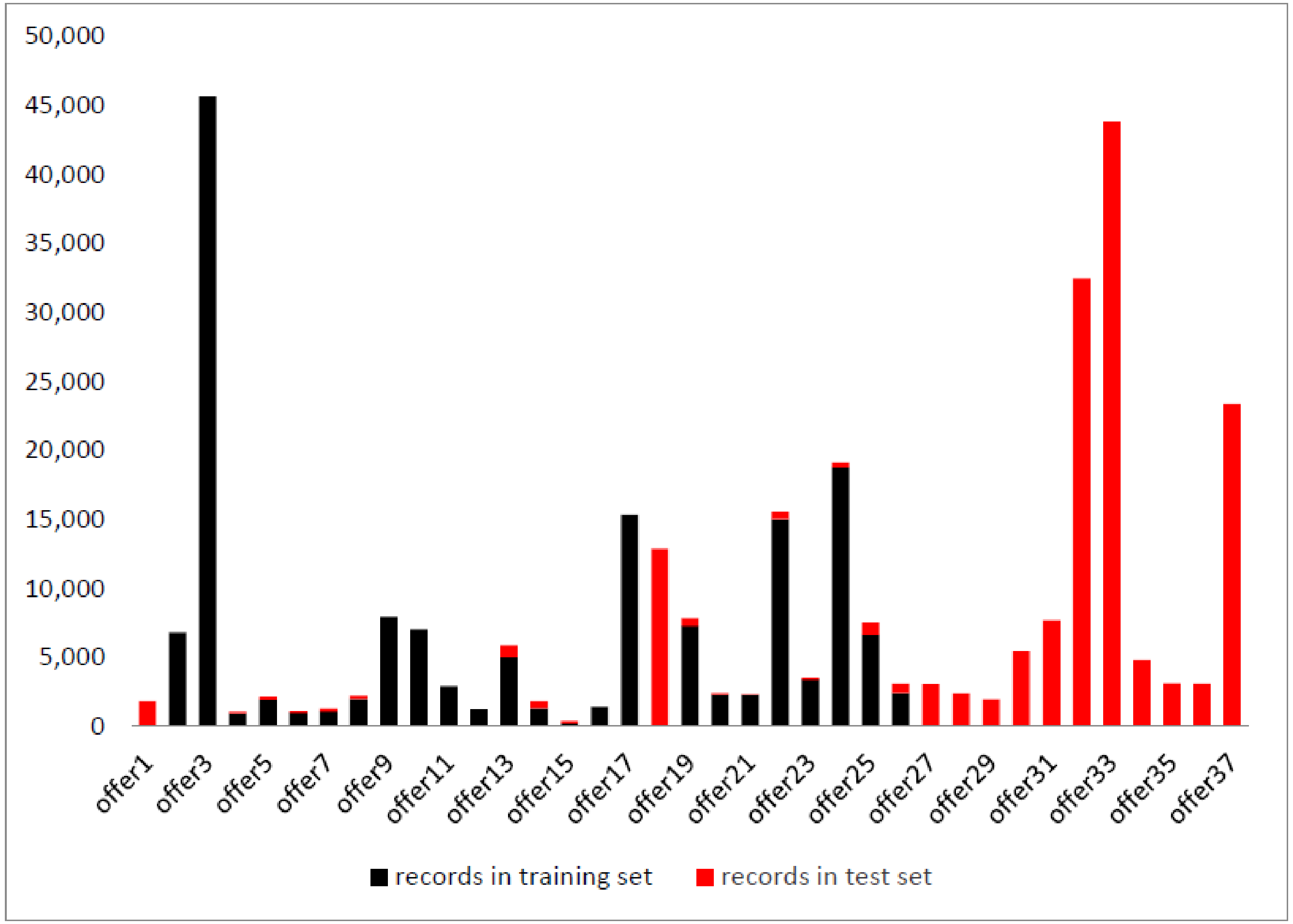


“Challenges” of this challenge

- Datasets were big
- You had to create the features yourself.
- Irregular testing environment because:
  - Train and test data had different customers
  - Train and test data had in general different offers
  - Test data may be well in the future
  - Focused on acquisition. Limited history of customer and offer.
  - Offers’ propensity to buy varies significantly

“Challenges” of this challenge

- Dat
- You
- Irre

Offer	Propensity to buy
offer2	0.507
offer24	0.434
offer17	0.424
offer25	0.378
offer26	0.341
offer22	0.321
offer23	0.305
offer19	0.285
offer15	0.230
offer5	0.214
offer4	0.210

Handling Big data…

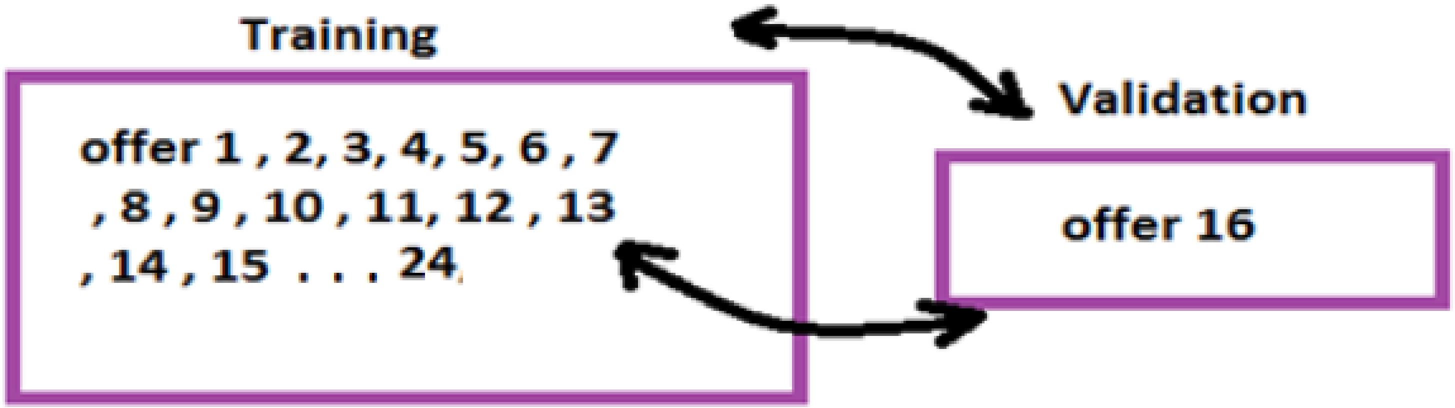
- With indexing
- Dataset already sorted by customer
- Create different file for every customer
- Create different file for every category, brand, company.
- All sorted by time

Handling irregularity

- Explored different cross validation.
- Stratified Kfold based on offer
- Leave-one-offer-out

Handling irregularity

- Explored different cross validation
- Stratified
- Leave-one



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- + concatenation

Handling irregularity

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prediction_offer_2	Target
0.91	1
0.81	1
0.77	1
0.65	1
0.52	1
0.46	0
0.34	0
0.23	0
0.2	0
0.05	0

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prediction_offer_4	Target
0.4	1
0.35	1
0.28	1
0.24	1
0.18	1
0.17	0
0.15	0
0.14	0
0.1	0
0.07	0

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Validation schemas	AUC_CV	AUC_TEST
Stratified K-Fold (K=5)	0.683	0.579
Stratified K-Fold (K=10)	0.699	0.578
Stratified K-Fold (K=15)	0.712	0.576
Leave-one-offer validation	0.655	0.588
Leave-one-offer + concatenation	0.632	0.601

Strategies for recommenders

- Content-based
- Collaborative filtering
- Hybrid

Content-based

- *a customer who has bought from the same, company, brand and category will have higher chance to buy the products once offered*
- Features exploiting **product hierarchy** versus **customer** and **time**

Content-based

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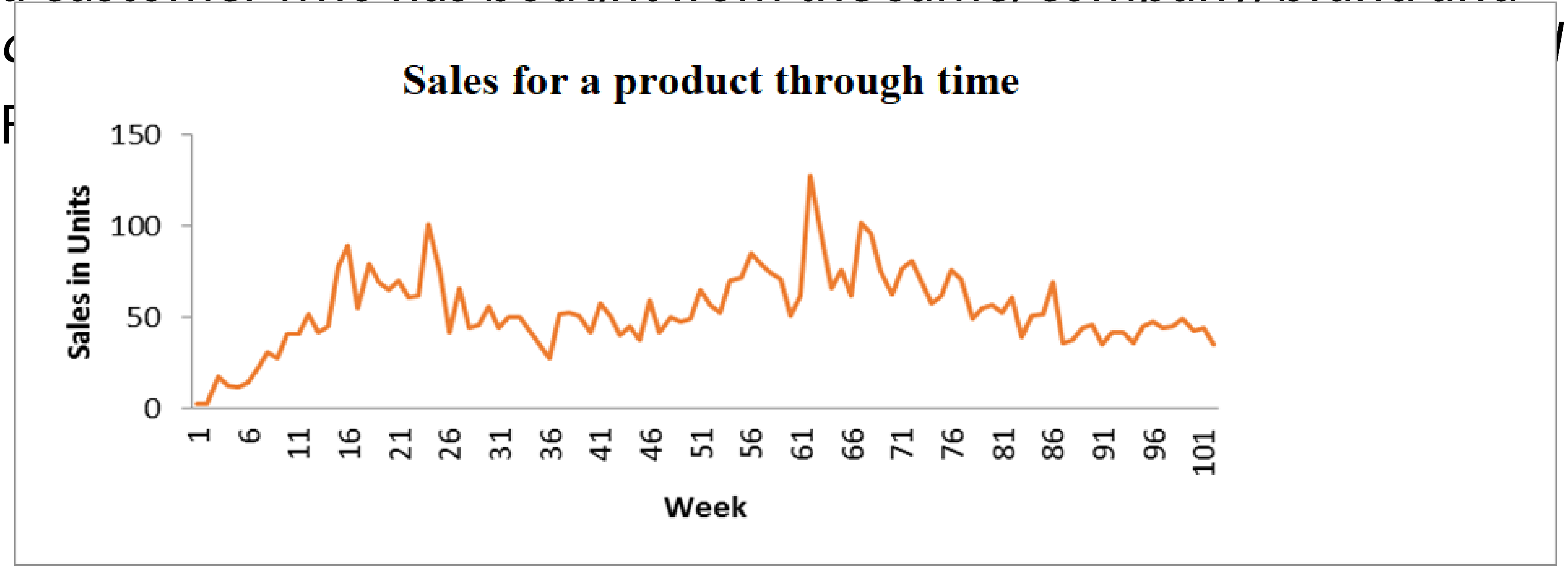

Content-based

- *a customer who has bought from the same, company, brand and category will have higher chance to buy the products once offered*
- Features exploiting **product hierarchy** versus **customer** and **time**
- Time intervals were last 30,60,90,120,180 and 360 days
- Features selected through forward cross validation

Content-based

category_brand_30	Times bought the same category&brand in last 30 days
category_brand_60	Times bought the same category&brand in last 30 to 60 days
category_brand_90	Times bought the same category&brand in last 60 to 90 days
category_company_30	Times bought the same category&company in last 30 days
category_company_60	Times bought the same category&company in last 30 to 60 days
brand_company_30	Times bought the same brand&company in last 30 days
brand_company_60	Times bought the same brand&company in last 30 to 60 days
brand_company_90	Times bought the same brand&company in last 60 to 90 days
brand_company_120	Times bought the same brand&company in last 90 to 120 days
brand_company_180	Times bought the same brand&company in last 120 to 180 days
brand_company_360	Times bought the same brand&company in last 180 to 360 days
brand_company_over360	Times bought the same brand&company in more than 360 days
category_brand_company_30	Times bought the same category&brand&company in last 30 days
category_brand_company_60	Times bought the same category&brand&company in last 30 to 60 days

Content-based

- *a customer who has bought from the same, company, brand and category will have higher chance to buy the products once offered*
- Features exploiting **product hierarchy** versus **customer** and **time**
- Time intervals were last 30,60,90,120,180 and 360 days
- Features selected through forward cross validation
- Big values capped – missing values replaced with -1
- Modelling using **Ridge regression** on the actual repeat counts
- Scored **0.610**+ in the test data

Collaborative Filtering

- *Would the customers have bought the product, had they not received the offer?*
- A model for every offer in train and test
- Target variable natural logarithm of the times a customer bought the product 90 days BEFORE receiving the coupon.

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- *Would the customers have bought the product, had they not received the offer?*
- A model for every offer in train and test
- Target variable natural logarithm of the times a customer bought the product 90 days BEFORE receiving the coupon.
- Features based on users' activity
    - Counts of popular categories, brands, companies
    - **R**estricted **B**oltzmann **M**achines to summarize purchase activity on least popular.
    - Average amount purchase, total visits ,distinct brands/categories/companies
    - Total discounts/returns, visits in weekends, spend in weekends
- GBM (form sklearn) on the log of counts
- Scored 0.616+ on the test

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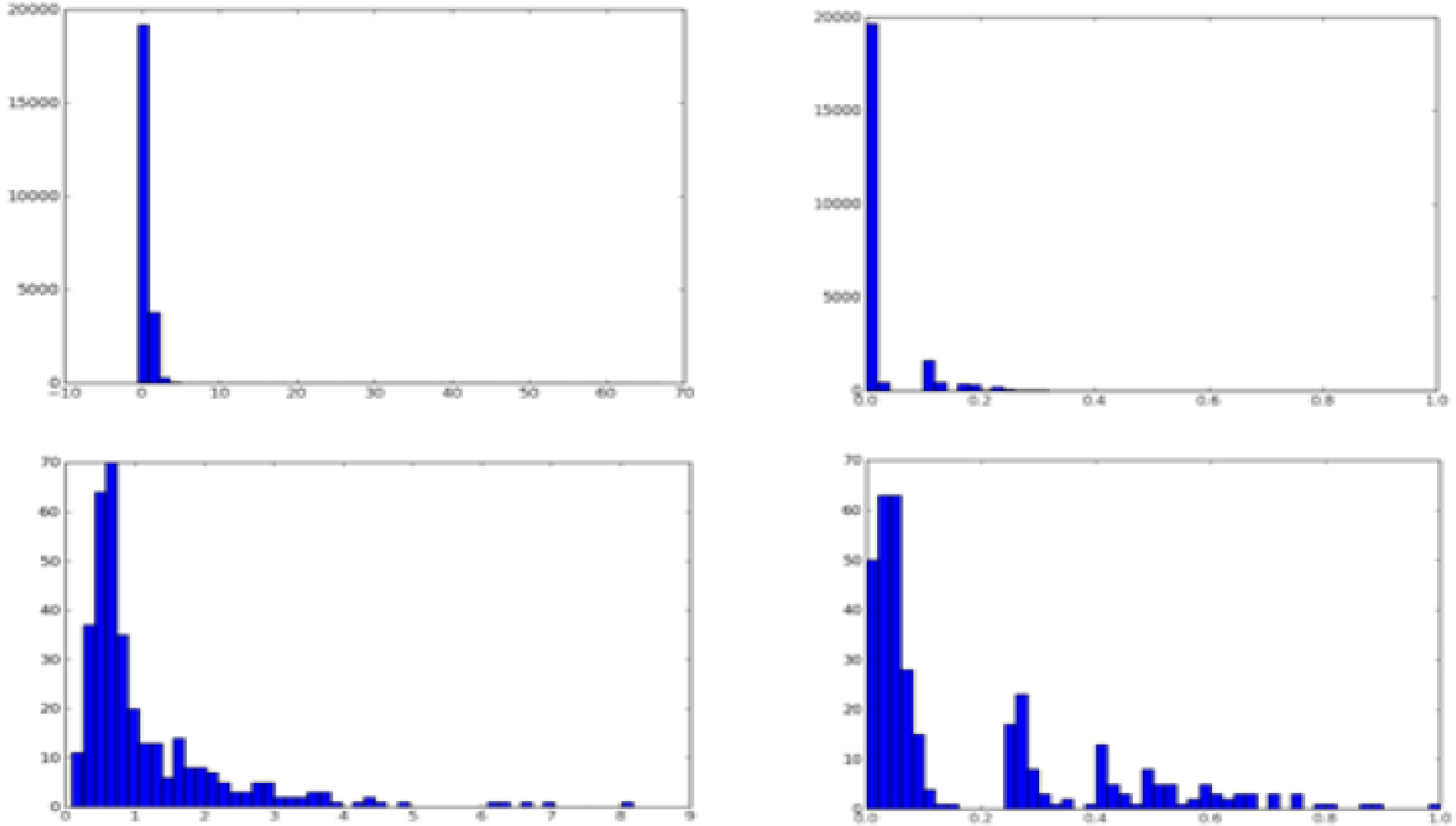

Combination

- Both models trained on different targets – tough to combine normally
- However irrespective of scores, distributions looked similar
- Converted to ranks and take average

Strategies	AUC_TEST
Strategy 1: Content-based	0.610
Strategy 2: Collaborative filtering	0.616
$strategy1_{rank} \times 0.5 + strategy2_{rank} \times 0.5$	**0.626**