Recommendation Systems as Anomaly Detectors for Market Abuse Detection

July 2020

Summary

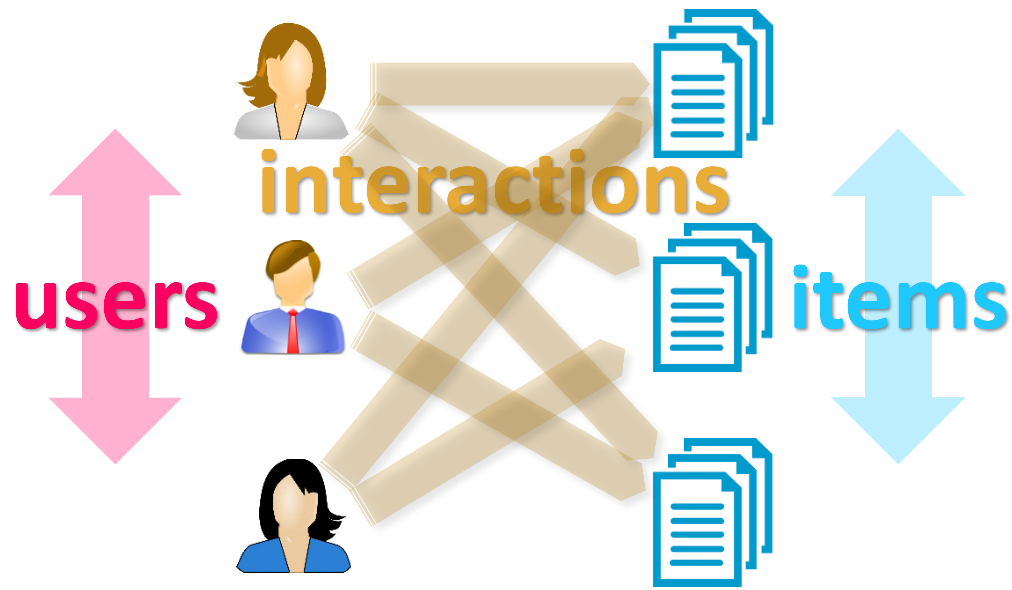
- **RecSys as Anomaly detector**
  - ~~*How does it work*~~
  - Requirements
  - Delivery
- **Anomaly detection in MAD**
  - as is
  - would be
- **RecSys for MAD**
  - empirical experiment
  - results
- **Recap and prospects**

RecSys
as Anomaly Detector

RecSys as Anomaly detector — How does it work

In a nutshell and beyond the underlying mechanisms of operation, a RecSys is an engine capable of **profiling user** and **items** based on their past **interactions**.

Its main feature is that it is able to do so not just on a single-user basis, but **looking at them as a whole**, allowing to portray traits of each user behavior *even for those who rarely interacts*.



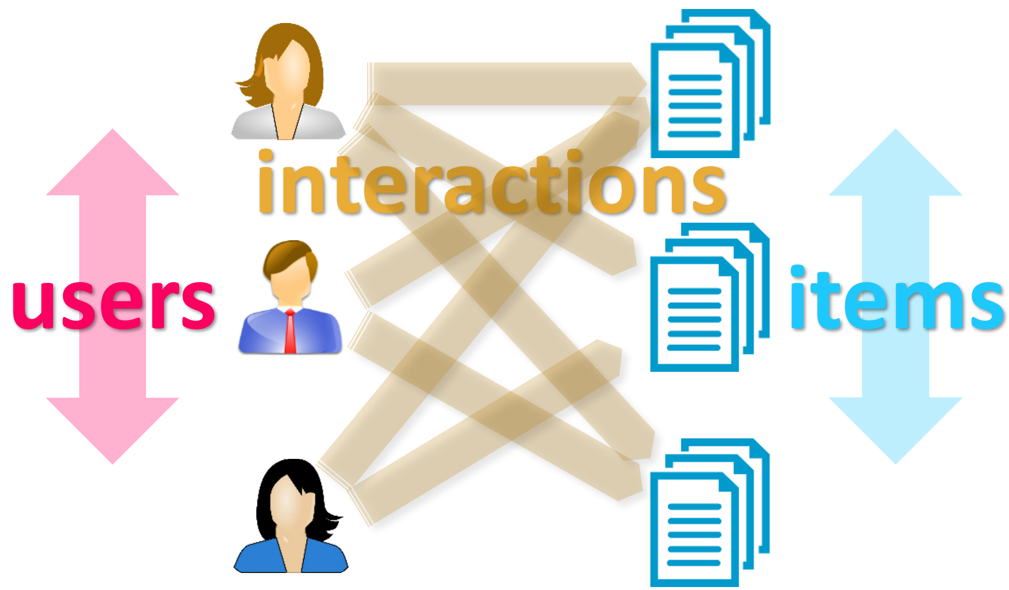
The use for which they were designed is to be able to **recommend** items to users.

The use we are making of them is the opposite: to judge, in retrospect, whether a post-training interaction is in line or not with the behavior that the user has maintained in the training period — an **anomaly detector**.

RecSys as Anomaly detector

Requirements

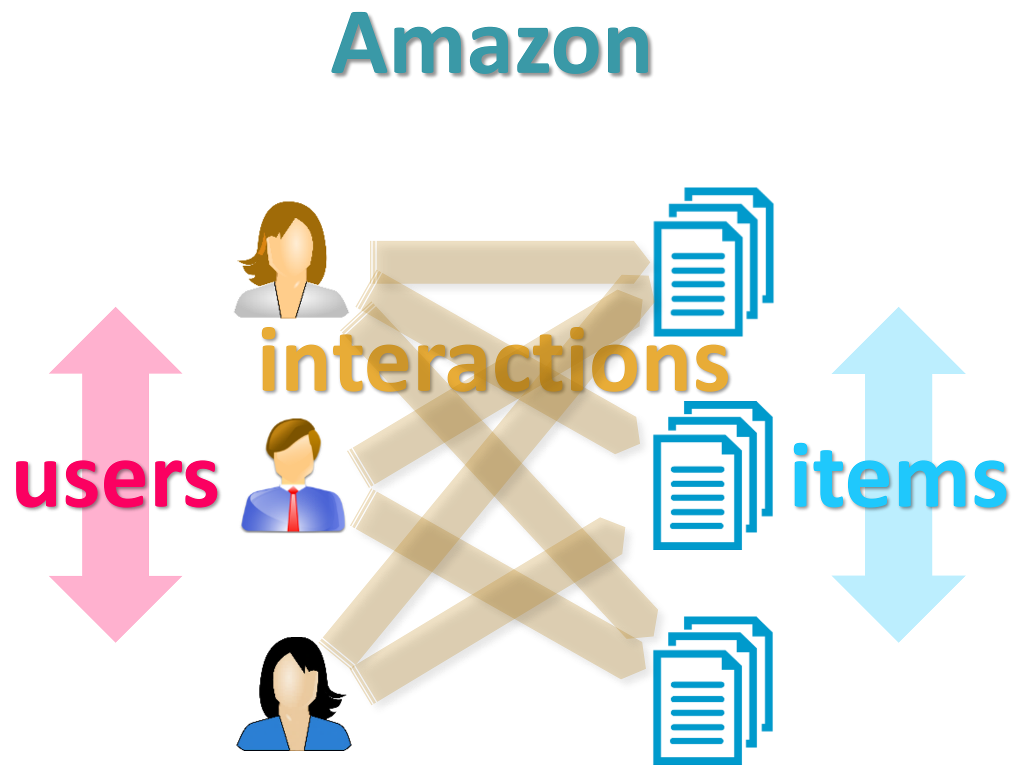
The numerical methods behind this type of approach are generic enough to be able to examine **any dataset**, as long as you can find two categorical dimensions to use in the roles of **user** and **item**, and a third quantitative metrics to be used in the **interaction** role, that can be thought as a proxy of some "compatibility score" through which to calibrate the RecSys.



RecSys as Anomaly detector

Requirements

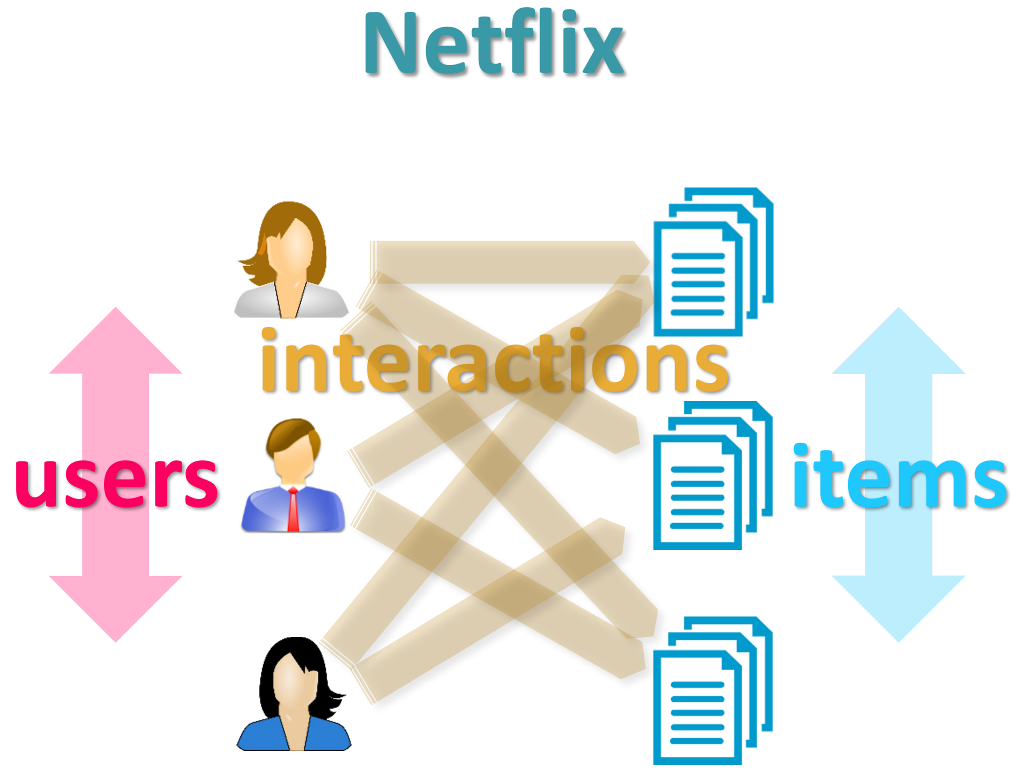
- **Users**
  - customers
- **Items**
  - retail goods
- **Interactions**
  - purchases
  - browsing activity



RecSys as Anomaly detector

Requirements

- **Users**
  - customers
- **Items**
  - series and movies
- **Interactions**
  - rating
  - viewing activity

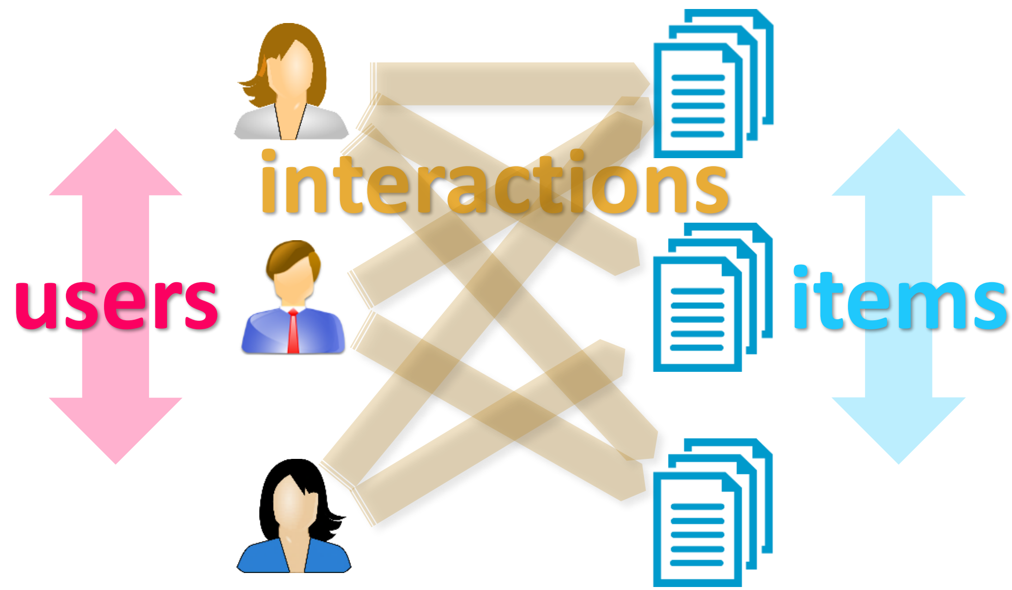


list

RecSys as Anomaly detector — Requirements

- **Users**
  - customers
- **Items**
  - securities
  - countervalues
- **Interactions**
  - number of trades
  - volume requested
  - RFQ hit-rate
  - etc...

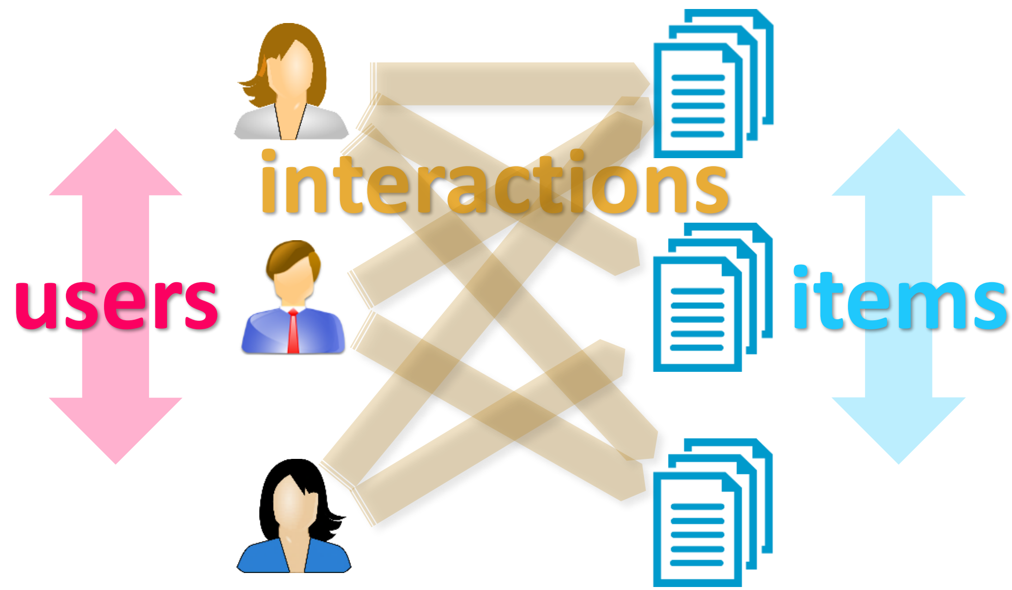
B2C markets



list

RecSys as Anomaly detector

Once calibrated through some past interaction data, the RecSys will profile user and items based just on their mutual interactions in such a way to:



- gather similar users and gather similar items
- suggest items from similar user
- judge whether a user and an item fit together...
- **...or not: report anomalous user-item interactions**

Anomaly Detection in MAD

Anomaly detection in MAD

as is

- **Monitoring** the data flows of a **financial market place** with the aim **to find anomalous** and suspicious **behaviors** of market participants
  - more than 50 algorithms set up **by the Regulator**.
  - several **metrics** (function of prices, volumes, order frequencies, executed trades, etc…) have to be **limited to certain specific ranges of values**
  - monitoring **is demanded to market participants** who have to:
    - equip themselves with monitoring tools
    - implement normative patterns
    - fine-tune thresholds

Anomaly detection in MAD would be

- Machine Learning (**ML**) methodologies can provide more **automated solutions**
  - an **unsupervised algorithm** could autonomously learn typical/anomalous behaviors
    - use the ML alarms to clean up the normative patterns alarms
    - use ML information to fine tune normative patterns thresholds
    - ML is **non-parametric** so it has not to be re-adjusted on market condition changes
- ML techniques need very large amount of data, while lots of subjects in a financial market trade very little
- A RecSys is able to learn patterns and profile users/items not just on a single-user basis, but **looking at them as a whole**, allowing to portray traits of each subject behavior, *even for those who rarely interacts*.

RecSys
for
MAD

RecSys for MAD — empirical experiment

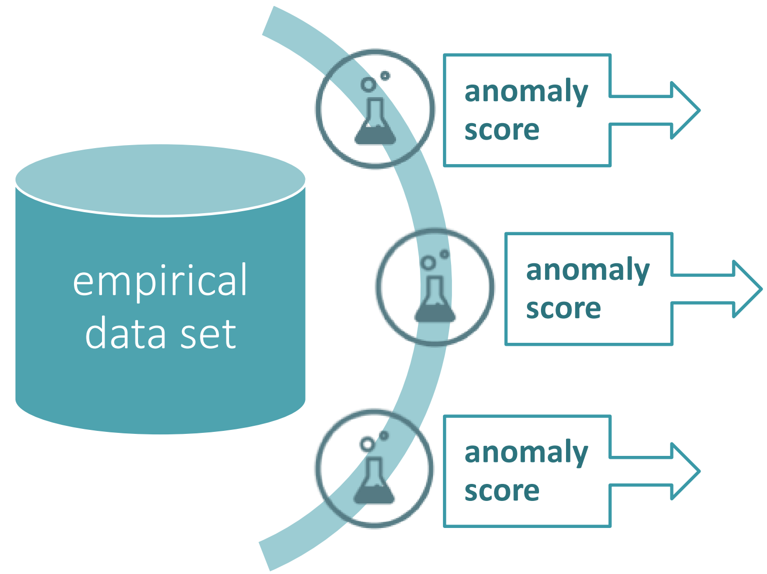
- **Dataset**
  - ~ 1.7 M executed trades
  - 3 months (Aug-Nov 2019)
  - ~200 subjects
  - ~ 5k+ securities

- **Workflow**
  - a definite time window of past data is fed into the RecSys
  - it calibrates and makes its own *users* and *items* representations
  - future operations are submitted to the calibrated RecSys as (user, item) pairs for each occurring trade
  - the RecSys will return a score that can be interpreted as an affinity value or, more interesting for our purpose, as an anomaly score

RecSys for MAD — empirical experiment

- **What kind of patterns?**
  Select what data fields to be used as the three main roles of a RecSys:

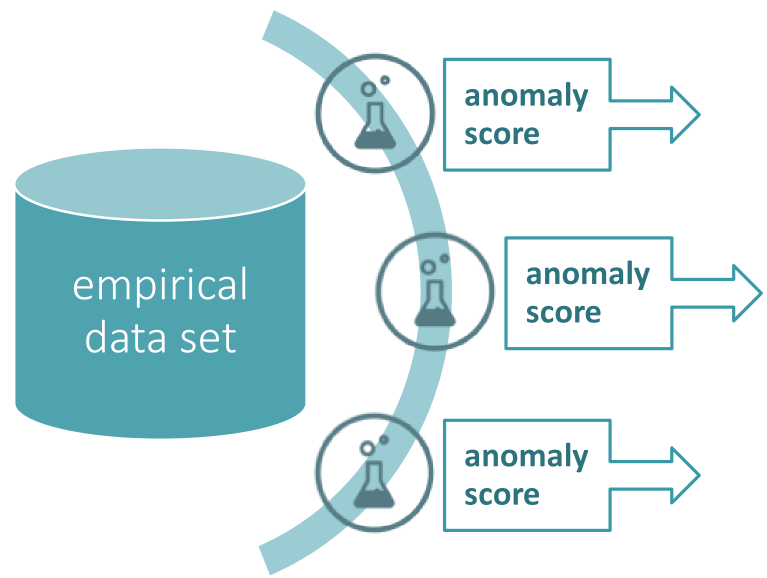
  - **user**
    - subject
  - **item**
    - ISIN
    - countervalue (log-binning)
    - ISIN + *countervalue-level-per-user*
  - **interaction**
    - (proper normalized) count of transactions belonging to the (**user**, **item**) pair



RecSys for MAD

empirical experiment

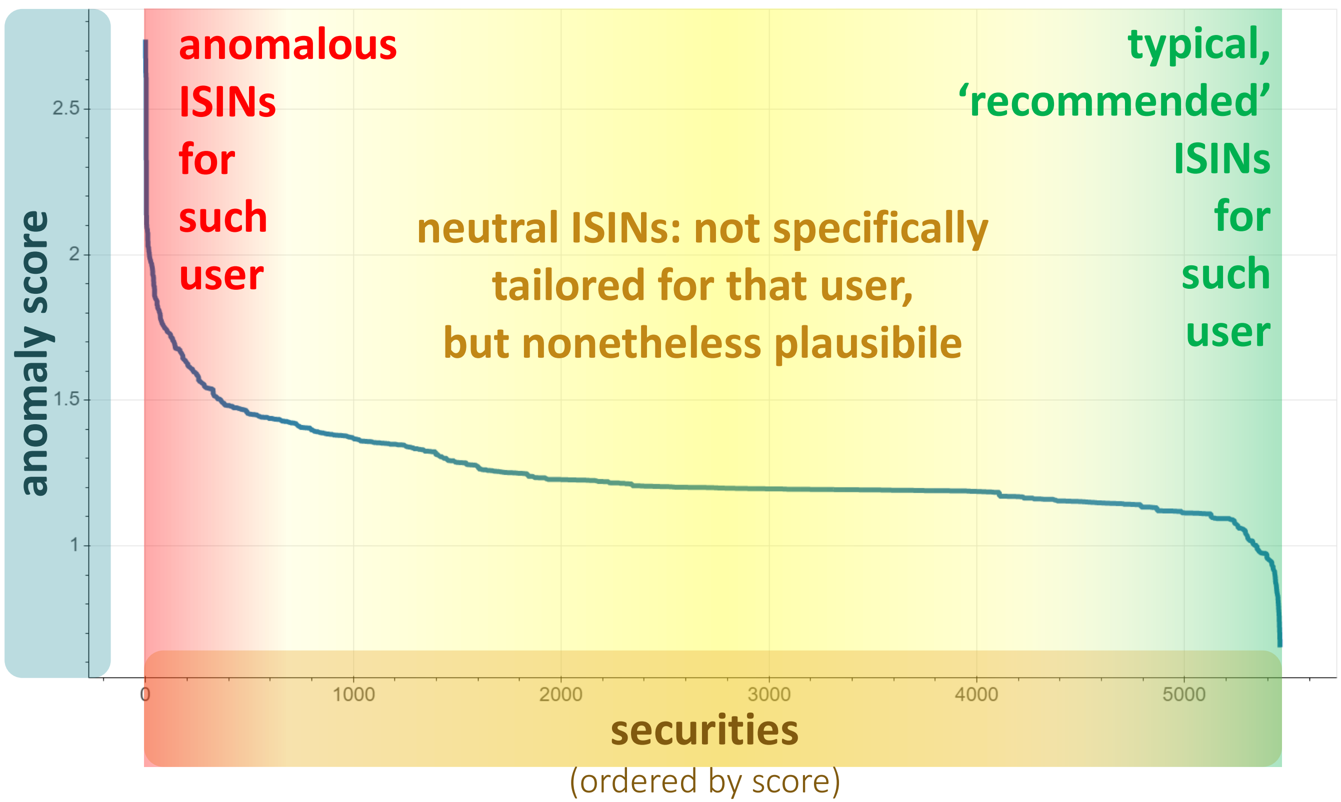
- **Each choice corresponds to a different RecSys**
- **Different RecSys are not necessarily competing against each other**
  - Any RecSys which is able to calibrate successfully,
    i.e. to capture patterns of common usage
    (and, by complement, patterns of anomaly usage)
    between its pair of user/item dimensions,
    can be used to setup a battery of detection tools
    which cooperate to raise alarms
    each on a specific aspect of the user's behaviour.



RecSys for MAD

results

- **anomaly scores for a single user: RecSys [subject, ISIN]**
  - **all** securities available in the dataset were given a score for each user, not just the possibly small set of items she already dealt with in the training dataset.



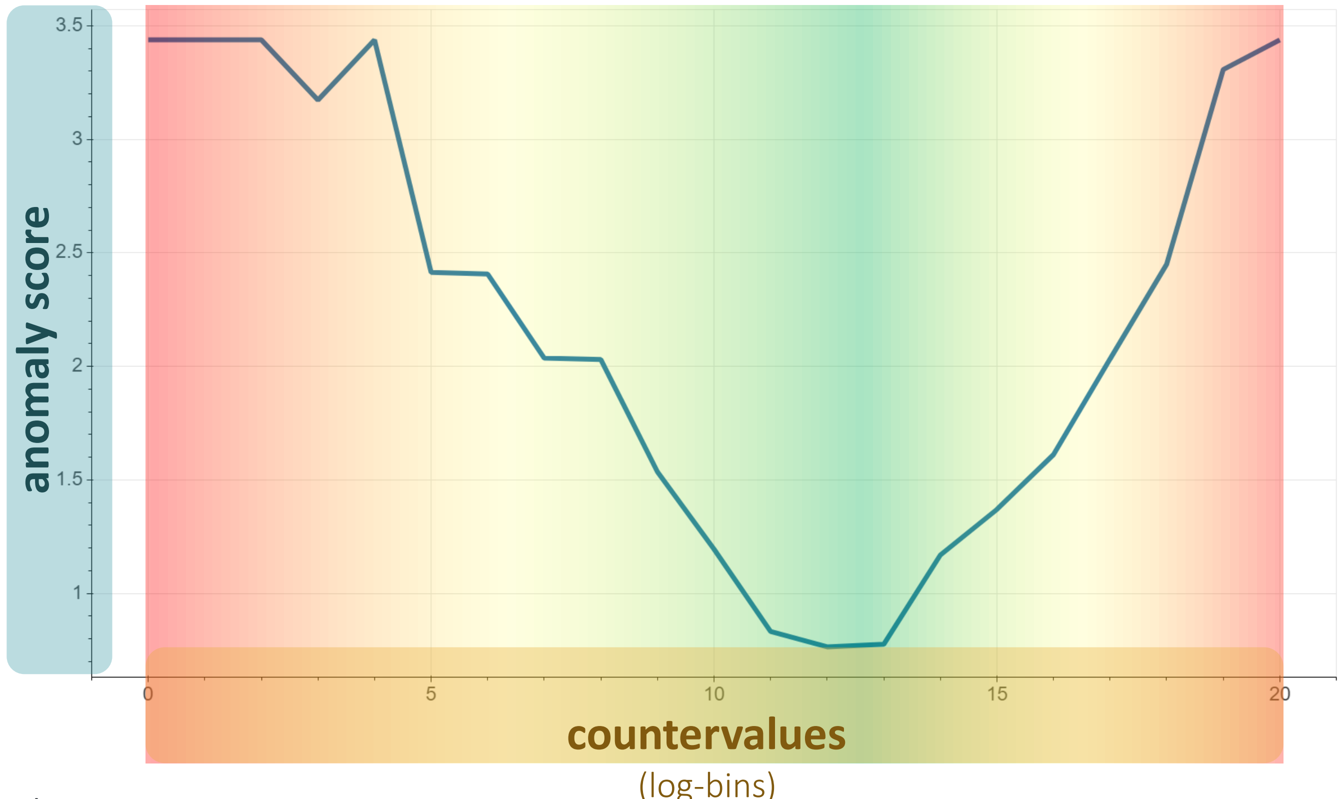
RecSys for MAD

results

- **anomaly scores for a single user: RecSys [subject, countervalue]**

- Here *item* dimension is not categorical and instead has its own metric: so the log-bins were not sorted on the x-axis by the score, but were left in their natural order

- The 'simple' bell-shape of this output resembles a (vertical reflected) countervalues distribution: a natural pattern for each subject is just to have a main operating interval with increasingly reduced excursions moving away from it.



- A simple statistical analysis could be enough? Well: not all users have, taken alone, enough operation to allow a single-user statistical profiling.

List

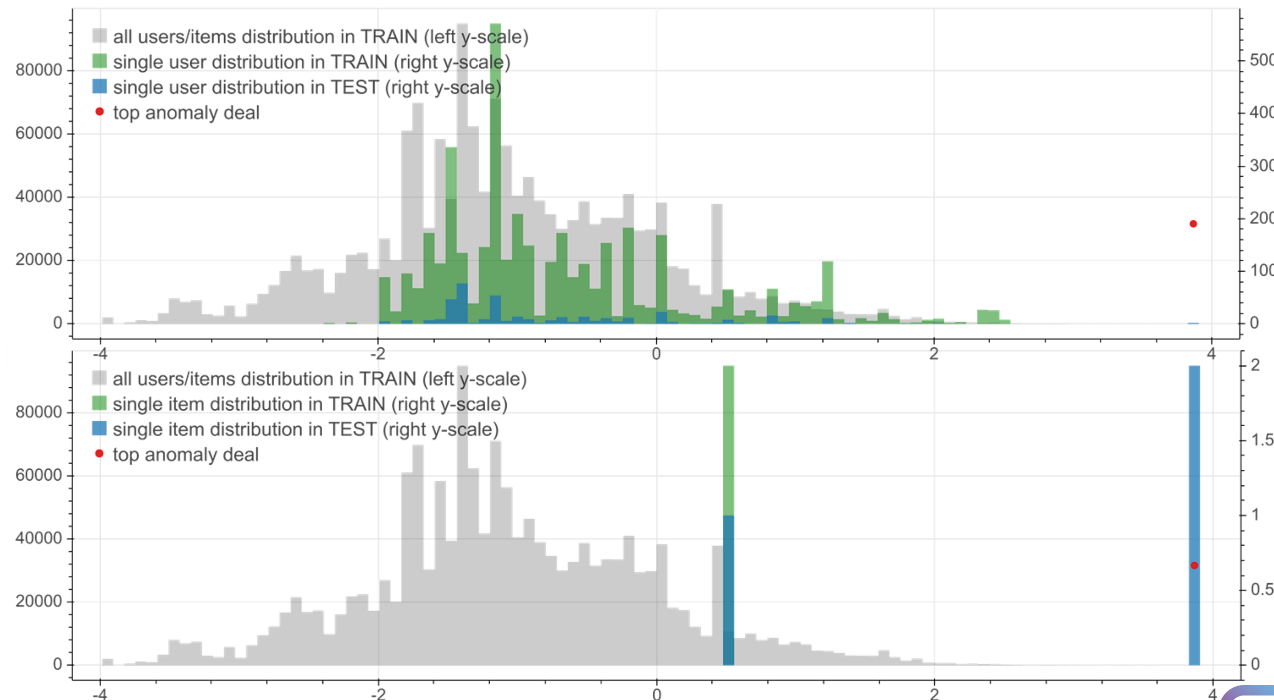
RecSys for MAD

results

Backtesting

- a small sample of the available data was taken out of training and used as a test bed for trained systems
- as a self-consistency check, one can inspect the dataset looking for items similar to the one reported as the most anomalous one in the test dataset.
- Comparison of anomaly scores distributions:
  - in training dataset
    vs
    in testbed dataset
  - for most anomalous user
    vs
    for most anomalous item
- as a reference, in red is marked the most anomalous point

DATE	SUBJECT	ISIN	#	n-score	z-score
2019-11-15	1000456	JP3942800008	1	0.972784	3.851117
2019-11-11	1000456	JP3942800008	1	0.972784	3.851117
2019-11-13	1043896	CH0002187810	2	0.944832	3.374233
2019-11-12	1043896	US92823T1088	5	0.943670	3.363270
2019-11-15	1043896	IT0005388449	1	0.939825	3.314311
2019-11-13	1043896	IT0005388449	1	0.939825	3.314311
2019-11-12	1043896	IT0005388449	2	0.939825	3.314311
2019-11-14	1009036	GB0009039941	2	0.939060	3.307272
2019-11-11	1009036	US6443931000	1	0.938117	3.270927
2019-11-15	1043896	SG1P32918333	1	0.936573	3.220750



Recap
and
prospects

Recap and prospects

- **Recap**
  - We experimented with a dataset similar to those available for MAD, applying RecSys techniques
  - Preliminary results clearly show interesting potential of applying such tools in a production environment as ancillary facilities to monitor traders activities looking for unusual behaviors.
- **Pro**
  - Being an unsupervised ML approach, it's mostly non-parametric, which is crucial in such a diversified behaviors framework
  - Not being a per-user approach, it can be successfully applied even with a large population of moderate or small operation users

Recap and prospects

- **Outlook**
  - The approach is quite generic: several possible RecSys can be setup, for the same dataset, each aimed at monitoring specific traits of users behavior.
  - OTC markets, where usual metrics are not available, and so usual algorithms cannot be implemented, is a further field of application.

Thank You