# PRODUCTION CASE

# REALTIME RECOMMENDATIONS ON SCALE USING K-NEAREST NEIGHBOURS

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# Machine Learning Reply, a Reply AG company

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**#1** fastest growing technology consulting firm

Annual turnover of **1 billion** Euro

**8.000** Employees


*Source: Reply Group*

# Machine Learning Reply, a Reply AG company

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*From strategic approach to implementation and operation, Machine Learning Reply covers the entire lifecycle on generating data and turn valuable insights into efficient actions.*

# OUTLINE

1. GOAL
2. HOW WE TACKLED IT
3. DIMENSION REDUCTIONS
4. APPROXIMATE KNN
5. RESULTS

# 1. GOAL

# Goal: intelligent coupon assignment for new partner

**Customer:** Benefit Program, running personalized and partner-specific promotions

**Problem:**

- for new partners, no usage data exists yet
- existing personalization models fail

# Goal: intelligent coupon assignment for new partner

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**Cooperation with many Partners**

- A lot existing data

**New Partners**

- Happens frequently
- no data in the beginning

**Unsupervised Model**

- Make use of existing data
- SparkML

# 2. HOW WE TACKLED IT

# How we tackled it

| Customer | Neighbour1 | Neighbour2 |
|---|---|---|
| Julia | Hans | Franziksa |
| Georg | Ingrid | Peter |
| … | … | … |

**Realtime Demands**

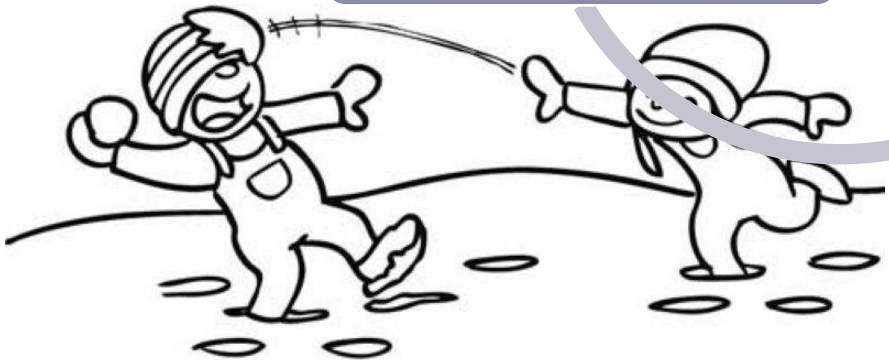
- want to send out new coupons in realtime

**Snowball Idea**

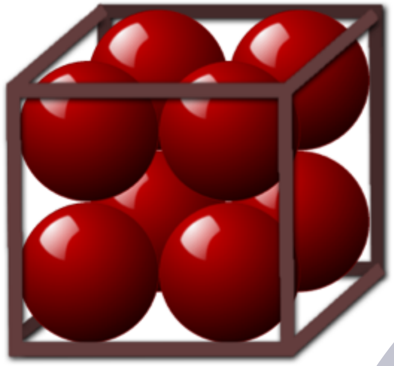
- if someone uses a coupon, also play it out to similar customers

**Solution**

- precompute similar customers
- KNN



# Input Data Challenge



## Input Data

- User * Partner Matrix
- how often they haved used coupons
- 30+ Mio. Users
- 650+ Partners

| User | P1 | P2 | P3 | … |
|---|---|---|---|---|
| Sandra | 1 | 0 | 23 | … |
| Michael | 0 | 0 | 2 | … |
| Tom | 4 | 11 | 3 | … |
| … | … | … | … | … |

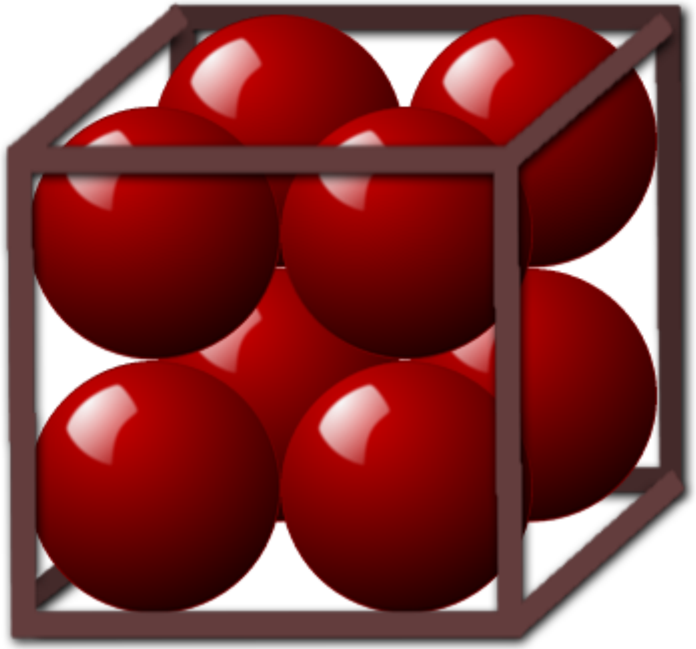
## Problems

- Curse of Dimensionality
- need to scale using Spark

## Solution

compare different…
- distance functions
- dimension reductions
- KNN approximations

# high dimension is n > 9



hypercube of side 4
(packed with unit-radius spheres)

radius of inner sphere:

$$r_n = \sqrt{n} - 1$$

*""" Worse yet, when n>9, we have […] that $r_n$ > 2, and thus the point ( $r_n$,0,0,…,0) on the central sphere lies outside the hypercube of side 4,*

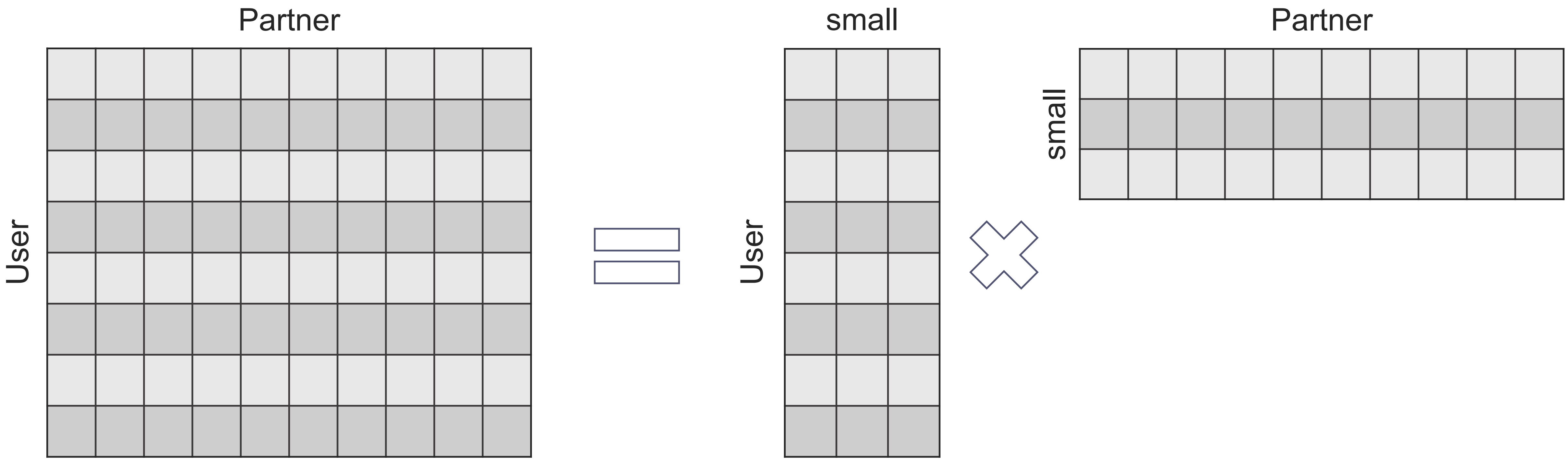
*even though it is "completely surrounded" by the unit-radius hyperspheres that "fill" the hypercube (in the sense of packing it). The central sphere "bulges" outside the hypercube in high-dimensional space."""*

*https://stats.stackexchange.com/questions/99171/why-is-euclidean-distance-not-a-good-metric-in-high-dimensions*

# 3. DIMENSION REDUCTIONS

# Collaborative Filtering = Matrix Factorization



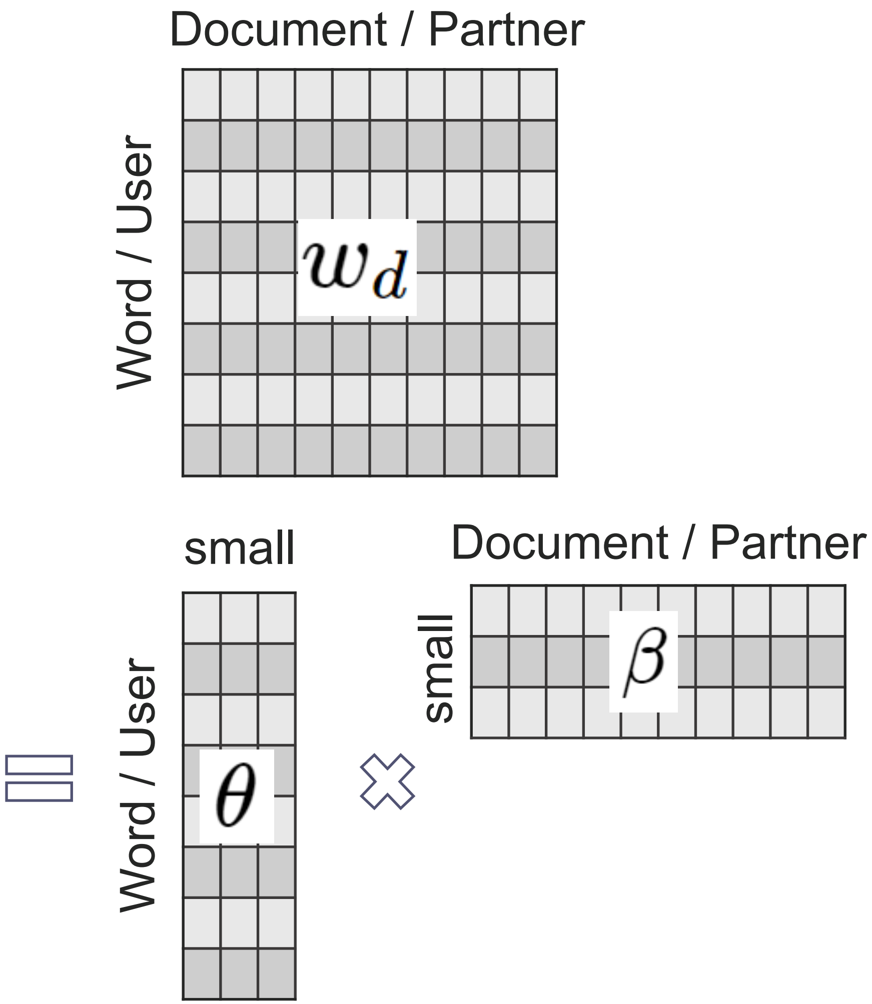



$$r_{ij} = < \mathbf{u_i}, \mathbf{m_j} >, \forall \ i, j$$

Y. Zhou et al. 2008

# Topic Modelling = Probabilistic Matrix Factorization






$$p(w_d|\theta, \beta) = < \theta_{d\cdot}, \beta_{\cdot w} >, \forall d, w$$

$$r_{ij} = < \mathbf{u_i}, \mathbf{m_j} >, \forall \ i, j$$

- Document-WordProbability matrix $w_d$
- Document-TopicProbability matrix $\theta$
- Topic-WordProbability matrix $\beta$

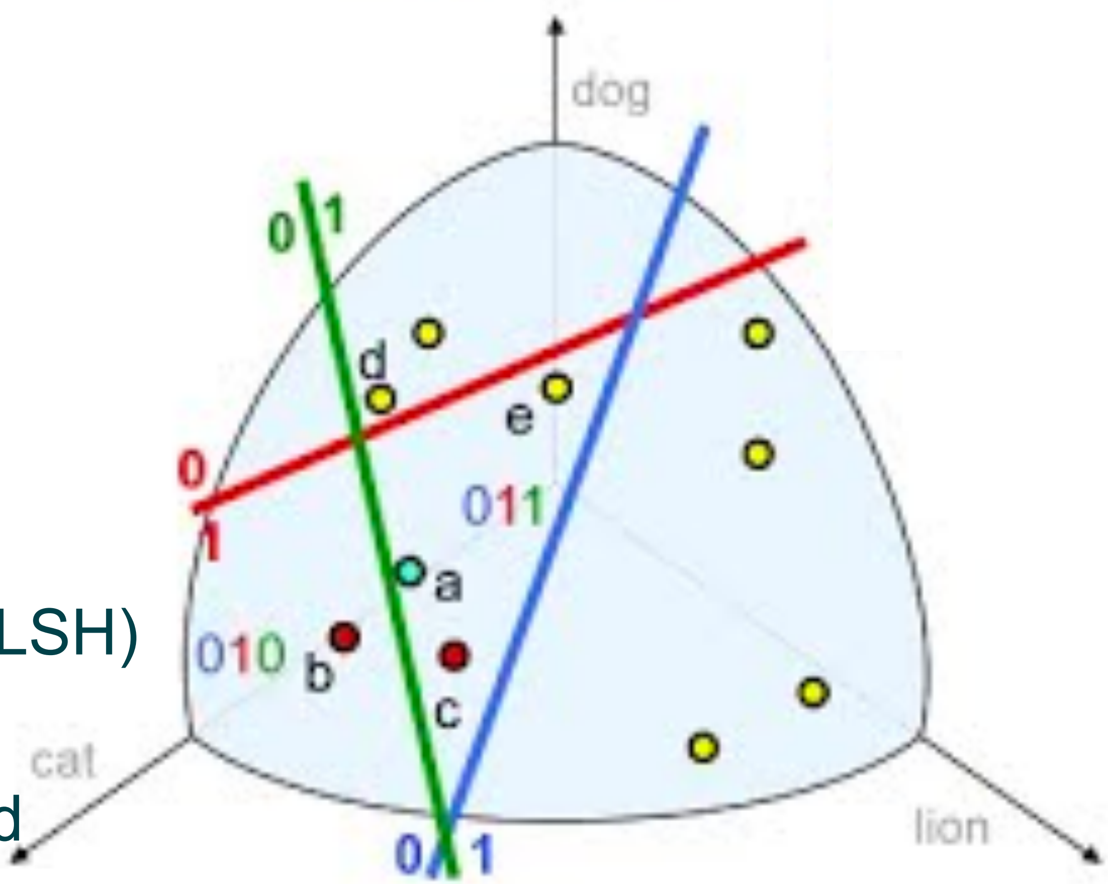
M.Hoffman et al. 2010

# 4. APPROXIMATE KNN

# Approximate KNN

**Problem:**
- Brute Force KNN is **quadratic** in runtime
- Computation time: **a whole month** (on-premise)

**Best Solution:**
- Approximate with Local Sensitive Hashing (LSH)
- Computation Time: **3 hours**
- Constraint: Only subset of metrics supported
- Still challenge to scale this properly
  https://github.com/linkedin/scanns



# 5. RESULTS

# Results

**Target Score:** How many neighbours actually use coupons at the same Partners?

**Distance:** Cosine Distance

**Dimension Reduction:** Collaborative Filtering worked best for Dimension Reduction

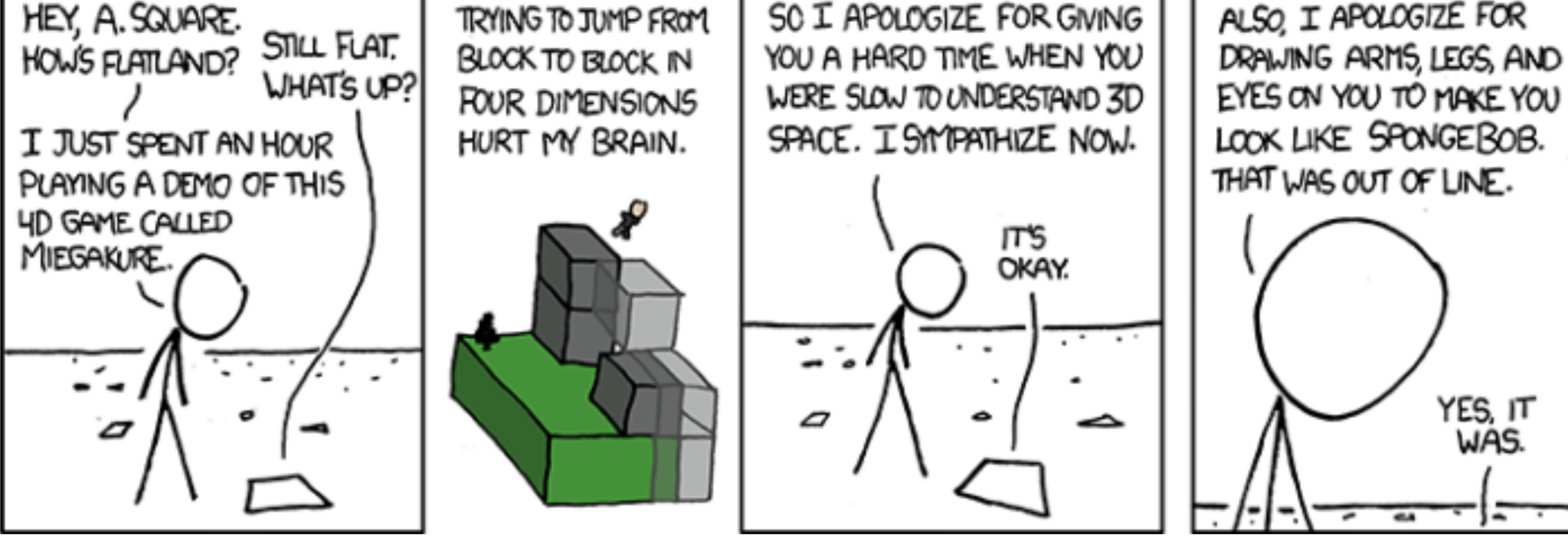
**Approximation:** LSH was that good in final performance, that we haven‘t used dimension reduction at all in the final KNN

**Running now in production**

# SUMMARY

# Summary

- intelligent coupon selection without having training data
- Snowball idea + realtime requirement
- Curse of Dimensionality, n > 9
- Collaborative Filtering / Topic Modelling
  = Matrix Factorization / Probabilistic MF
- Best scalable KNN Approximation: LSH
- In production out there and assigning coupons today ☺




# Thank you very much for your attention!

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**We are hiring!**

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