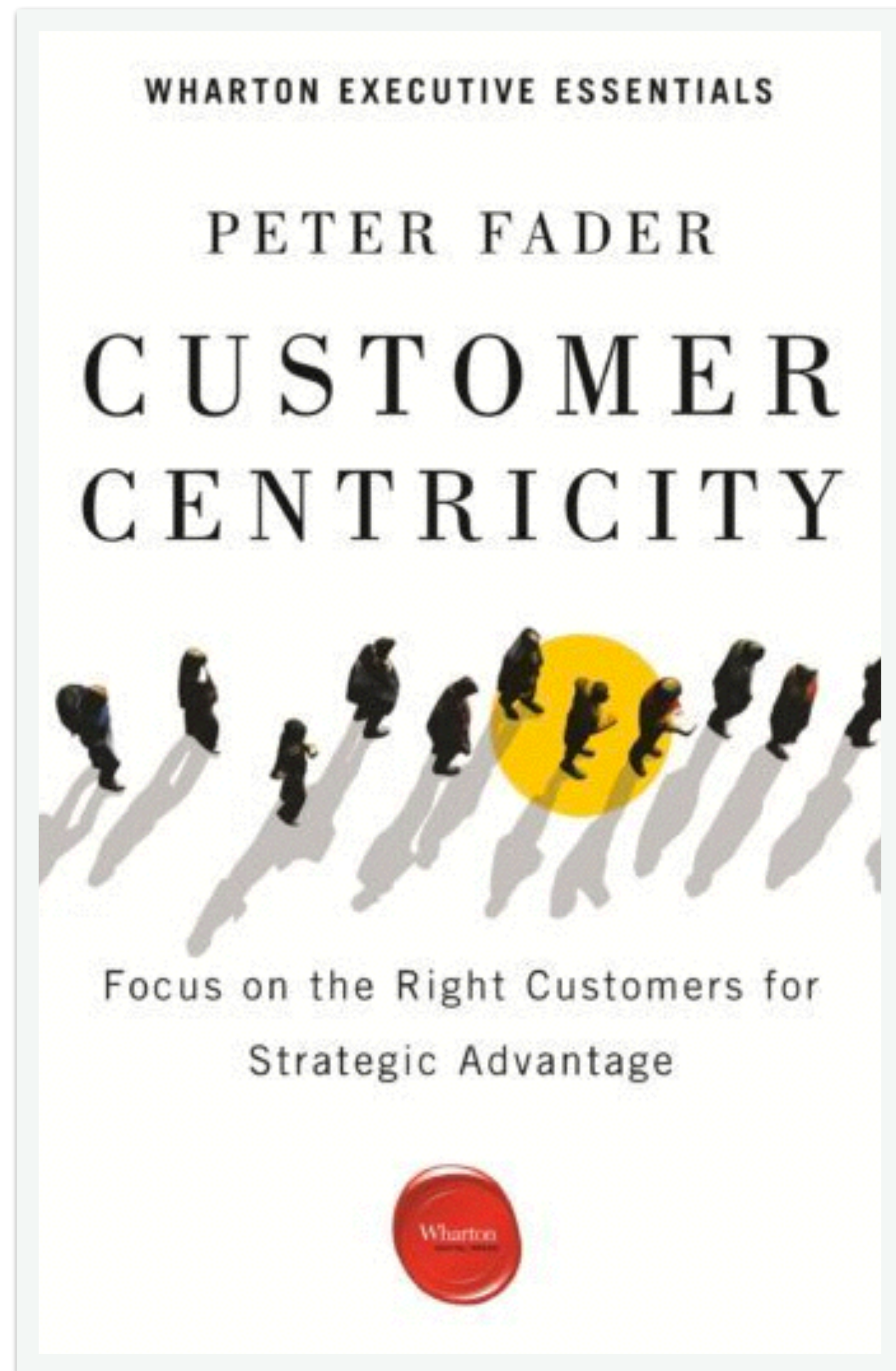


Customer centric data science

Ewan Nicolson
Principal data scientist
Skyscanner



Customers are
individuals

Customers are different
to each other

*Not about customer
service — that's
separate dimension*

Great approach for data science

- Wonderful dataset to work with
- Solve problems in novel ways
- Solve a real human problem

How to get a customer centric dataset

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

Strong user ID

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

Every interaction

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

Storage

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

No silos

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

....

(user id_N, timestamp_N, event details_N)

Consent to use

(user id₀, timestamp₀, event details₀)

(user id₁, timestamp₁, event details₁)

(user id₂, timestamp₂, event details₂)

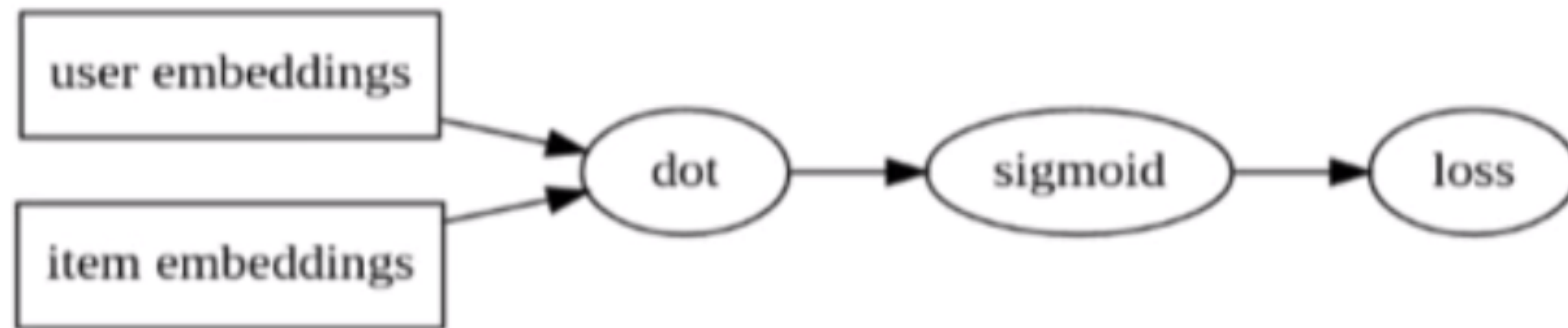
....

(user id_N, timestamp_N, event details_N)

**Avoid personal
data**

Why is this so great?

**Perfect dataset for personal
recommendations**



Embeddings

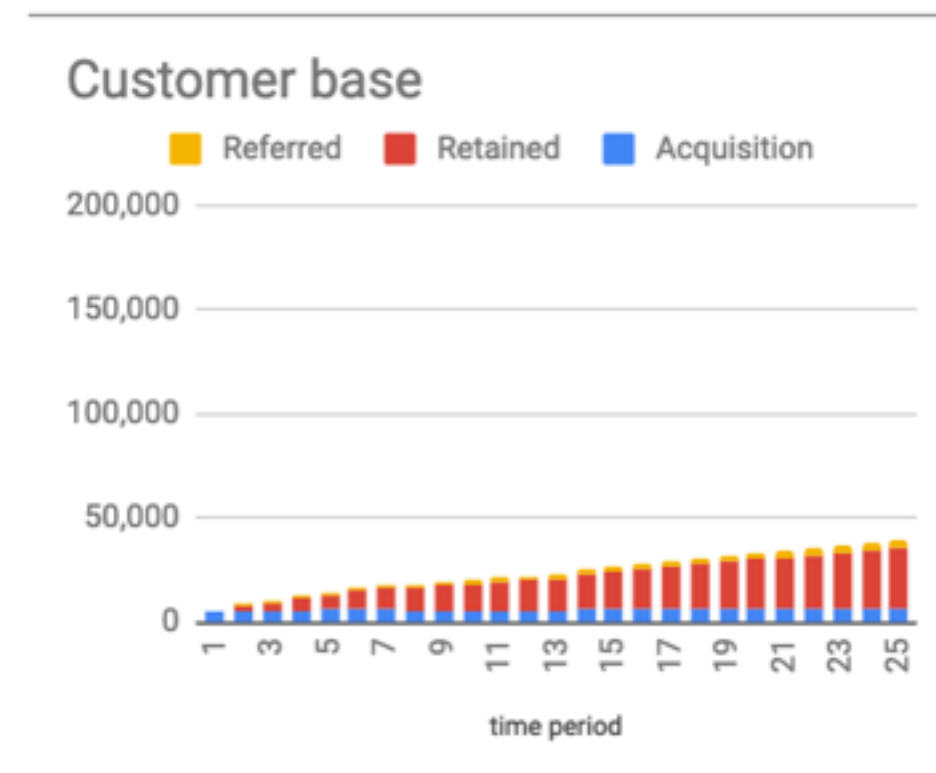
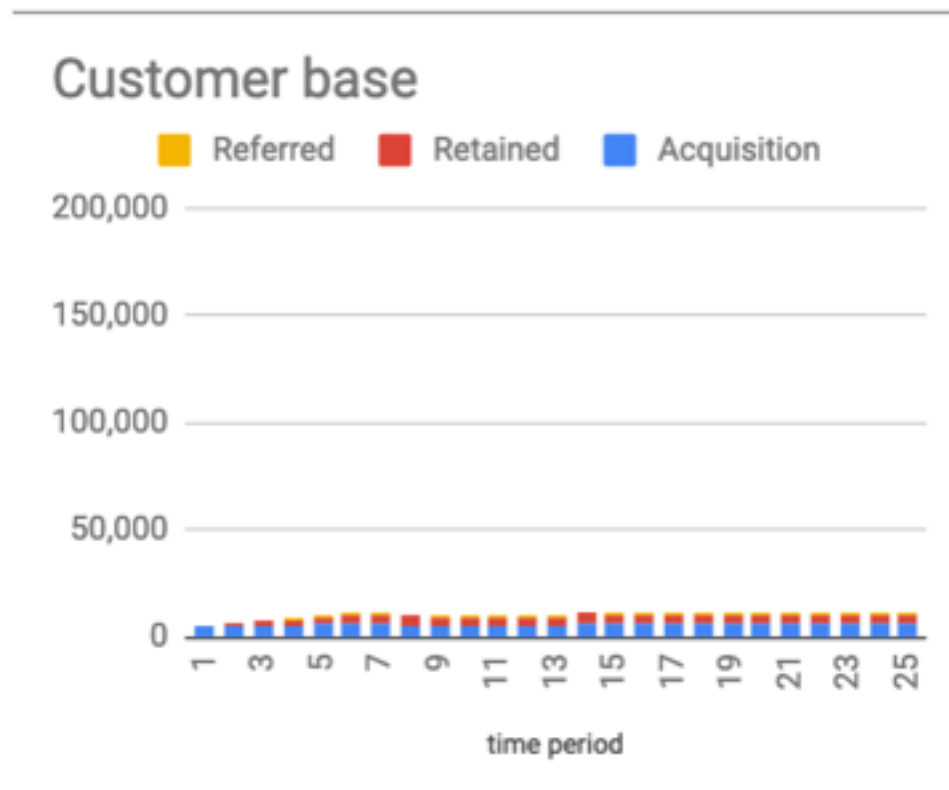

```
In [19]: movie = model.get_layer('movie_embedding')
movie_weights = movie.get_weights()[0]
movie_lengths = np.linalg.norm(movie_weights, axis=1)
normalized_movies = (movie_weights.T / movie_lengths).T

def similar_movies(movie):
    dists = np.dot(normalized_movies, normalized_movies[movie_to_idx[movie]])
    closest = np.argsort(dists)[-10:]
    for c in reversed(closest):
        print(c, movies[c][0], dists[c])

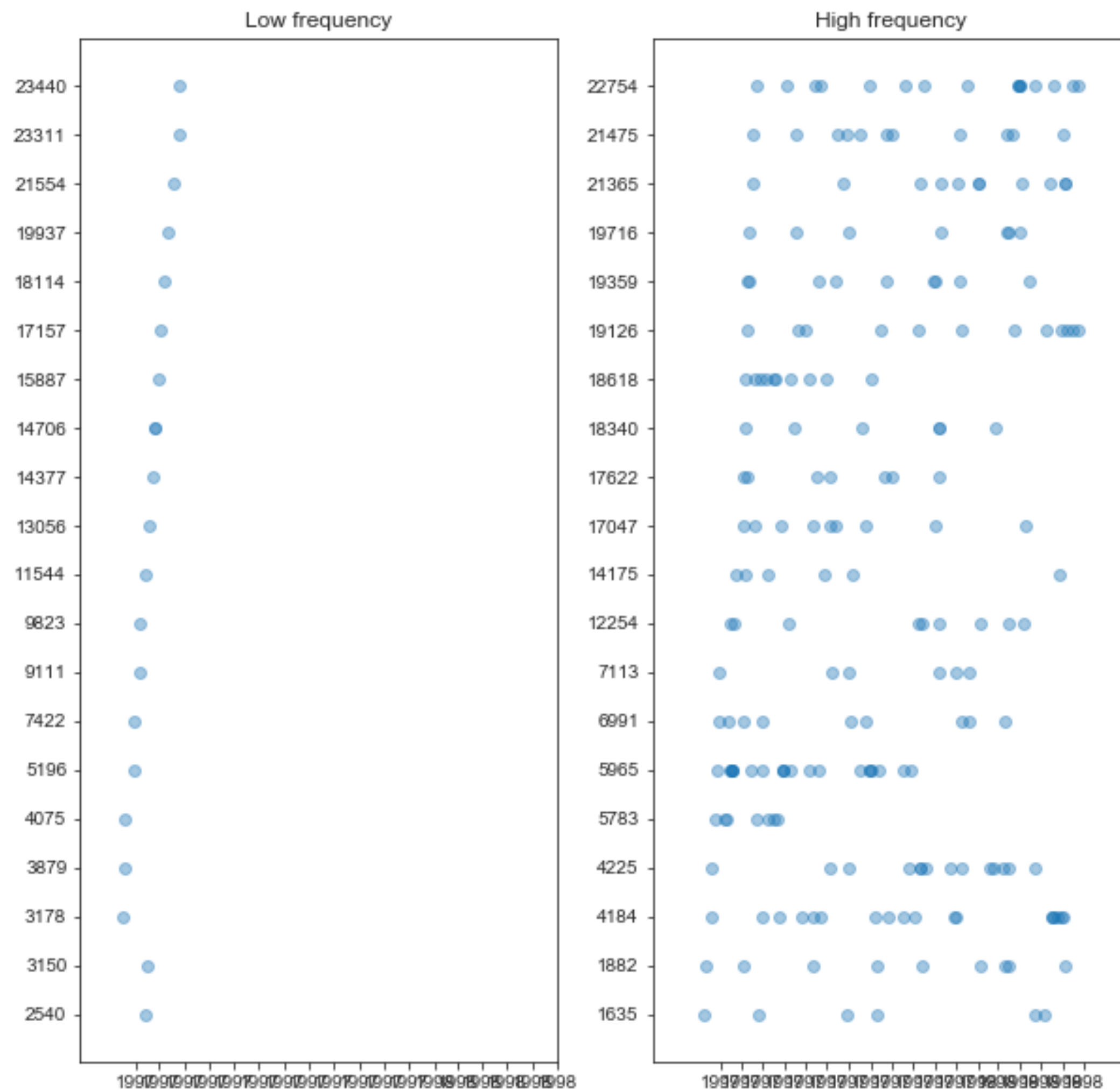
similar_movies('Rogue One')
```

```
29 Rogue One 0.9999999
3349 Star Wars: The Force Awakens 0.9722805
101 Prometheus (2012 film) 0.9653338
140 Star Trek Into Darkness 0.9635347
22 Jurassic World 0.962336
25 Star Wars sequel trilogy 0.95218825
659 Rise of the Planet of the Apes 0.9516557
62 Fantastic Beasts and Where to Find Them (film) 0.94662267
42 The Avengers (2012 film) 0.94634
37 Avatar (2009 film) 0.9460137
```

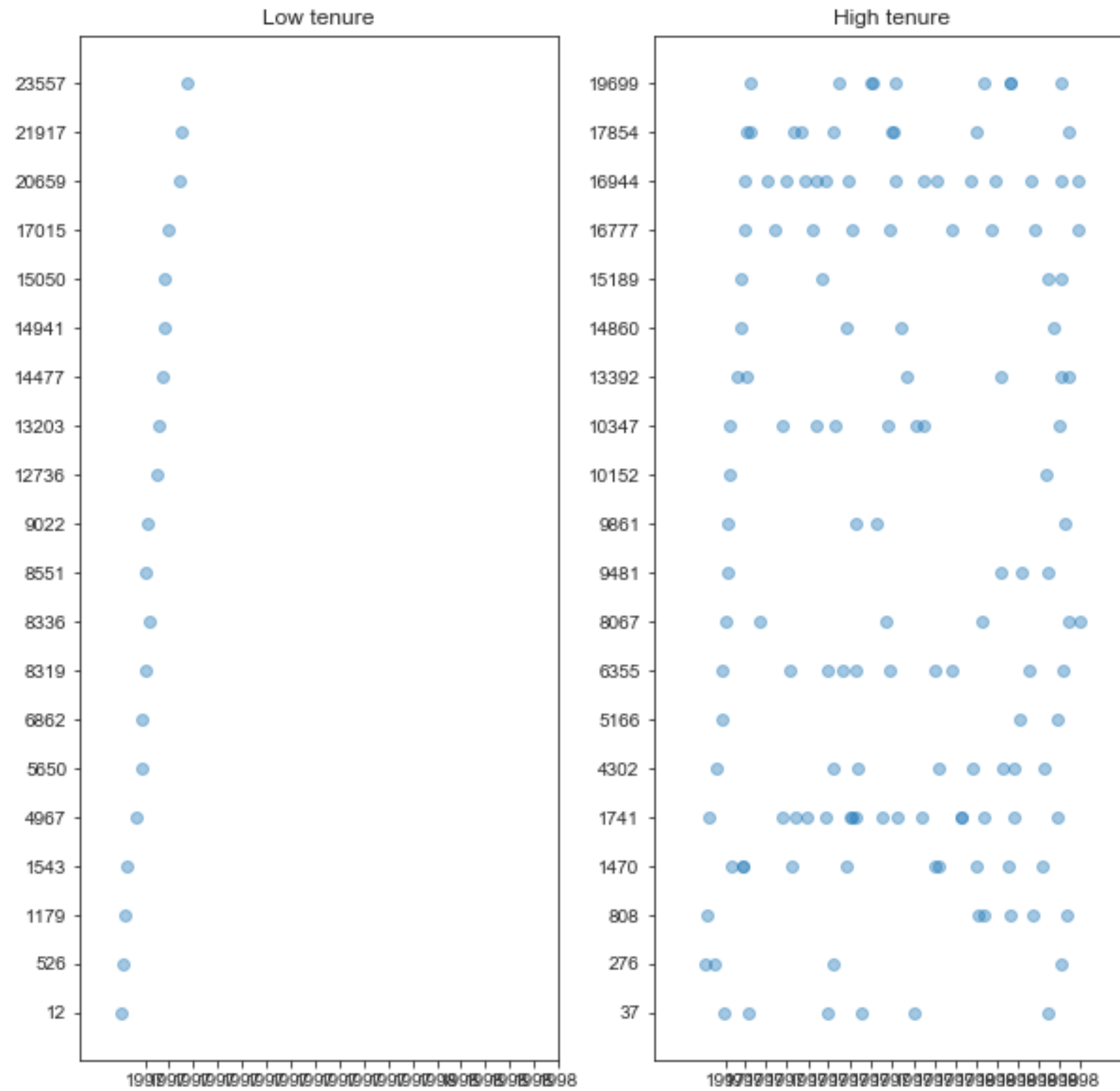
**Understand different
longitudinal behaviours**



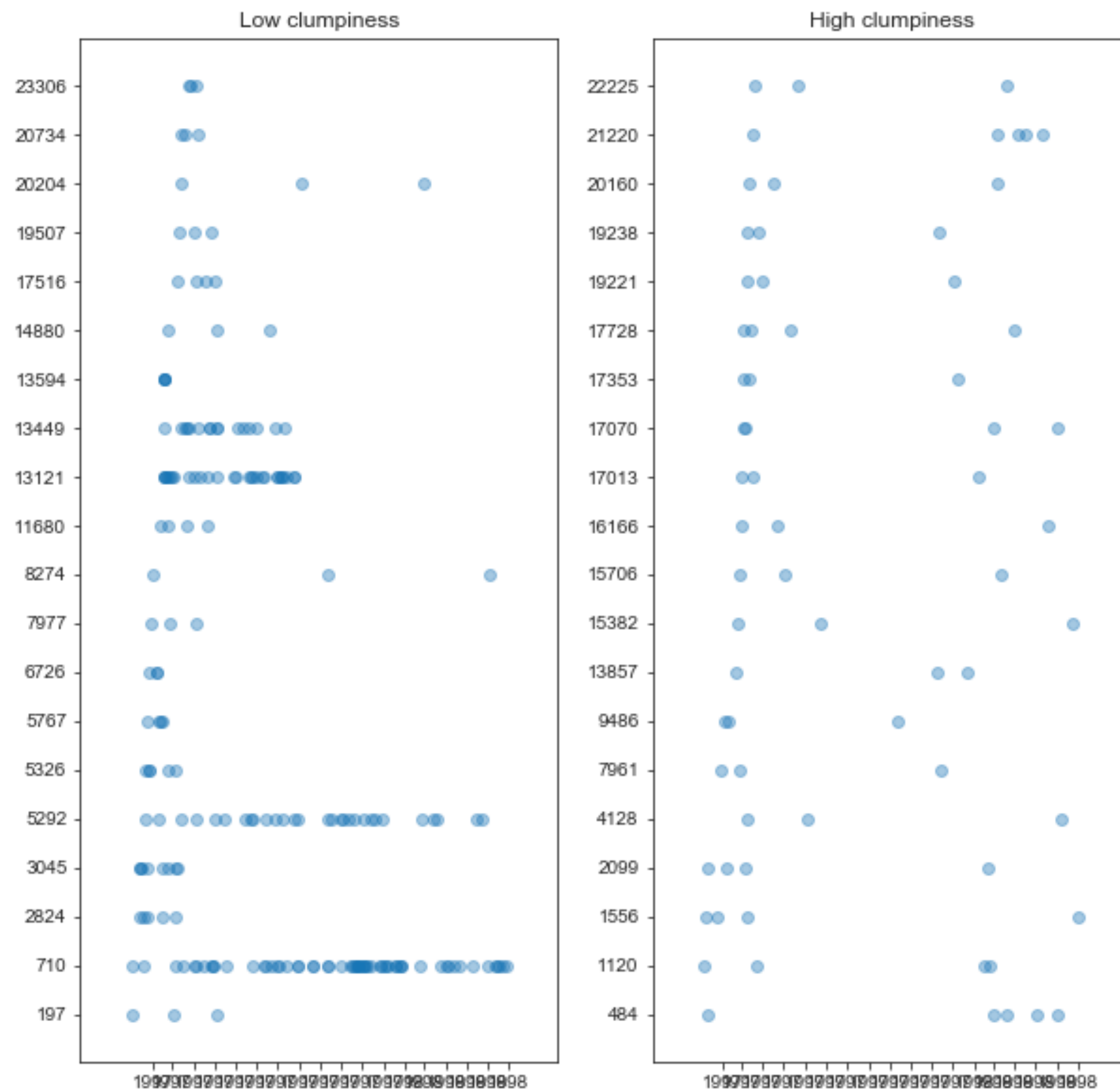
**Long term
retention
means growth**



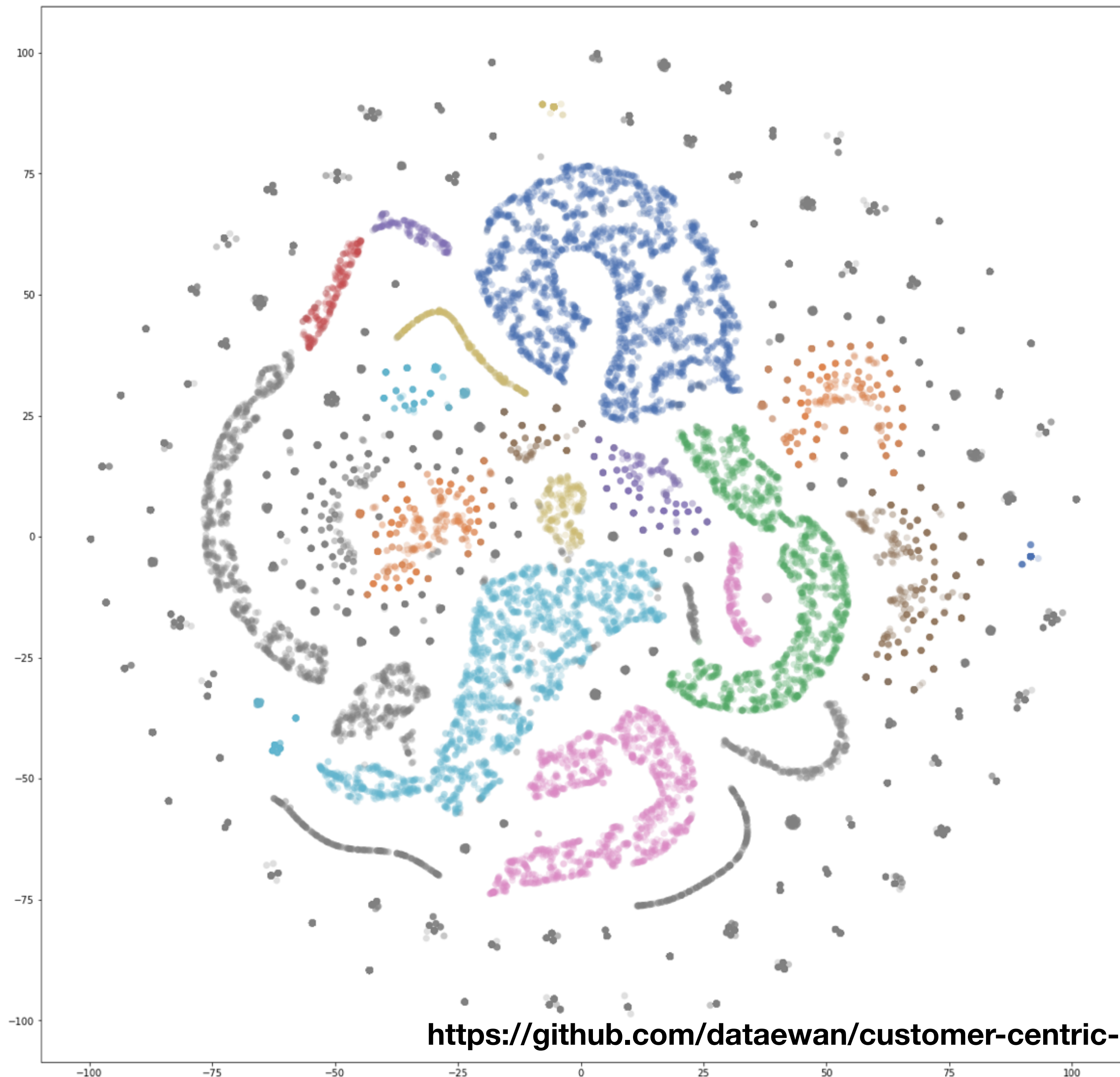
Frequency



Tenure



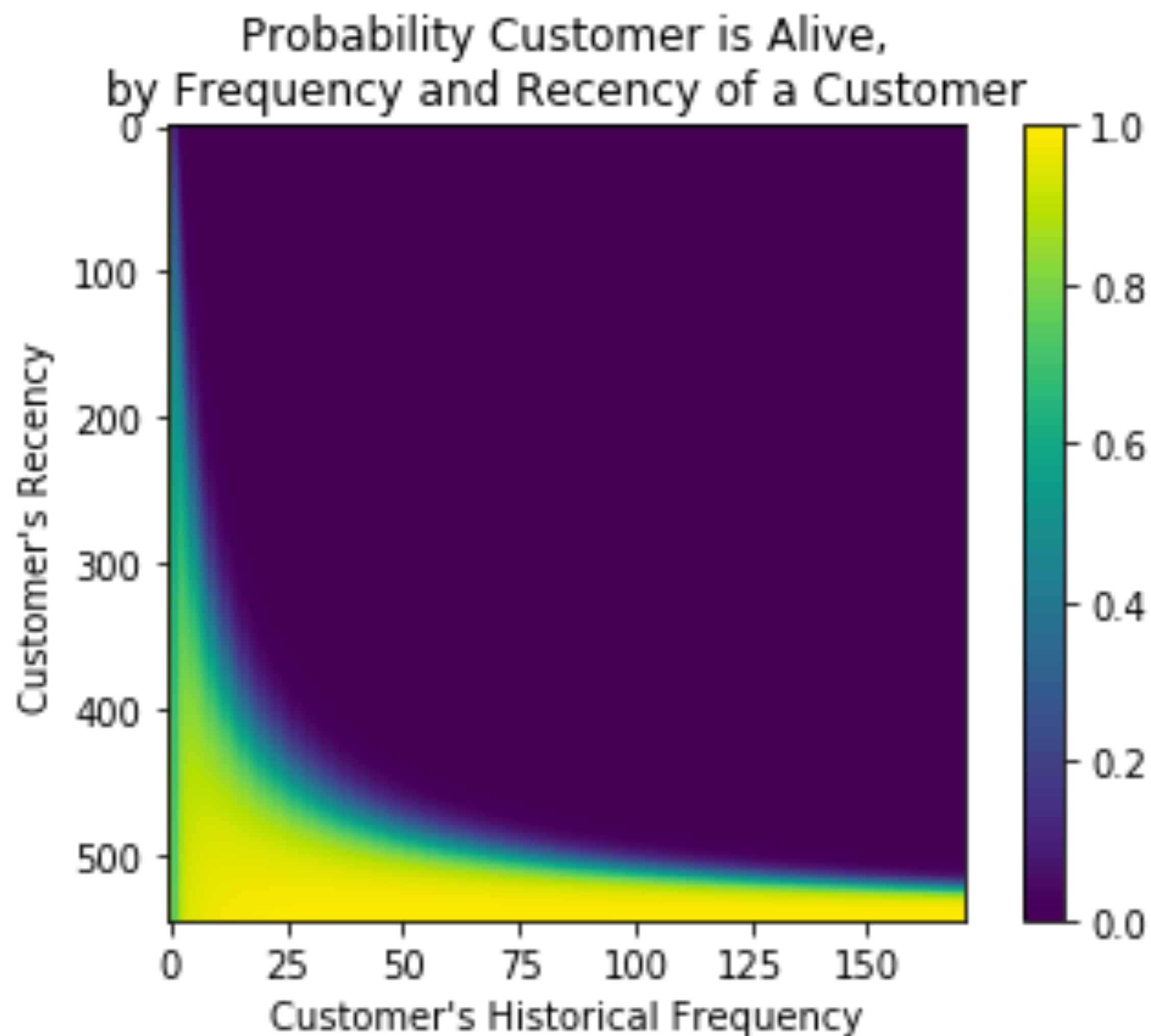
Clumpiness



Customer segments

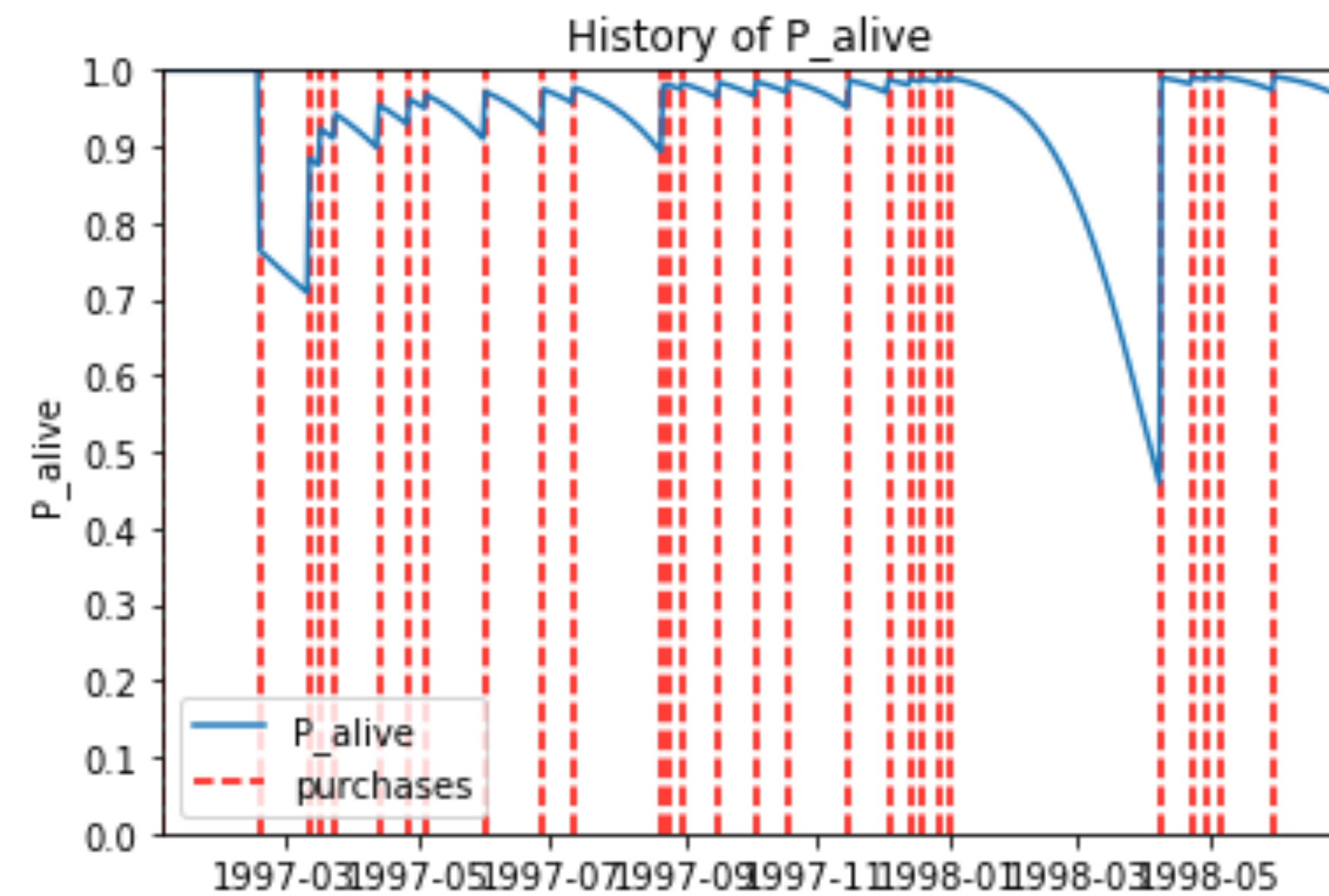
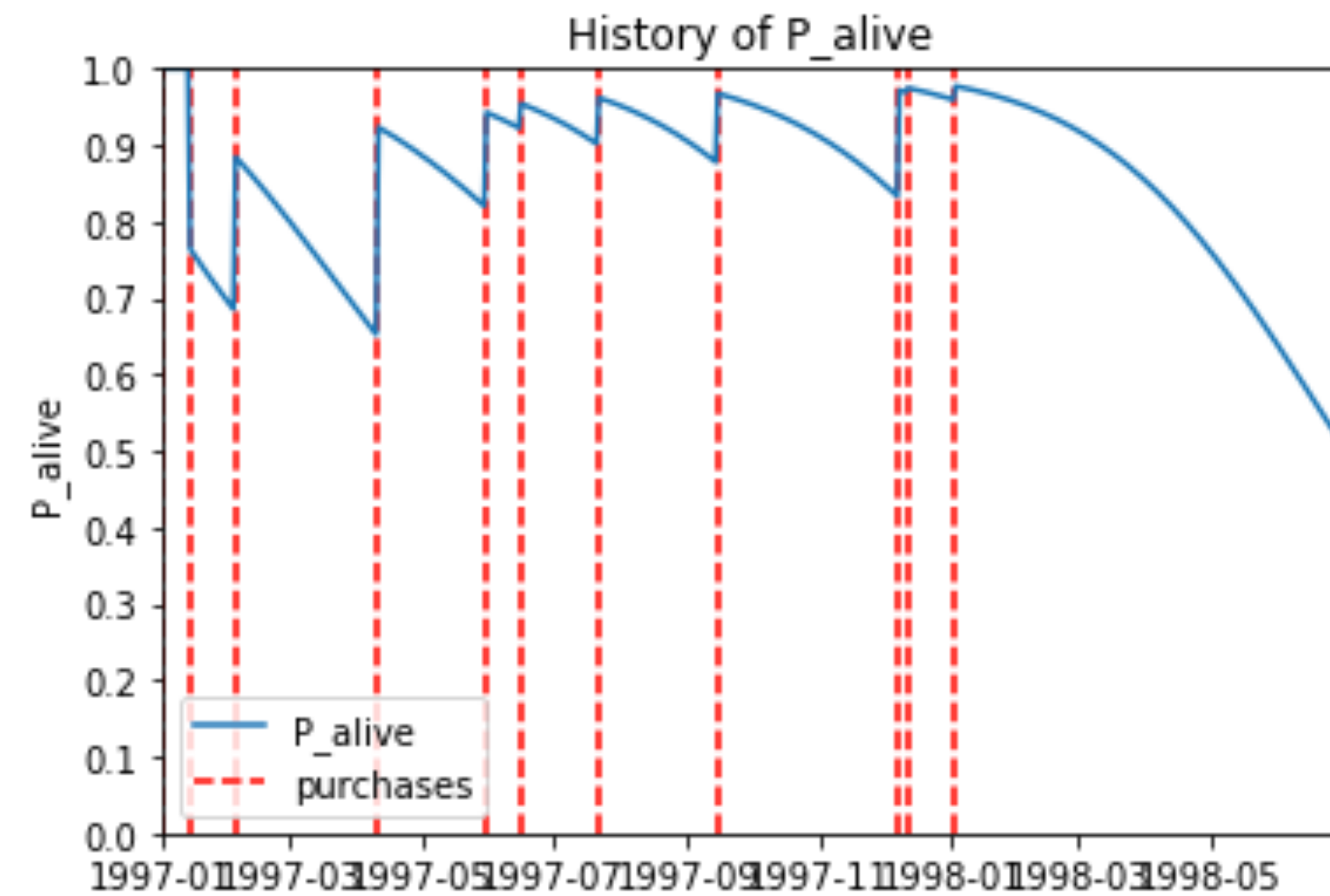
https://github.com/dataewan/customer-centric-ds/blob/master/notebooks/segmentation_cdwow.ipynb

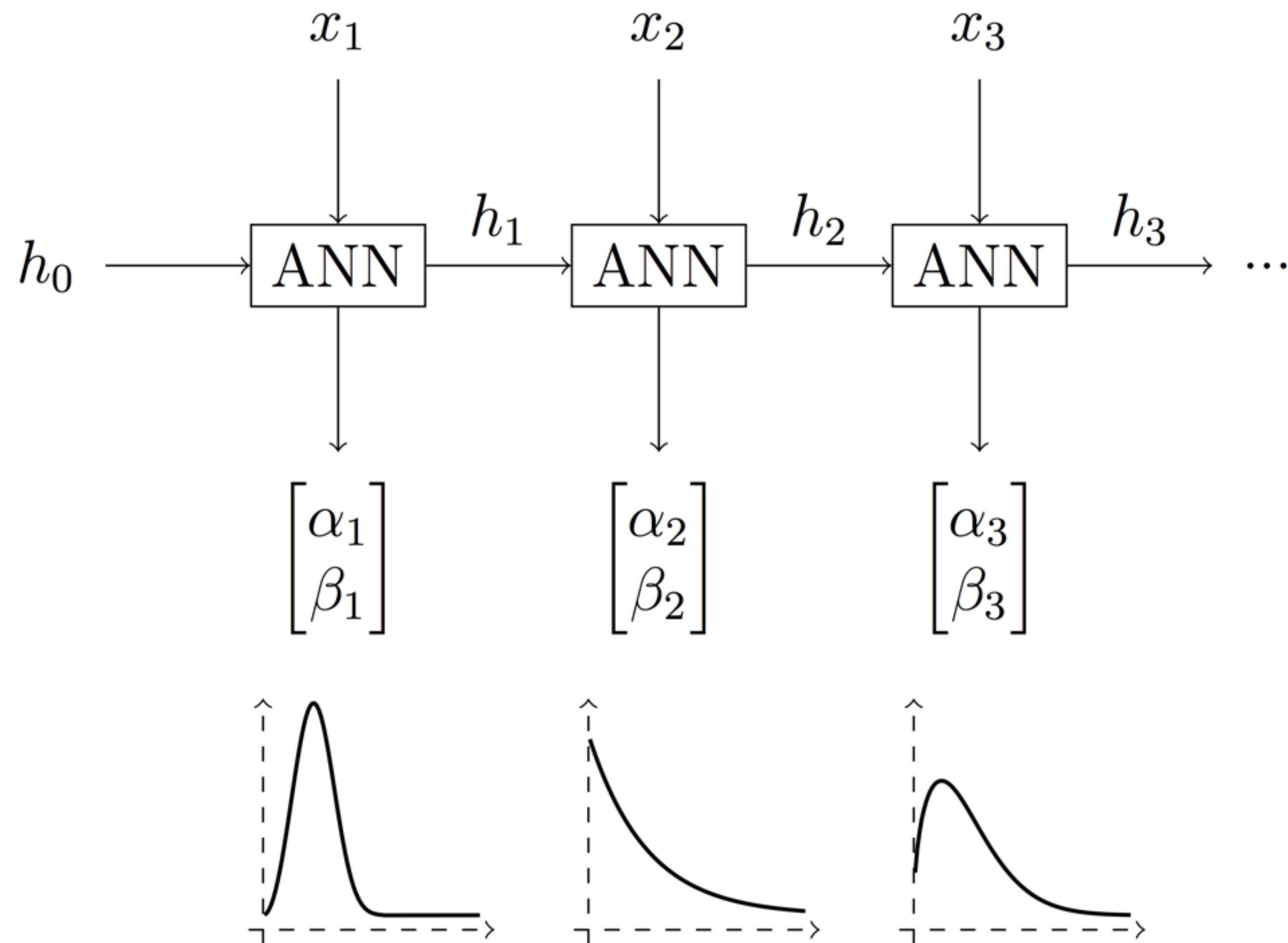
Customer lifetimes



Predicting probability of churn

Predicting probability of churn





Recurrent neural networks for churn

Customer Centric Data Science

Good data
science
perspective

Solves a real
human
problem