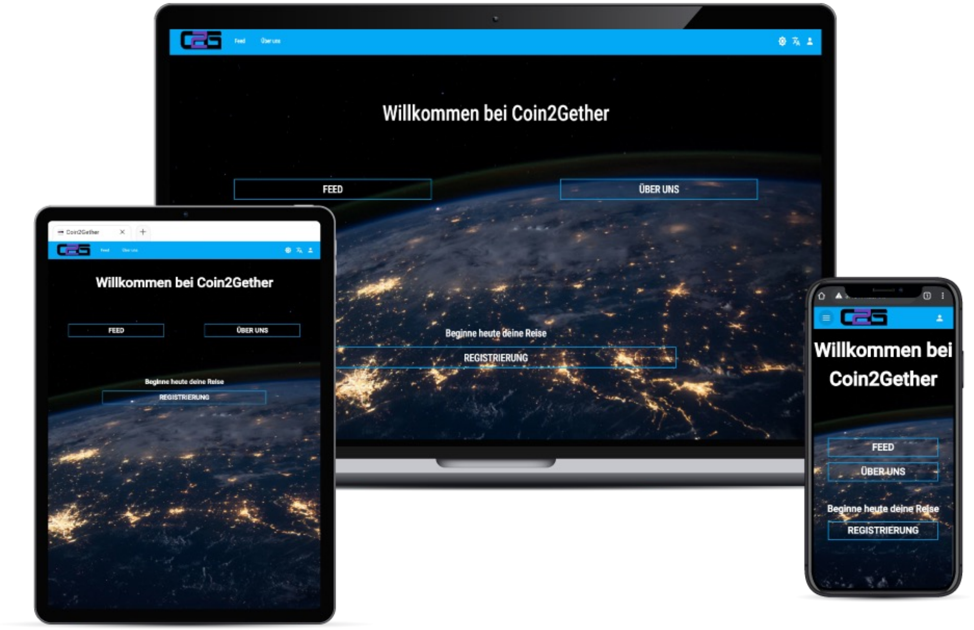
C2G Goes AI

Idea



*It requires a **personal assistant** who knows C2G like the back of his hand. That assistant should help you **connect** with other innovative and creative minds and **support** you in operating the platform.*

- Share **lessons learned** and **motivation** from recent trades
- **No more scams** - Wannabe guru **failures** are **transparent**
- Publish **blog posts** on relevant crypto topics
- **Connect** with a network of **crypto enthusiasts** & **specialists**
- Be **rewarded** with **followers** for **smart thoughts** and **content**
- **Become wealthy** through the expert **knowledge** of the **community**

Coin2Gether

in

78

Seconds

C h a t b o t


WHO ARE WE?
CHATBOTS!!!
WHAT DO WE DO?
Sorry, I don't understand what you are trying to say.
Hello
Sorry, I don't understand what you are trying to say.

Question Answering vs. Chatbots

Question Answering

- QA models have question pool
- Related to a subject area
- Low interactivity

Chatbots

- Able to answer more questions
- It is not limited to one subject area
- High interactivity

BERT

Bidirectional Encoder Representations from Transformers

- Based on Transformer language models
- Inputs are processed bidirectionally
- Texts are analyzed from both sides
- BERT models consist of DNN´s


RULE BASED
PATTERN ACTION
imgflip.com

Intent Classification

1. objective is defined
2. chatbot leads dialog to the defined objective

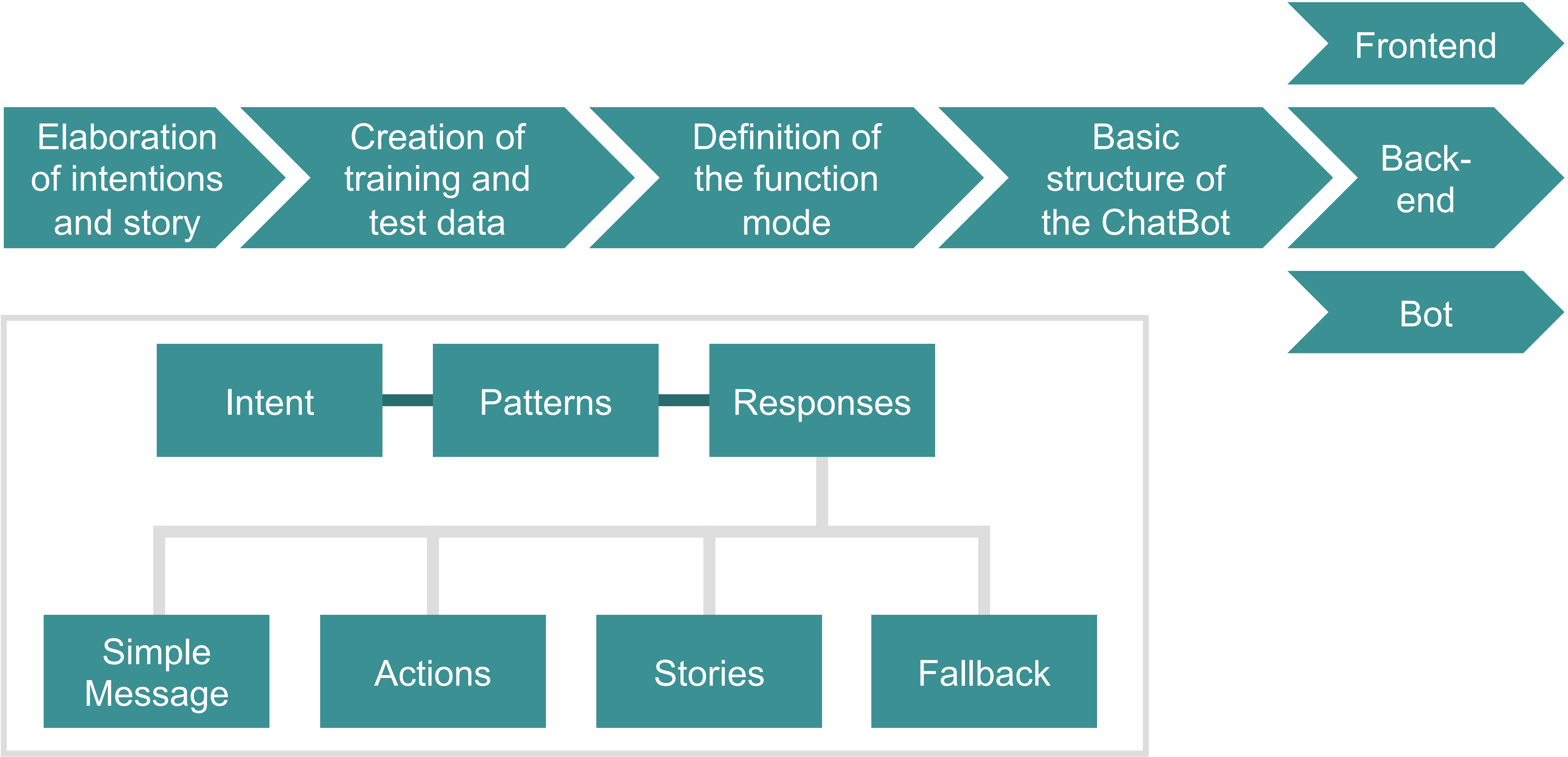
Question Answering

- **Existing text**
- **Classified according to the user's goal**

Dialogue Policy

- **Structure of the conversation**
- **Rules for dialogue**

Procedure


Frontend
Elaboration of intentions and story
Creation of training and test data
Definition of the function mode
Basic structure of the ChatBot
Back-end
Bot
Intent
Patterns
Responses
Simple Message
Actions
Stories
Fallback

Structure of the chatbot

Input

Create
a
post
for
me
!

Lemmatizer

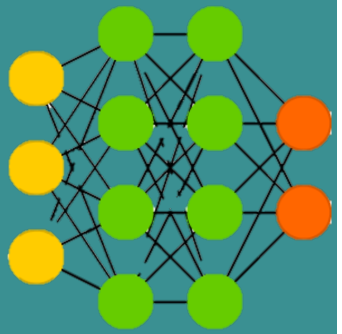
Remove special characters

Create
a
post
for
PRON

Bag of words

0
1
0
0
1
0
1
0
1
1

Predict/train



Results of the chatbot

Vector

BoW

Stacked

BERT

	Sentence	Tag	Tag_parent	predicted_tags	matches	probas*	predicted_tags_if_not_fallback
10	supercalifragilisticexpialidocious	fallback	fallback	greeting	False	0.254159	greeting
11	Get me to the homepage.	navigate_homepage	navigate	find_homepage	False	0.479911	find_homepage
17	Expose the page where I can make a post.	navigate_create_post	navigate	find_create_trade	False	0.964732	find_create_trade
18	Display the page for creating a trade.	navigate_create_trade	navigate	action_logout	False	0.498036	action_logout
21	Hello bot.	greeting	greeting	about_bot_background	False	0.380586	about_bot_background
29	Alexa is better than you.	about_bot_other_bots	about_bot_other_bots	joke	False	0.341779	joke

**Fallback-Threshold = 25%*

Results of the chatbot

Vector

BoW

Stacked

BERT

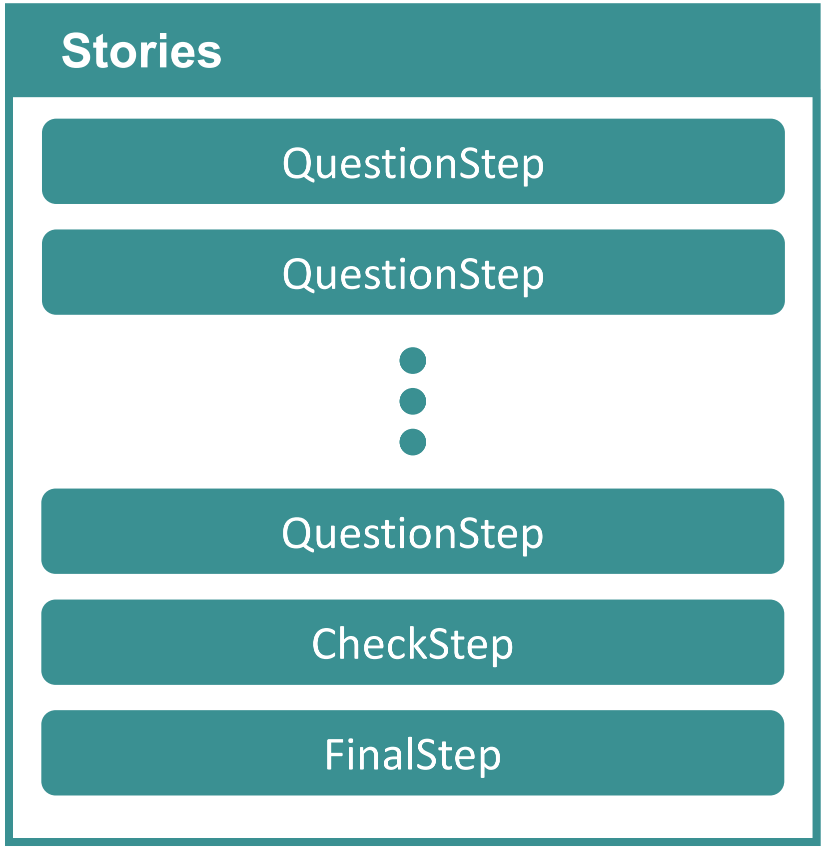
```
# wrong prediction
text = 'Create a post.'
explain_choice(ig, text)
```

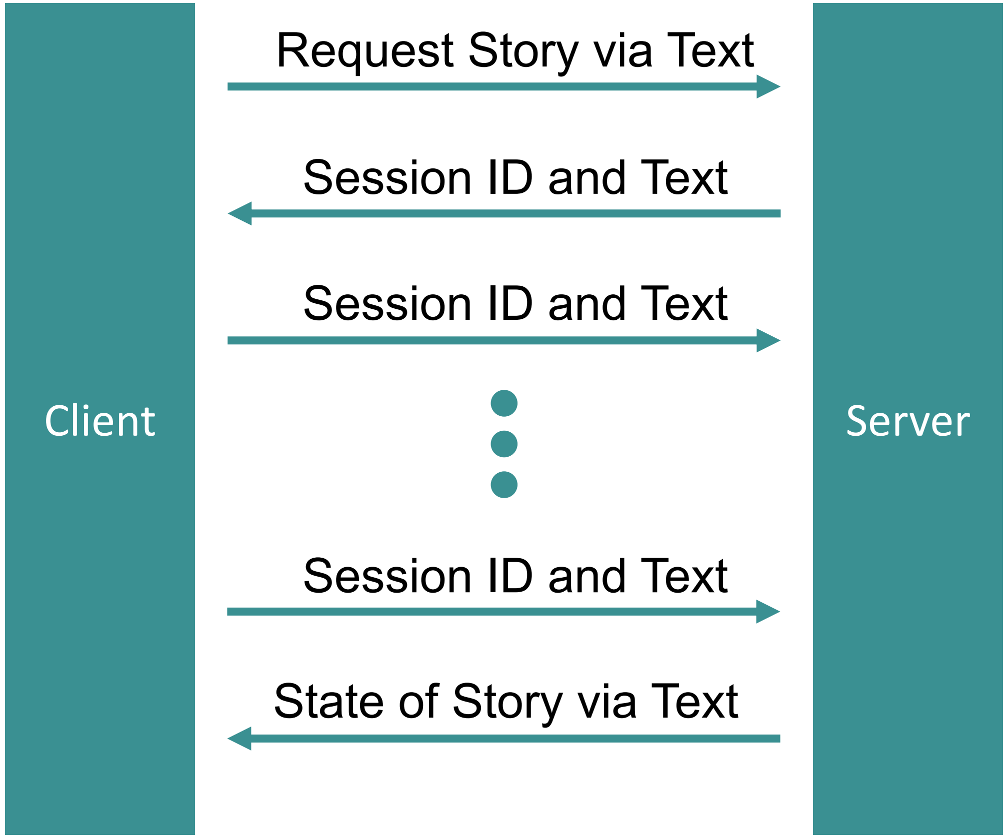
```
navigate_create_post
[(0.8853112790963429, 'post'), (0.22318878729466662, 'create'), (0.118740701145351, 'a')]
```

```
# correct prediction
text = 'Create a post for me.'
explain_choice(ig, text)
```

```
action_create_post
[(0.6527565482046565, 'post'), (0.2666675698634774, 'create'), (0.1877163463185576, 'for'), (0.1419184454426143, '-PRON-'), (0.01056351783490079, 'a')]
```

Backend


Stories
QuestionStep
QuestionStep
QuestionStep
CheckStep
FinalStep

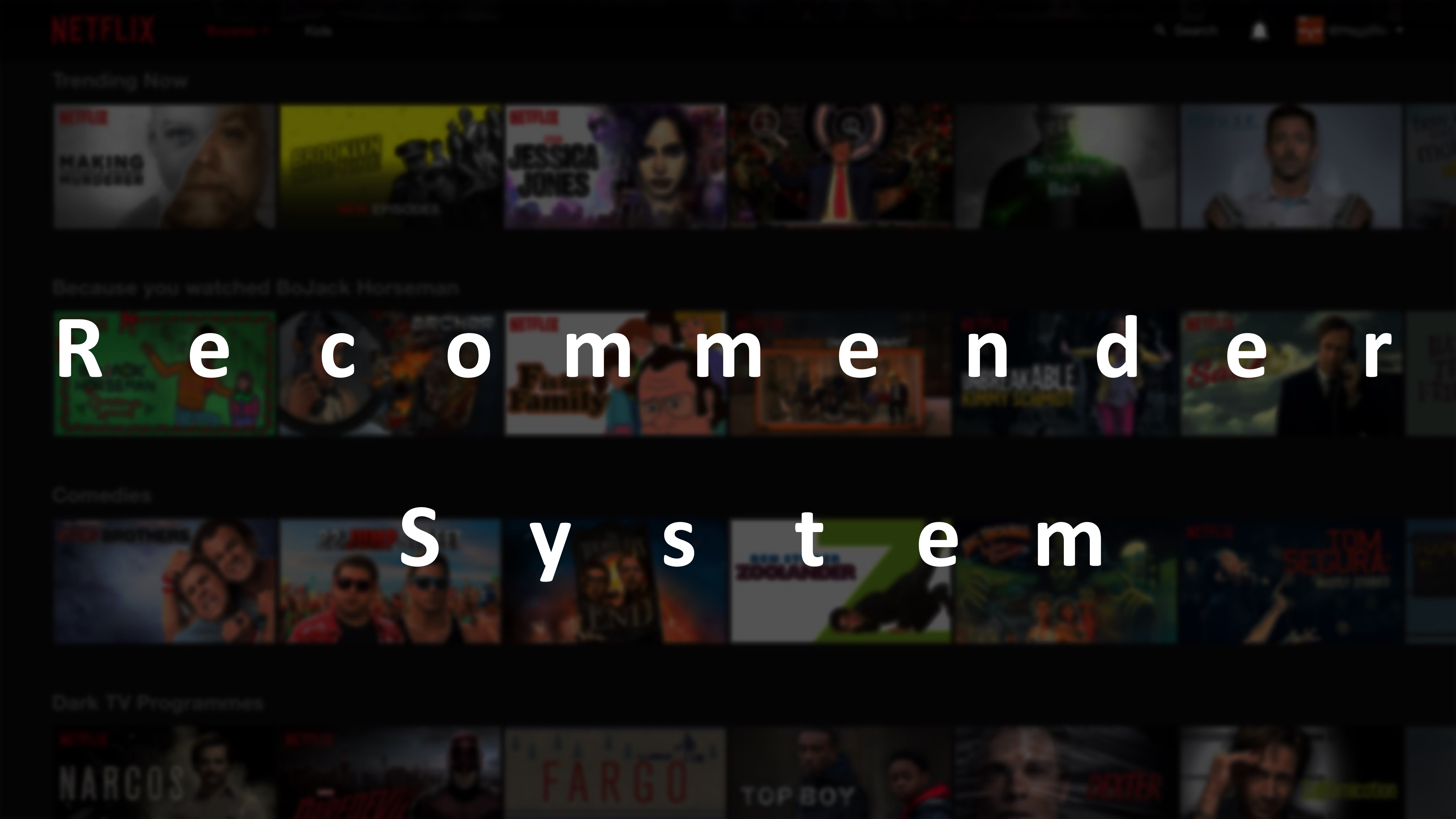

Client
Request Story via Text
Session ID and Text
Session ID and Text
Session ID and Text
State of Story via Text
Server

Outlook for chatbot development

Collection of requests from the past in database

Context awareness in the setting of stories


SAY CHATBOT
ONE MORE TIME
memegenerator.net

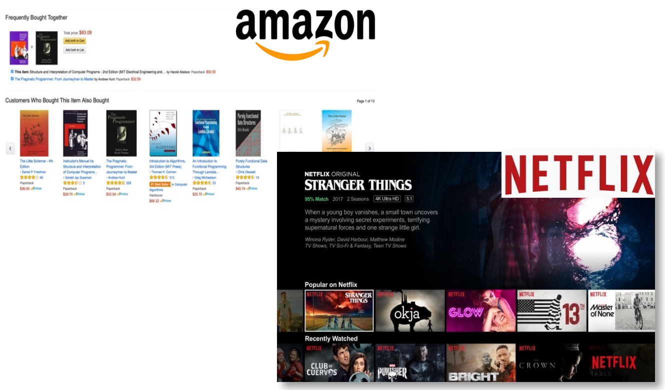


Recommender System

What is the goal of a recommendation system?

Principles

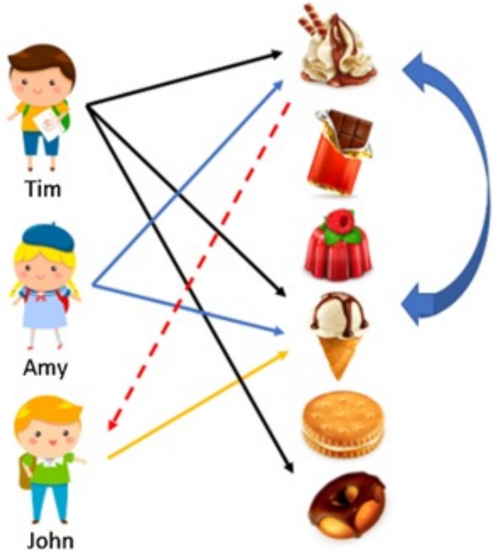
- Customers who bought this item also bought
- Generate the top N most matching items



Method

Collaborative Filtering

- Similarity of the products based on the common appearance



Further methods:

Challenges

Evaluations

- Recommendation systems belong to the category of unsupervised learning
- Different evaluation options with advantages & disadvantages

Combination of different data sources

- How can empirical recommendations be generated based on diverse and varied information?

Collaborative Filtering – Deep Dive

[Source](#)

Procedure for the memory-based method

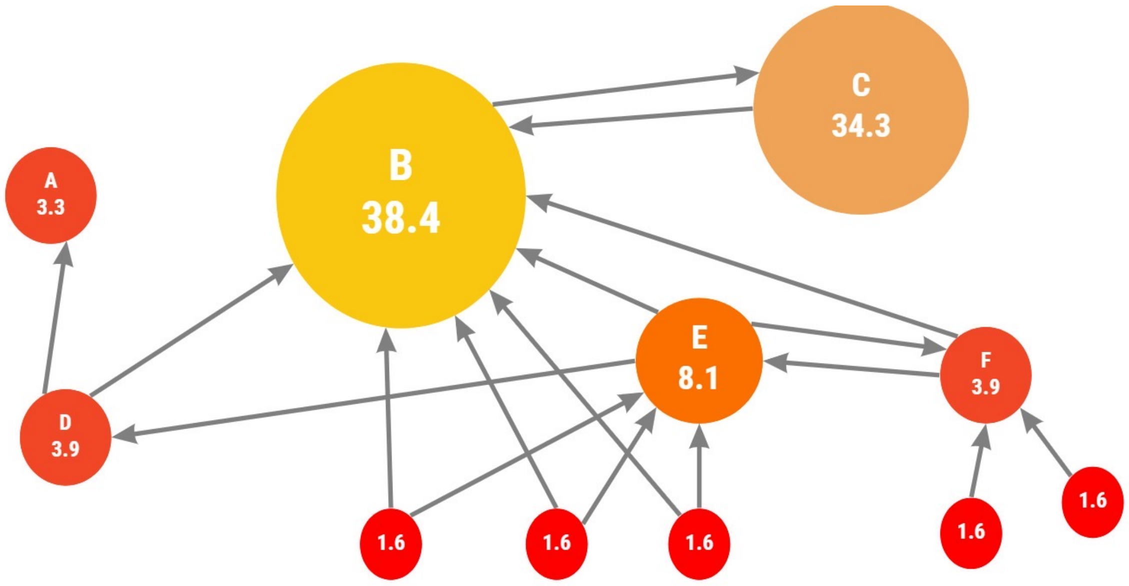
1. Matrix in "user item" format is given
2. Calculate the similarity matrix for the users by e.g. Cosine correlation:

$$\operatorname{simil}(x,y) = \cos(\vec{x},\vec{y}) = \frac{\vec{x}\cdot\vec{y}}{||\vec{x}|| \times ||\vec{y}||} = \frac{\sum\limits_{i\in I_{xy}} r_{x,i}r_{y,i}}{\sqrt{\sum\limits_{i\in I_x} r_{x,i}^2}\sqrt{\sum\limits_{i\in I_y} r_{y,i}^2}}$$

3. Using the cosine similarity matrix now identify the most similar users.
4. From the identified users, the associated user-item interactions can be taken into account for product recommendations


YOU KNOW WHAT PAGERANK IS?
PLEASE, TELL ME ALL ABOUT IT.

How to find relevant users?



- PageRank algorithm is a method to determine the link popularity of a node
- The more links pointing to a page, the higher is the weight of this node
- The higher the weight of the referring accounts is, the greater the effect is

Famous for: Google [1] Click me Twitter [2] Stanford

PageRank – Deep Dive

Iteratives Vorgehen

1. **t = 0**
   1. $PR(p_i; 0) = \frac{1}{N}$
2. For **t = 1** until the termination condition is fulfilled:
   1. Update PageRank for all nodes:

$$PR(p_i; t+1) = \frac{1-d}{N} + \mathrm{d} \sum_{j=1}^{N} \frac{PR(p_j; t+1)}{L(p_j)}$$

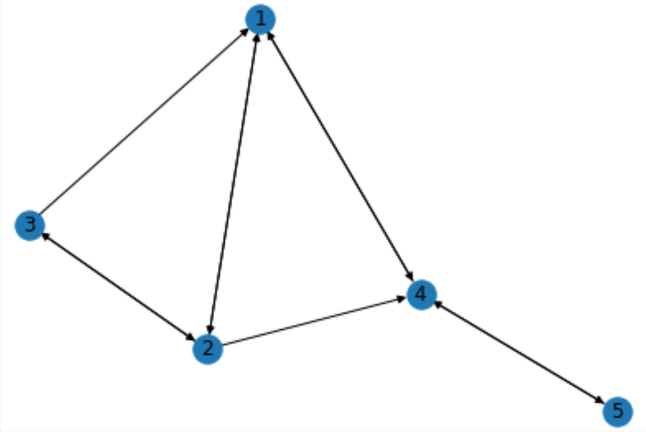
   2. Termination Condition :
      1. Achievement of the defined iterations
      2. Konvergenzbedingung

In practice:
- More efficient calculation through representation with matrices
- Network is mapped via an adjacency matrix

Proposed solution

Concepts

1 PageRank for ranking the relevance of users:



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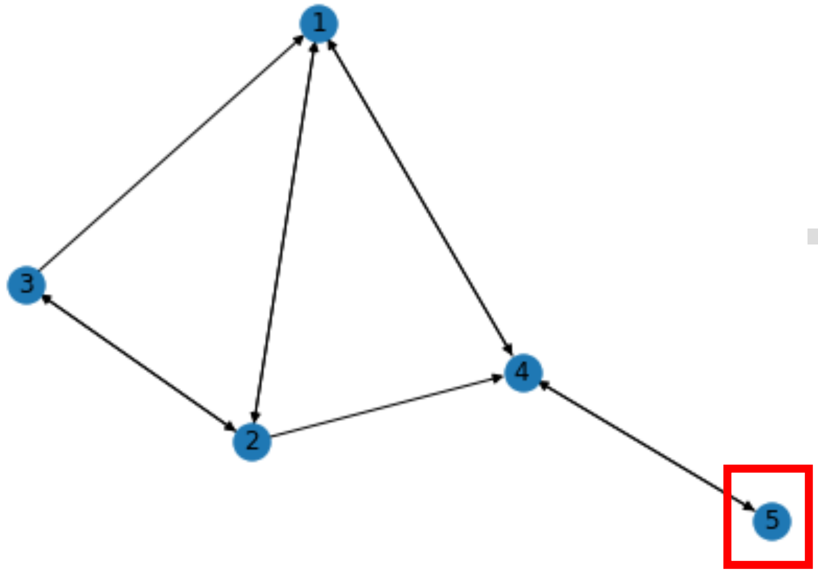
2 Collaborative filtering for identifying similar portfolios:

	BTC	ETHER	EURO	DOLLAR
1	0.500000	0.000000	0.000000	0.500000
2	0.000000	0.333333	0.333333	0.333333
3	0.333333	0.333333	0.000000	0.333333
4	0.250000	0.250000	0.250000	0.250000
5	1.000000	0.000000	0.000000	0.000000

Personalized PageRank



Graph G

```
nx.pagerank(G, personalization=
            {
                1:0.707,
                2:0.000,
                3:0.577,
                4:0.500,
                5:1.000,
            })
```

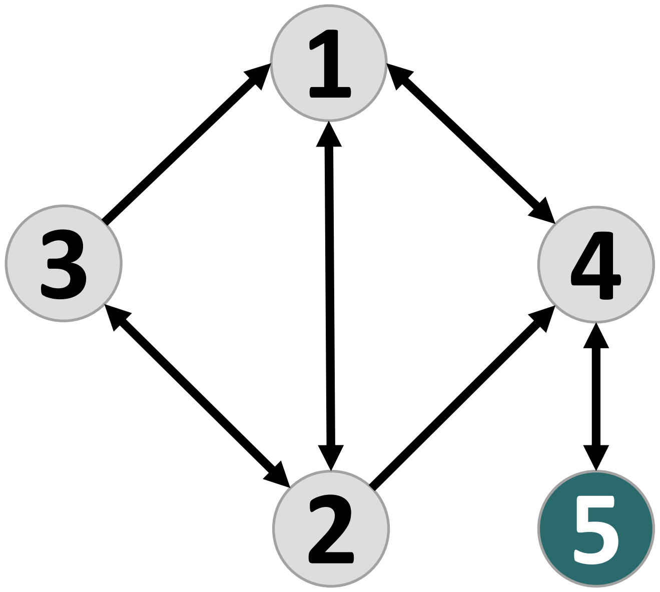
Personalization

	1	2	3	4	5
1	1.000000	0.408248	0.816497	0.707107	0.707107
2	0.408248	1.000000	0.666667	0.866025	0.000000
3	0.816497	0.666667	1.000000	0.866025	0.577350
4	0.707107	0.866025	0.866025	1.000000	0.500000
5	0.707107	0.000000	0.577350	0.500000	1.000000

Recommended Users;

1: 0.25
2: 0.14
3: 0.07

Which user should be recommended to user 5?



	1	2	3	4	5
1	1.000000	0.408248	0.816497	0.707107	0.707107
2	0.408248	1.000000	0.666667	0.866025	0.000000
3	0.816497	0.666667	1.000000	0.866025	0.577350
4	0.707107	0.866025	0.866025	1.000000	0.500000
5	0.707107	0.000000	0.577350	0.500000	1.000000

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                 {
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Personalization

Recommended Users:

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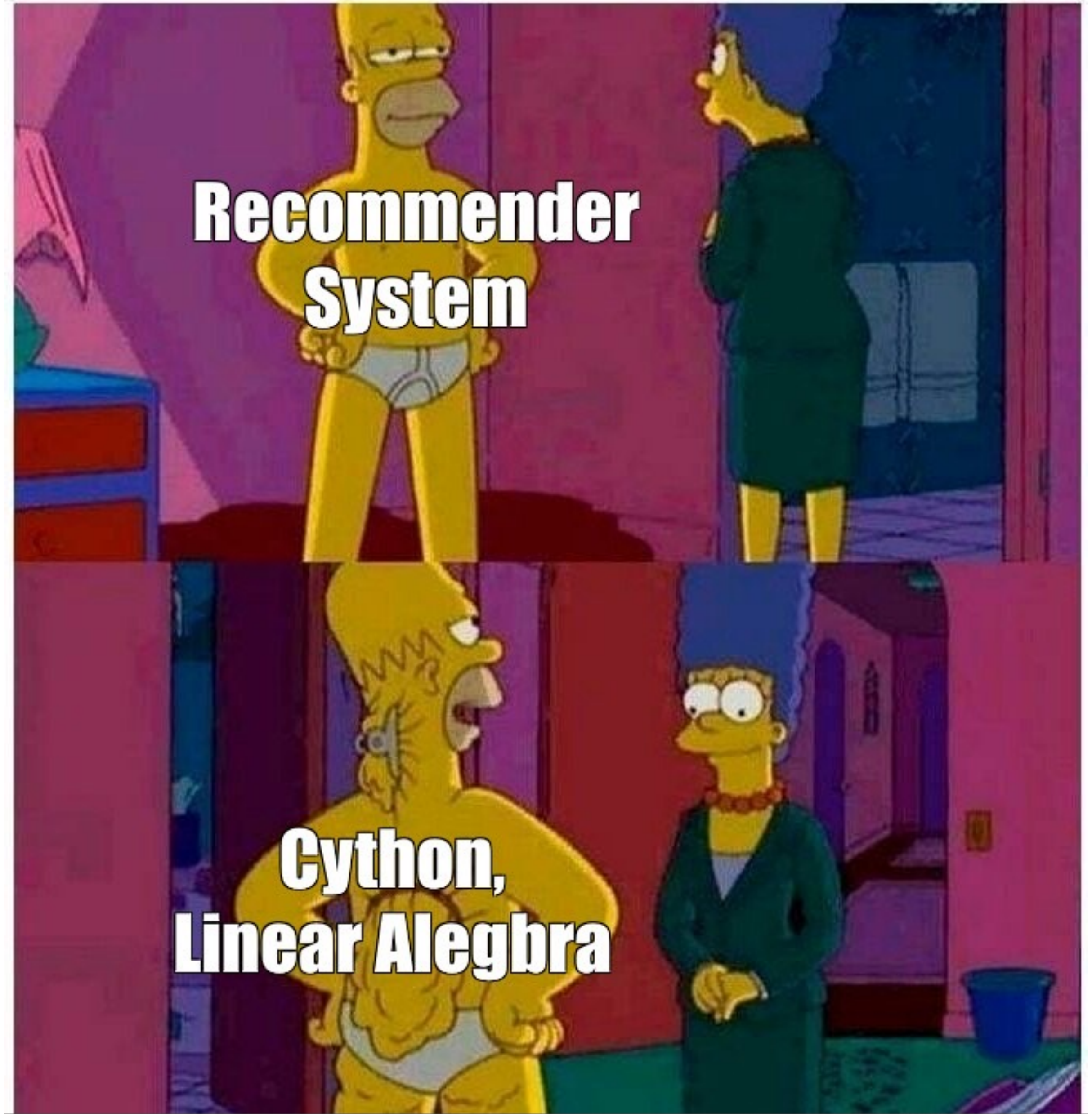
Recommender
System
Cython,
Linear Alegbra