Just One More!

Modeling Binge Watching Behavior

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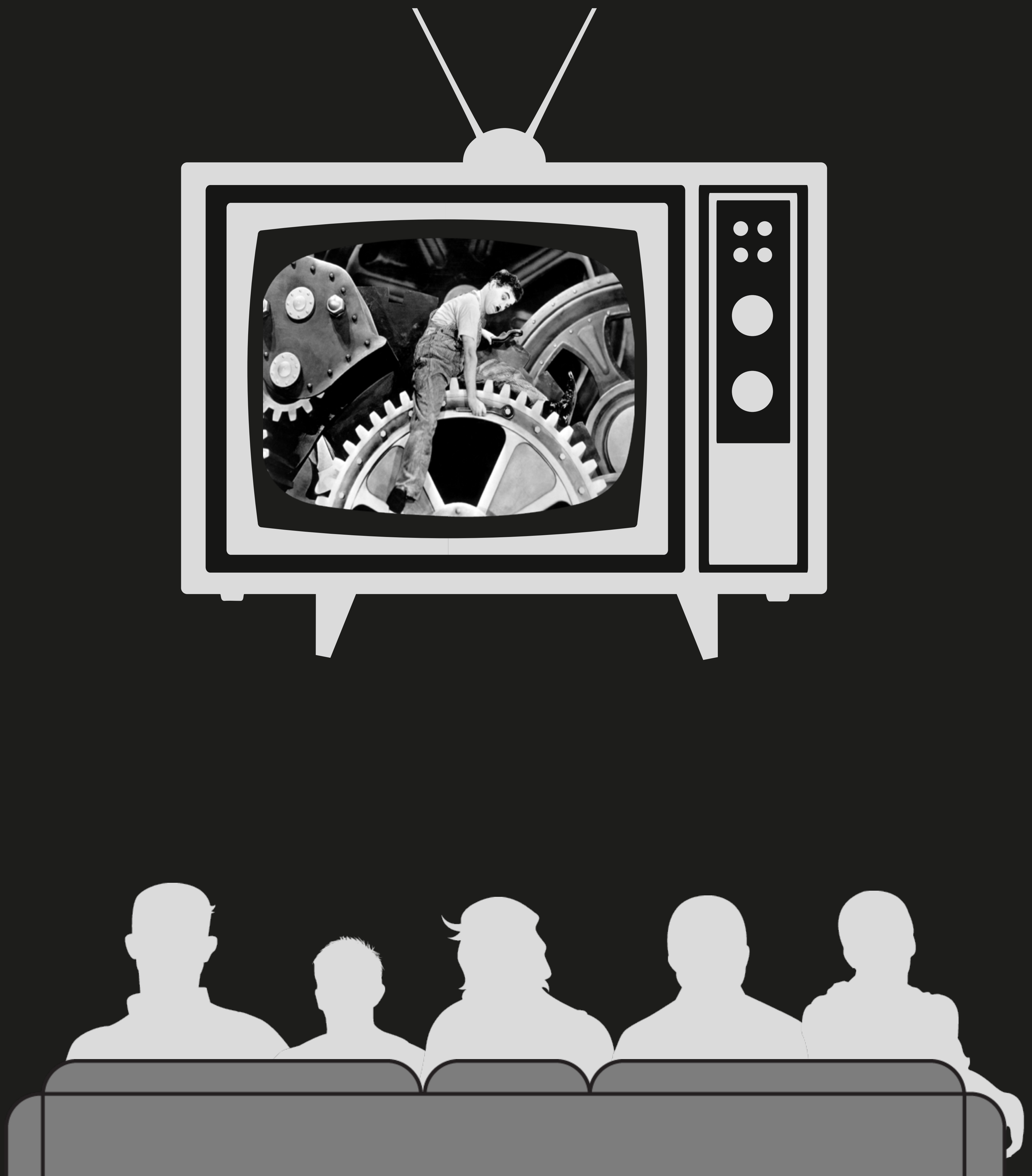
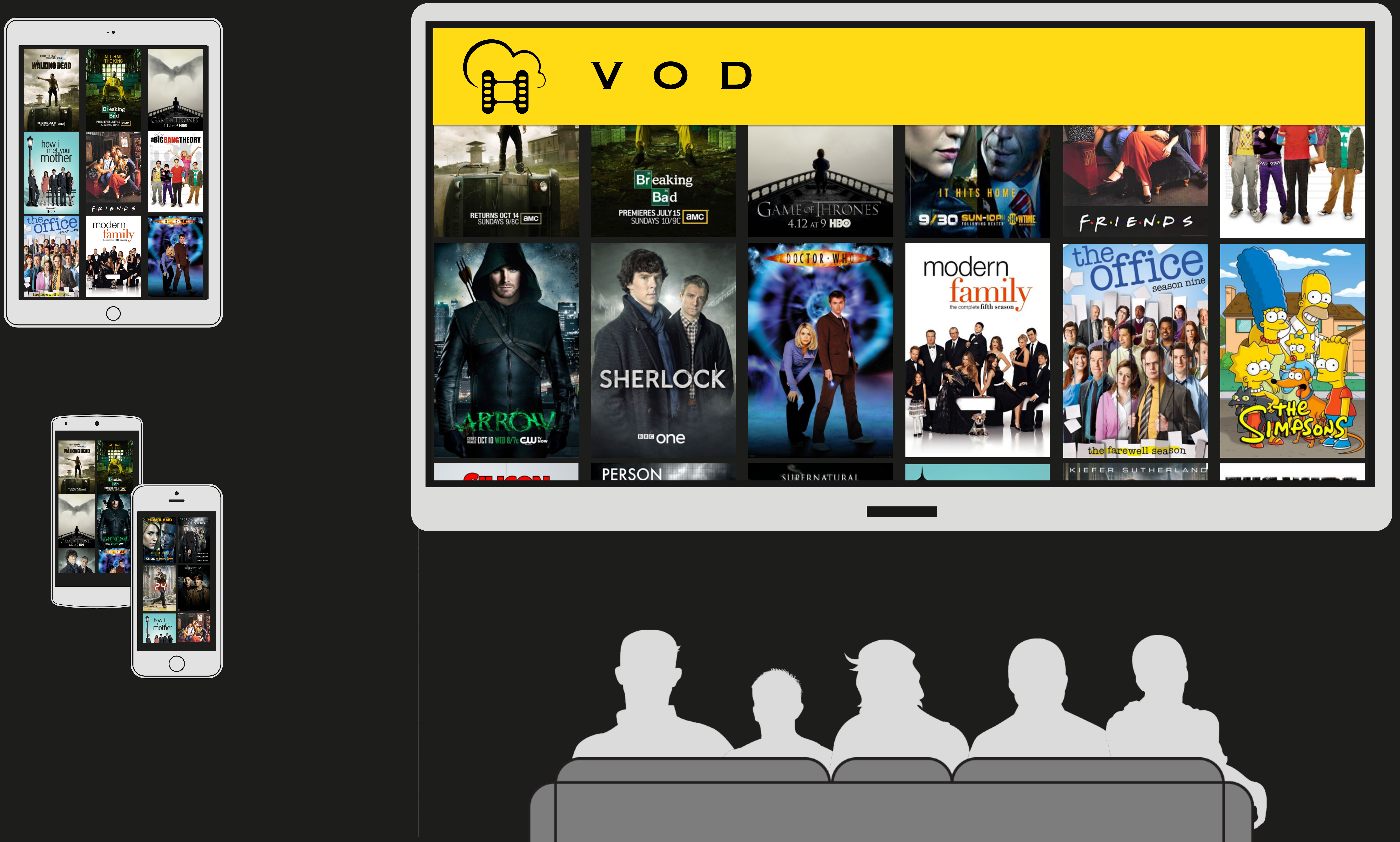
How people used to consume TV shows in the past



What about now ?
Video-on-demand enabled Binge Watching!



Binge watching is drawing a lot of media coverage

- Popular press and market research define binge watching as:

Watching multiple episodes of a television program in a single session

- Drawbacks:
  - Ignore external factors like type of content or time
  - Definition only based on survey data
  - They do not agree on the same episode threshold

TiVo 3 episodes
Netflix: 2 episodes

What exactly is binge watching ?

Is there a clear episode threshold ?

Are there other important features ?

Is it a consistent behavior ?

To answer these questions, we need an accurate model of viewing behavior

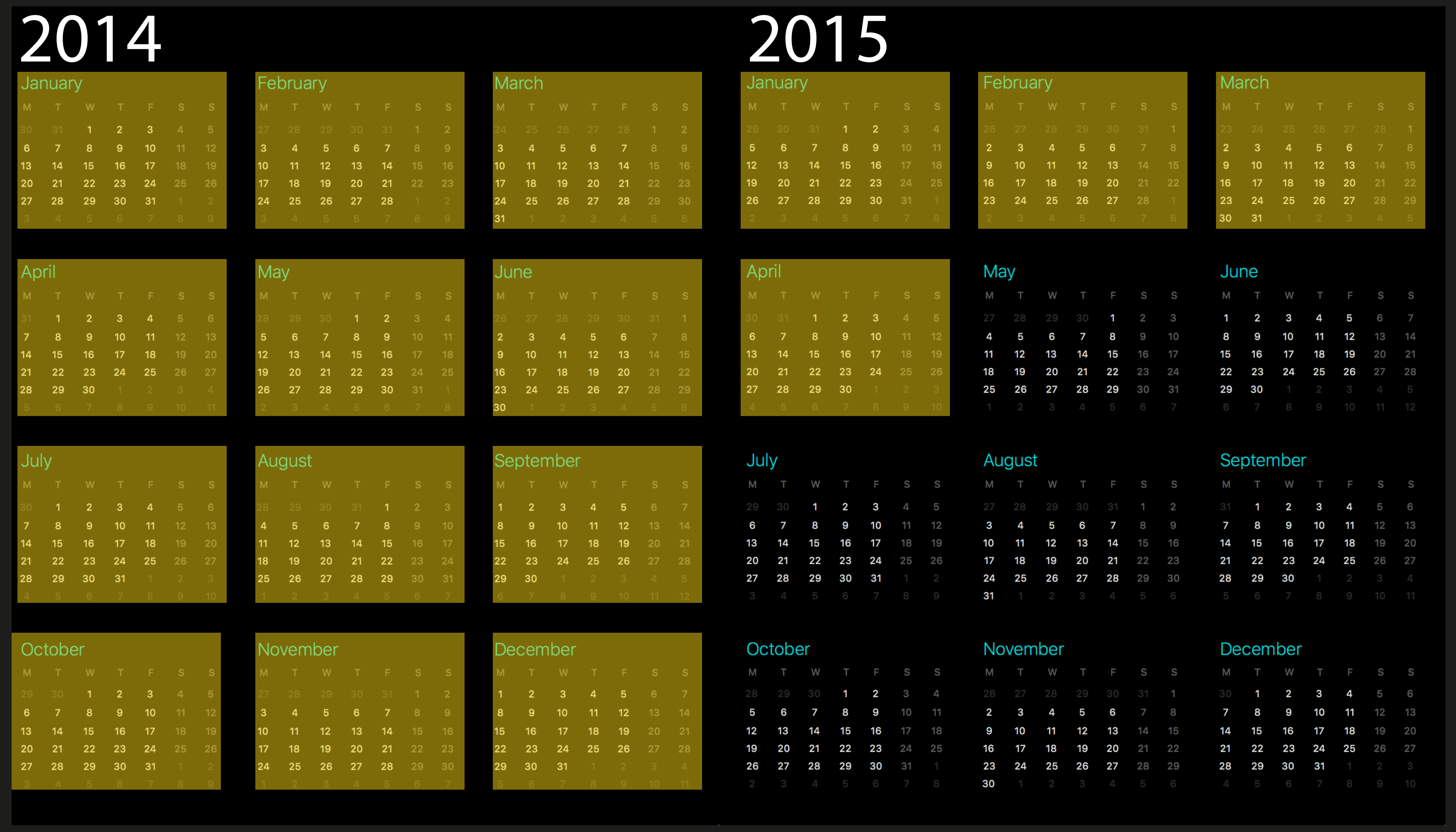
Objectives

Model viewing behavior
with a data-driven approach

Characterize binge watching
behavior through this model

VOD data

- Dataset:
  - Sampled data from 16 months of user interactions from a US-based VOD service
  - Available on many different devices: TV, smartphones and tablets
  - 65 popular television titles
  - 3,488 users
  - 26,404 viewing sessions



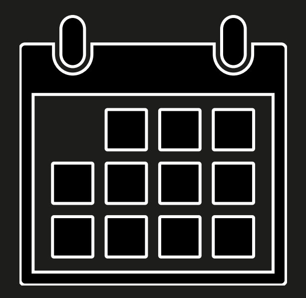
Modeling viewing behavior

Modeling viewing behaviour

- Goal: Model the number of episodes viewed in a session i
- Example:

  It's Saturday at 4pm , you start watching The Big Bang Theory on TV

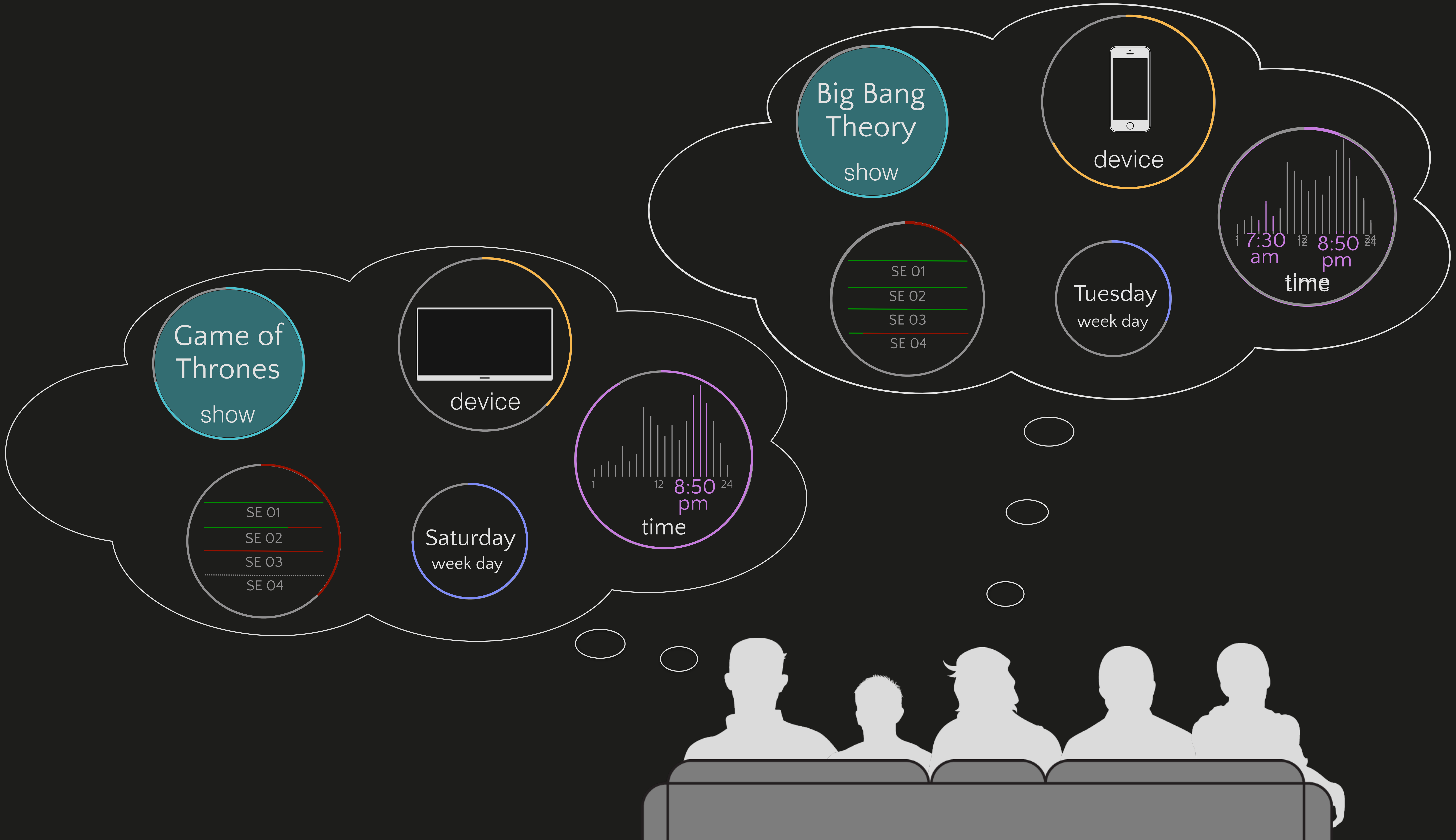
  What is the probability that you watch 1, 2 or 10 episodes?



Saturday

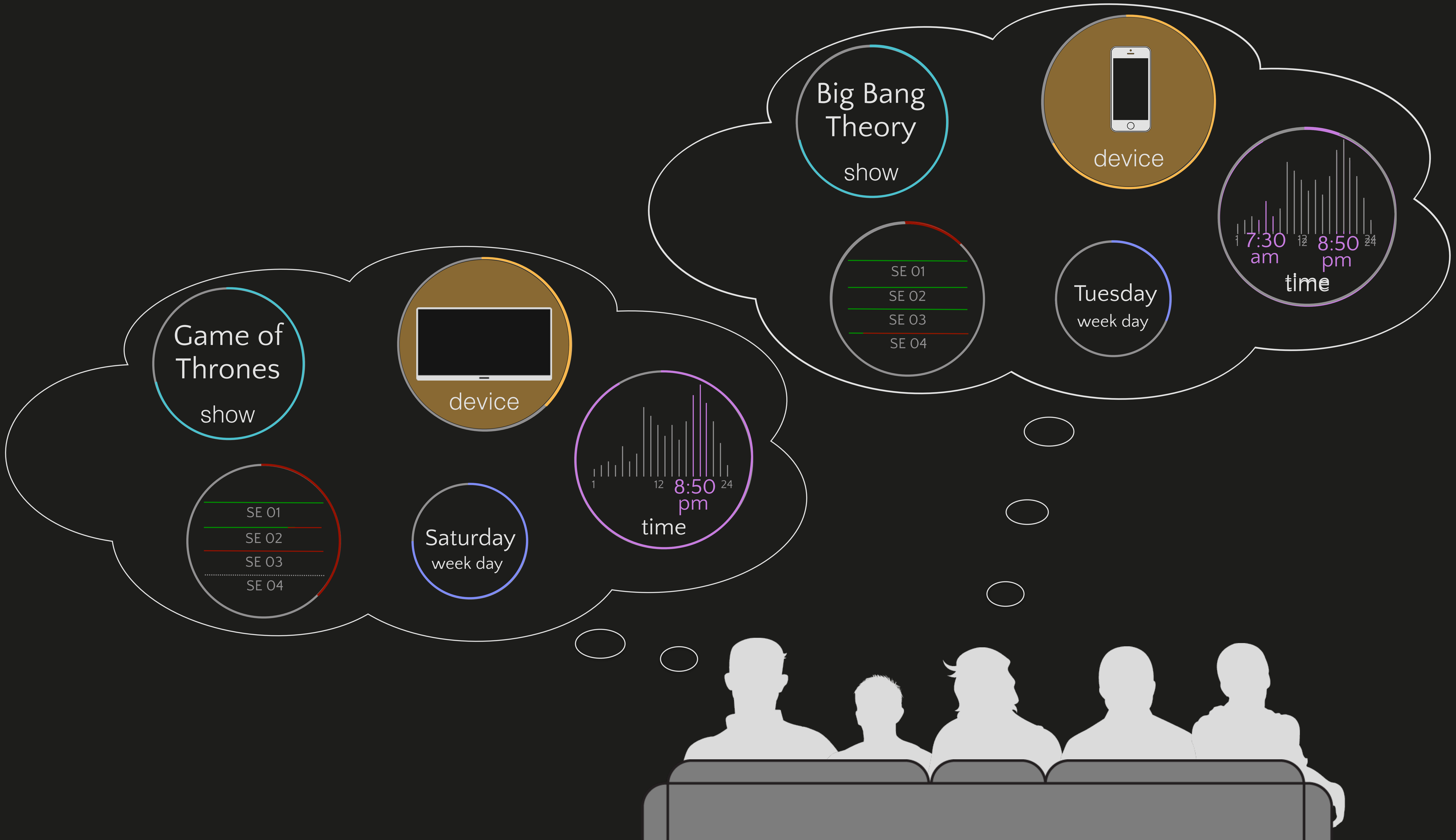
4 pm

Viewing behavior is influenced by many factors



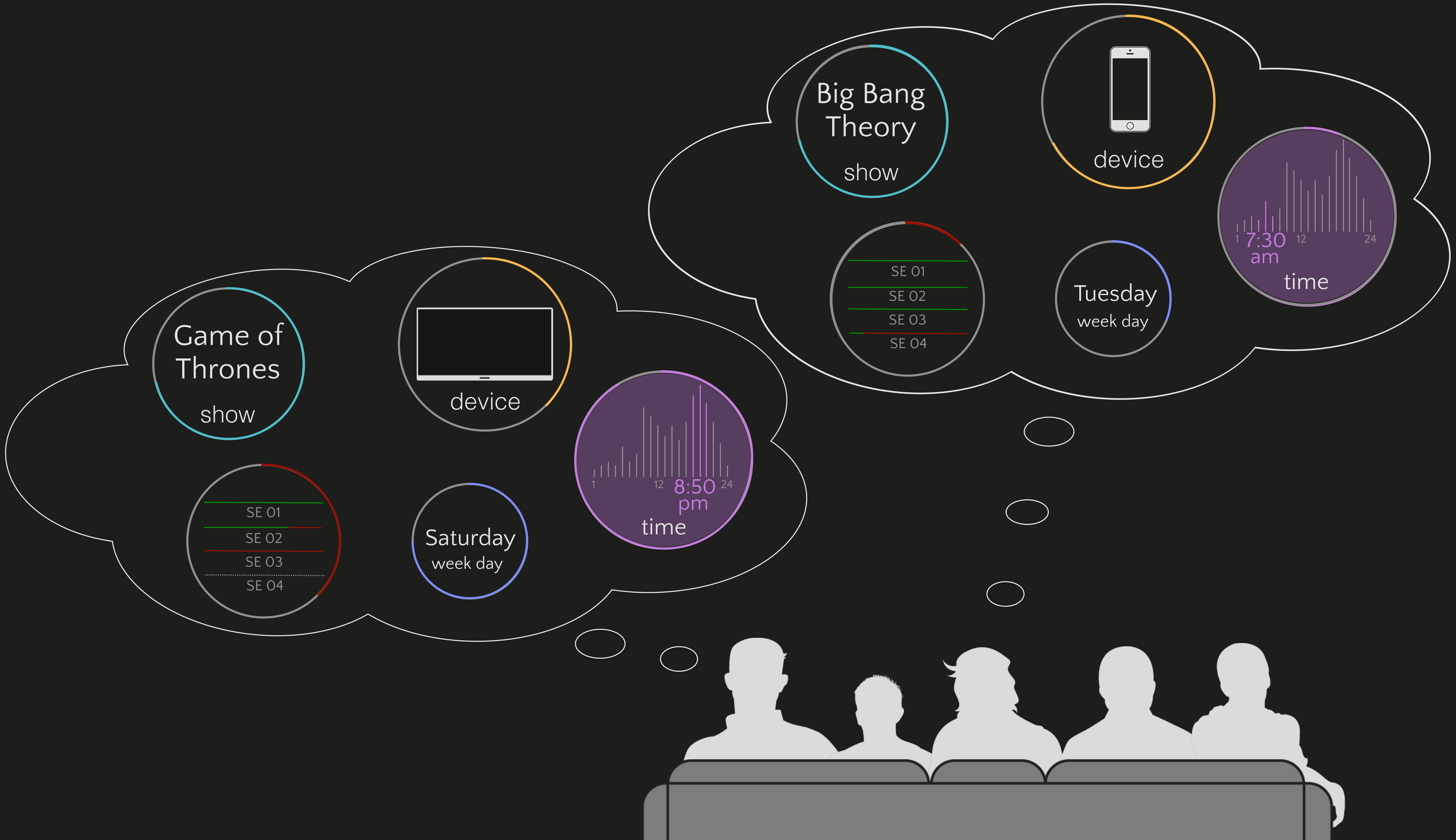
- *What content is viewed?*

Viewing behavior is influenced by many factors



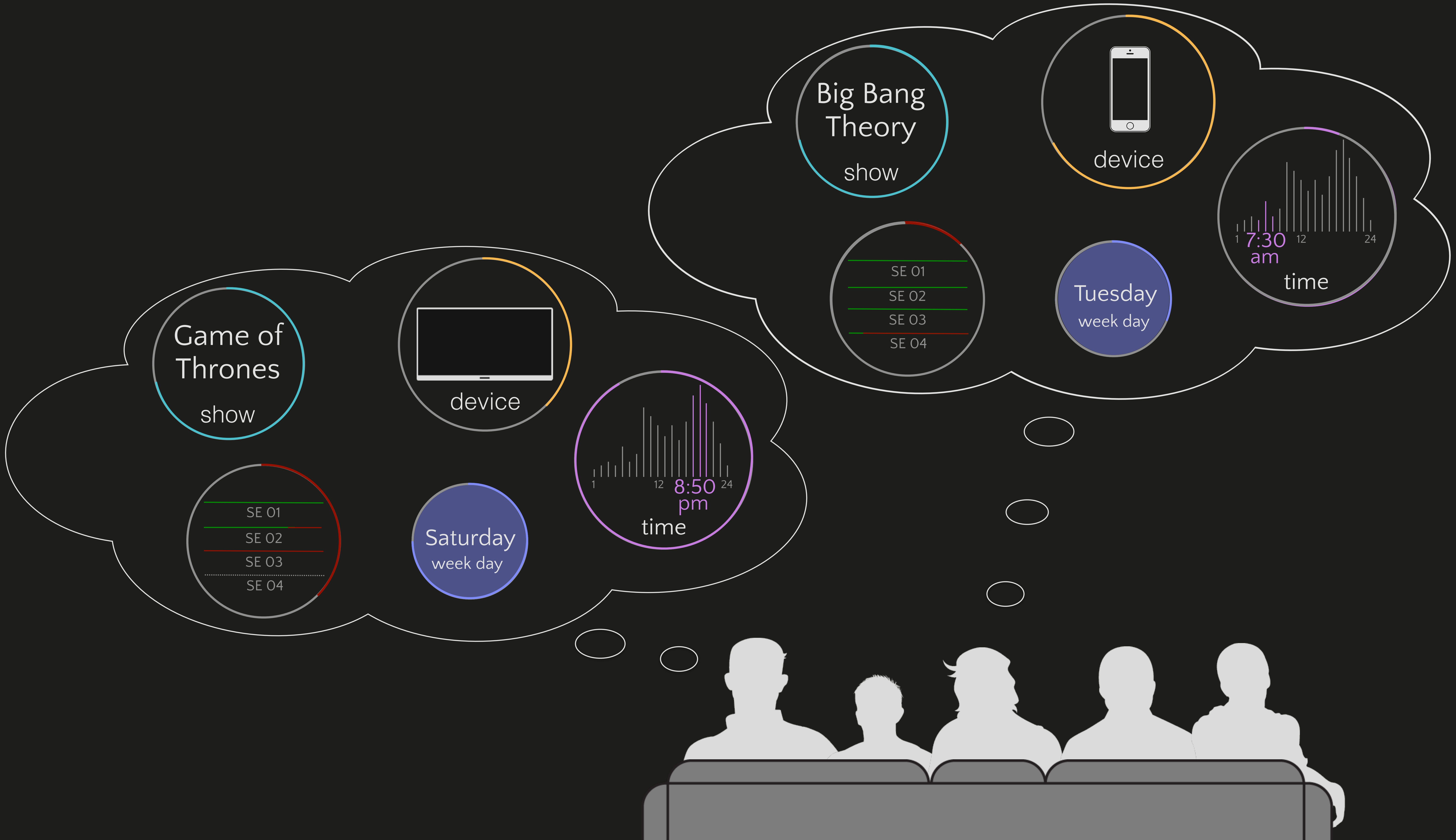
- *What content is viewed?*
- *On which device?*

Viewing behavior is influenced by many factors



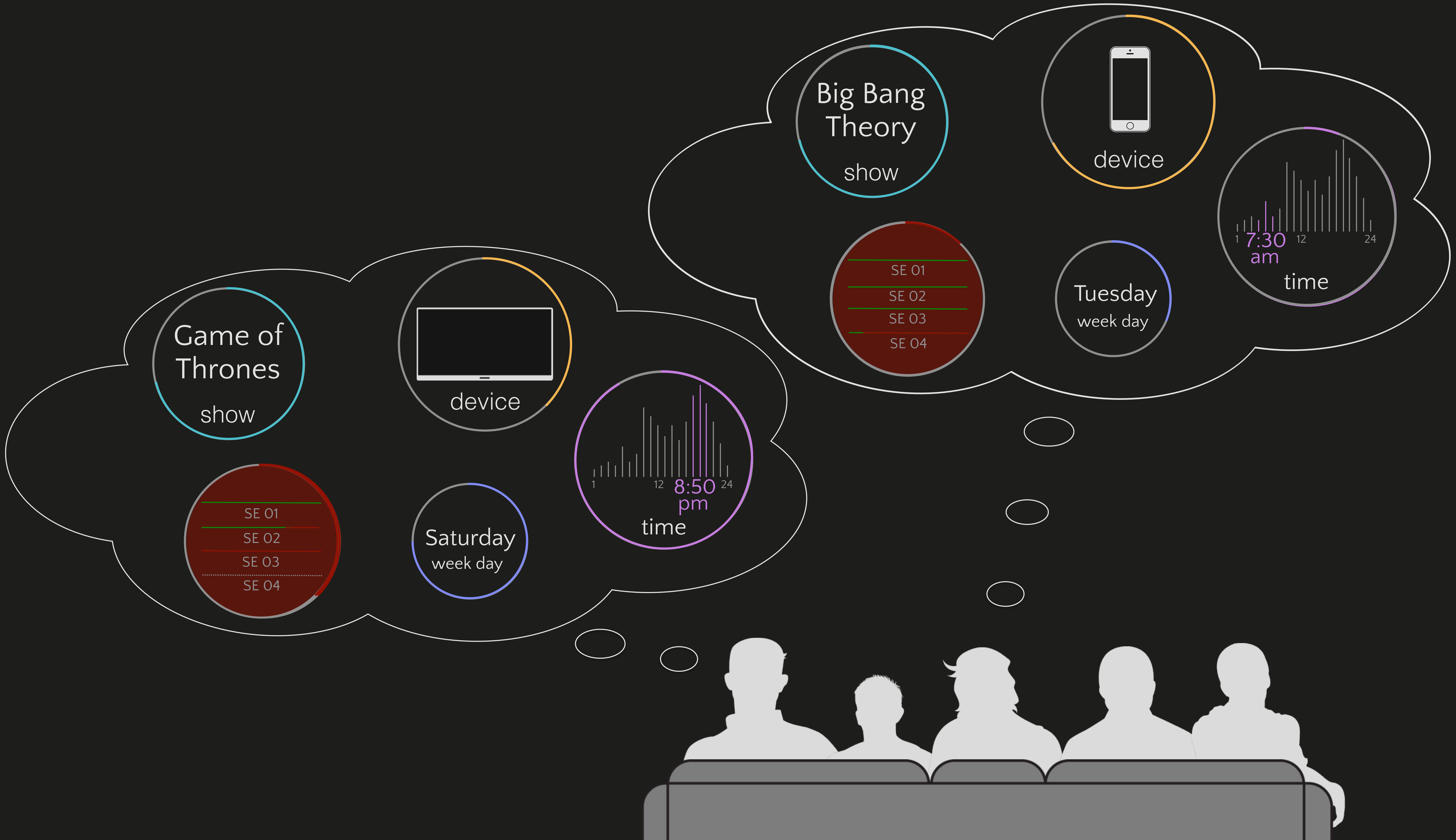
- *What content is viewed?*
- *On which device?*
- *What time is it?*

Viewing behavior is influenced by many factors



- *What content is viewed?*
- *On which device?*
- *What time is it?*
- *What day is it?*

Viewing behavior is influenced by many factors



- What *content* is viewed?
- On which *device*?
- What *time* is it?
- What *day* is it?
- Are there episodes *available* ?

Censored Poisson Regression with Latent Factors

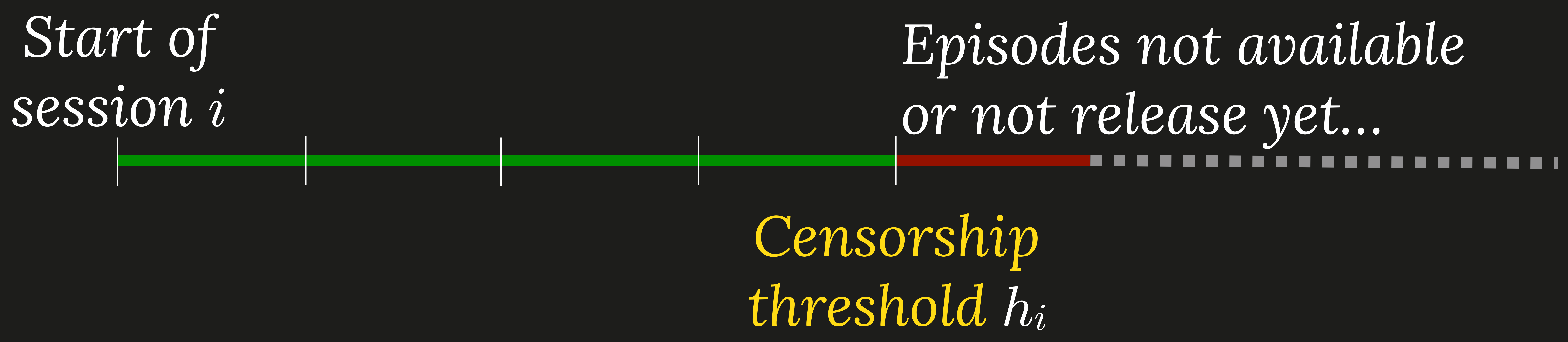
- Goal: Model the *number of episodes* viewed in a *session* i
- Assumption: There are *different* types of viewing *behaviors*
- Method: Model number of episodes v_i viewed in session i as a *Mixture of K Poisson* distributions:

$$f(v_i) = \sum_{k=1}^{K} \pi_k \left(\frac{\lambda_k^{v_i}}{e^{\lambda_k} \; v_i!} \right)$$

Likelihood of observing N independent sessions is then

$$\mathcal{L}\left(\{\lambda_k, \pi_k\}_{k=1}^{K} ; \mathbf{v} \right) = \prod_{i=1}^{N} \sum_{k=1}^{K} \pi_k \left(\frac{\lambda_k^{v_i}}{e^{\lambda_k} \; v_i!} \right)$$

Censored Poisson Regression with Latent Factors



with censorship indicator $c_i = \mathbb{I}(v_i = h_i)$

Likelihood of observing N independent sessions is then

$$\mathcal{L}\left(\{\lambda_k, \pi_k\}_{k=1}^{K}; \mathbf{v}\right) = \prod_{i=1}^{N} \sum_{k=1}^{K} \pi_k \left(\frac{\lambda_k^{v_i}}{e^{\lambda_k} \; v_i!}\right)^{1-c_i} \left(\Pr(v_i \geq h_i)\right)^{c_i}$$

Censored Poisson Regression with Latent Factors

- The context of a session influences the rate of consumption:
  - Device used
  - Time of the day
  - Content viewed
- Rate of consumption is also session dependent:

$$\log \lambda_{k,i} = \mathbf{x}_i^T \beta_k$$

where $\mathbf{x}_i$ is the vector of covariates of session i and β_k is the coefficient vector of component k

Likelihood of observing N independent sessions is then

$$\mathcal{L}\left(\{\beta_k, \pi_k\}_{k=1}^{K}; \mathbf{v}, \{\mathbf{x}_i\}_{i=1}^{N}\right) = \prod_{i=1}^{N} \sum_{k=1}^{K} \pi_k \left(\frac{\lambda_{k,i}^{v_i}}{e^{\lambda_{k,i}} v_i!}\right)^{1-c_i} \left(\Pr(v_i \geq h_i)\right)^{c_i}$$

Parameter estimation

- Maximum likelihood estimation of the model parameters:

$$\underset{\{\beta_k,\pi_k\}_{k=1}^{K}}{\operatorname{argmax}} \ \mathcal{L}\left(\{\beta_k,\pi_k\}_{k=1}^{K};\{v_i,h_i,\mathbf{x}_i\}_{i=1}^{N}\right)$$

Output

- β_k : coefficient vector of component k
- π_k : proportion of component k

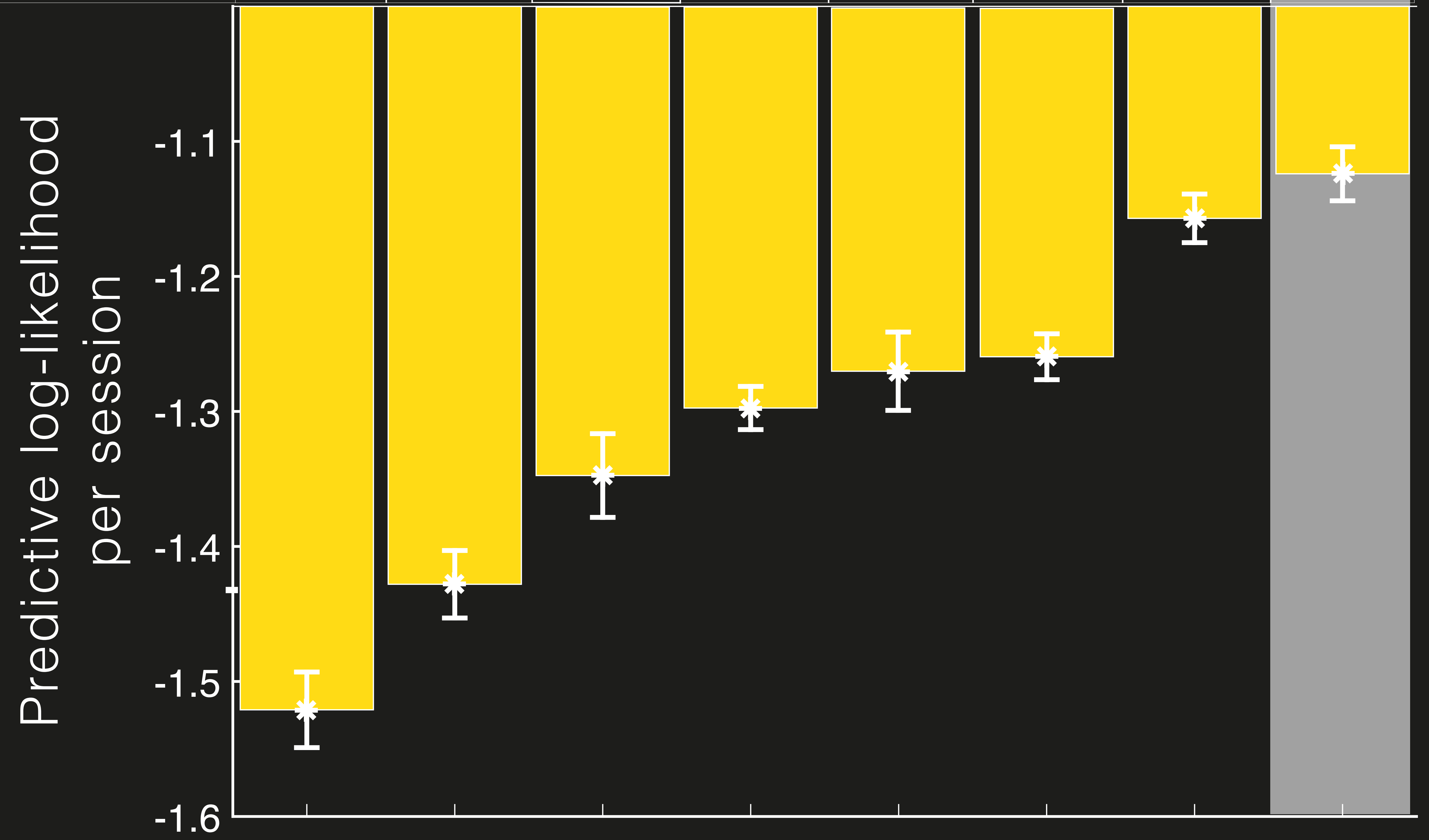
Input

- v_i : number of episodes in session i
- h_i : censorship threshold of session i
- $\mathbf{x}_i$: vector of covariates of session i

- Estimate using Expectation-Maximization

Model performance

Mixture	✗	✗	✗	✓	✗	✓	✓	✓
Censoring	✗	✗	✓	✗	✓	✗	✓	✓
Covariates	✗	✓	✗	✗	✓	✓	✗	✓



Predictive log-likelihood of the proposed model
compared to various baselines using cross-validation

Prediction

Will the user watch the next episode ?

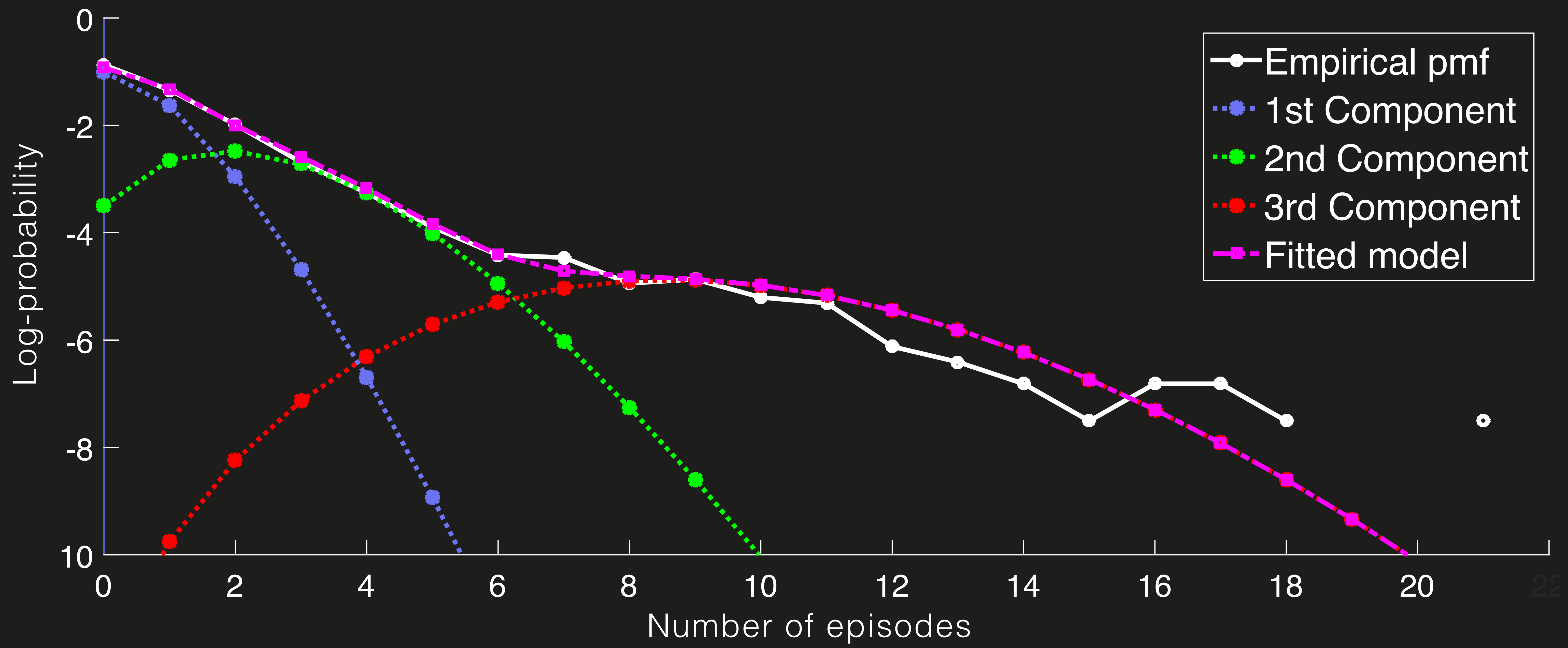
Will the user watch the next episode ?

- *Given the number v_c of episodes a user has already watched in the middle of a session*
- *Will they continue to watch the next one ?*
- *With our model:* $\Pr(v > v_c | v_c; \boldsymbol{\beta}, \boldsymbol{\pi}) = \sum_{z=1}^{K} p_z(v > v_c | v_c; \boldsymbol{\beta}, \boldsymbol{\pi}) p(z | v_c; \boldsymbol{\beta}, \boldsymbol{\pi})$

Description	Predictive AUC
Regularized Logistic Regression	0.631
Linear-SVM	0.617
Poisson Regression	0.539
Mixture of Poisson Regression	0.618
Censored Poisson Regression	0.642
Censored Poisson Regression with Latent Factors	**0.687**

Binge watching characterization

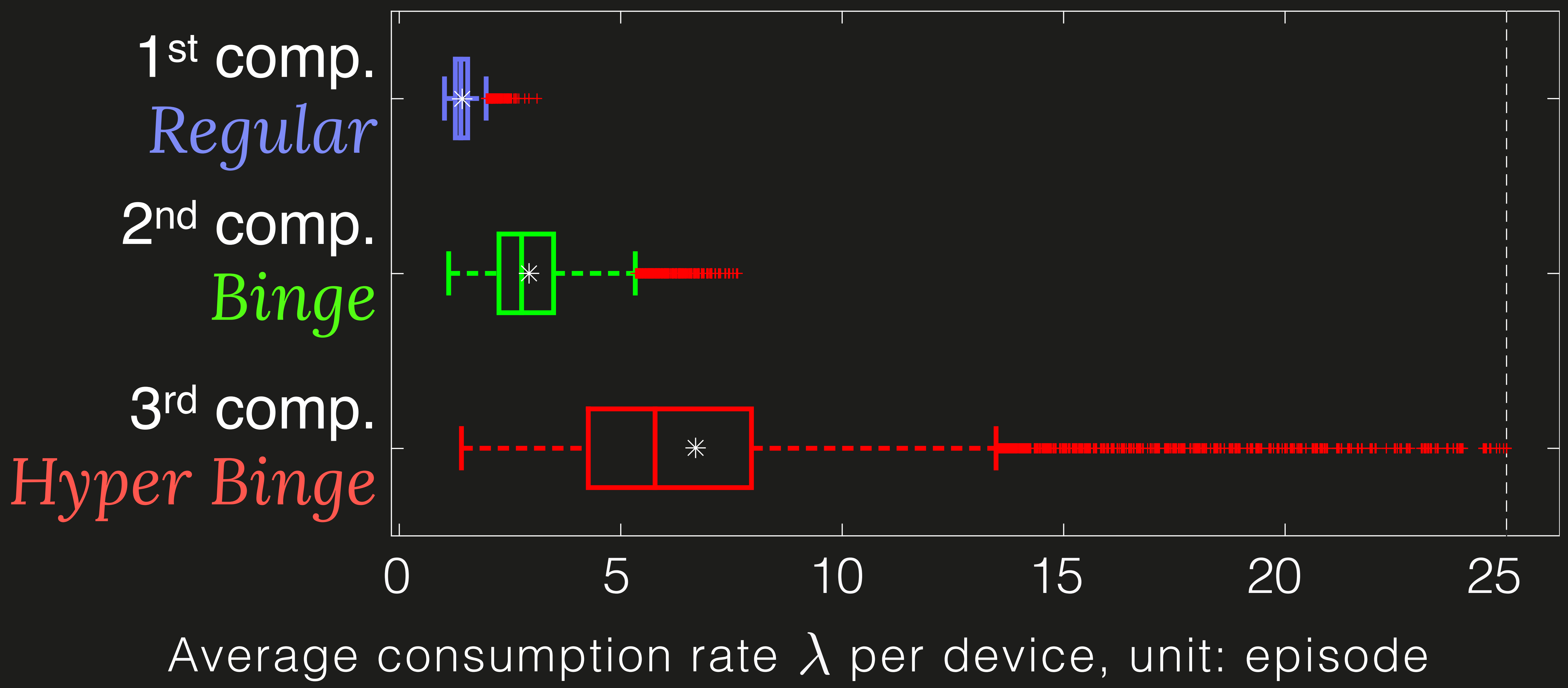
Identifying viewing behaviors



Distribution of number of episodes watched with our model for "The Big Bang Theory"

- *Learned mixture reveals K=3 distinct behaviors using cross-validation*
  - *1st component: Regular behavior*
  - *2nd component: Binge watching behavior*
  - *3rd component: Hyper-binge watching behavior*

Different types of Binge watching



- *How to identify the type of session ?*
  - *Using the mixture components of our model*
  - *The type of the session corresponds to its most likely component assignment*

Context aware binge watching definition

	Regular	*Binge watching*	*Hyper-Binge watching*
Smartphone	1.2	2.0	4.1
Tablet	1.3	2.0	5.2
TV	1.5	**3.0**	**7.3**

Average consumption rate λ per device, unit: episode

- *Threshold of TV is higher than mobile devices for both binge and hyper-binge watching behaviors*

Content aware binge watching definition

	Regular	Binge watching	Hyper-Binge watching
How I Met Your Mother	1.8	**4.9**	**14.0**
The Big Bang Theory	1.6	**3.6**	**9.0**
Homeland	1.3	2.1	3.7
The Walking Dead	1.4	3.1	7.0

Average consumption rate λ per show, unit: episode

- Threshold of non-narrative comedies is higher than narrative dramas for both binge and hyper-binge watching behaviors

Repeat binge watching or TV hangover?

	Regular	Binge watching	Hyper-Binge watching
Regular	82%	16%	2%
Binge	66%	30%	4%
Hyper-Binge	59%	32%	9%

Transition frequency of next session type

- A user currently binge watching is twice as likely to binge its next session compared with a user currently in a regular session
- Majority of binge watching sessions are not followed by binge watching sessions… Suggesting TV hangover.

Conclusion

Conclusion

Viewing context

Mixture of behaviors

Consumption censoring

Viewing behavior model

Binge watching definition

Binge eating

Binge gambling

Other potential applications of our model

Binge

Hyper-binge

Different types of binge watching behaviors were identified