Modelling TikTok video category transitions using Markov chains

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Abstract

In this paper, we develop a discrete-time Markov chain framework to model transitions between video content categories on TikTok based on observed sequential viewing behavior. Using a dataset of 65 consecutively viewed videos classified into six categories;motivational, dance, comedy, lifestyle, educational, and food, we estimate empirical transition probabilities and construct the associated transition matrix. We analyze the structural properties of the resulting Markov chain, establishing irreducibility, aperiodicity, and ergodicity, which guarantee the existence and uniqueness of a stationary distribution. The stationary distribution is computed explicitly and interpreted as the long-run exposure pattern across content categories under stable viewing dynamics. While the dataset is limited in size, the study is positioned as a methodological proof-of-concept demonstrating how classical Markov chain theory can be applied to analyze category-level navigation on short-form video platforms. The proposed framework is transparent, reproducible, and readily extensible to larger datasets and more complex sequential models.

Keywords and phrases: Markov chain; TikTok; stationary distribution; transition matrix.

1 Introduction

The rapid growth of short-form video platforms has fundamentally transformed patterns of online content consumption, with users increasingly engaging in continuous, algorithmically curated streams of videos. Platforms such as TikTok present users with sequences of heterogeneous content categories, where viewing behavior evolves dynamically over time. Understanding how users transition between content categories is therefore essential for analyzing exposure dynamics, content diversity, and long-term viewing behavior on such platforms. While modern recommendation systems rely heavily on complex machine learning architectures, simplified stochastic models remain valuable for capturing aggregate behavioral patterns and providing analytically interpretable insights into sequential content navigation[1, 2].

Markov chains provide a well-established mathematical framework for modeling sequential stochastic processes and have been widely applied in areas such as communication systems, mobility modeling, and online behavior analysis [3, 4, 5, 7]. Their appeal lies in their analytical tractability and ability to characterize long-run behavior through stationary distributions, making them suitable for studying equilibrium exposure dynamics in sequential data.

W. Suryaningrat et al [8] investigated the use of Markov chains to analyze and predict the evolution of discussions on Twitter related to coronavirus disease (COVID-19). Using tweet data collected at three

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observation points per day over a 13-day period, the authors modeled transitions between two activity states—low (0) and high (1)—defined relative to the mean or median tweet volume. The resulting transition dynamics indicated a persistent likelihood of high discussion activity, suggesting sustained public engagement throughout the observed period.
Similarly, A. S. Omer and D. H. Woldegebreal [9] provided a comprehensive review of Markov chain theory for discrete sources, with emphasis on applications in telecommunication systems. Their work covered classical and higher-order Markov chains, Hidden Markov Models, and practical methods for estimating transition probabilities from real data.
Recent years have also seen increasing academic interest in short-form video platforms, particularly TikTok, driven by their rapid adoption and distinctive recommendation mechanisms.Some studies analyzed TikTok recommendation exposure using user data donations, revealing systematic amplification and stable exposure patterns across content categories. Klug et al. [10] examined user motivations and usage behavior on TikTok, highlighting the importance of sequential content consumption, while Bucknell Bossen and Kottasz [11] explored engagement behavior among younger users. Complementary work has examined how audiovisual characteristics influence engagement in TikTok videos.
From a recommendation and modeling perspective, sequential and session-based user behavior has been shown to play a central role in predicting content consumption. Early work by Rendle et al. [12] introduced personalized Markov chain models for recommendation, while Hidasi et al. [13] and Sun et al. [14] demonstrated the effectiveness of neural and transformer-based architectures for sequential recommendation. More recently, Wang et al. [15] proposed category-aware models that explicitly incorporate category transitions in session-based recommendation systems.
In this paper, we apply Markov chain transition modeling to sequential data arising from social media consumption, with particular focus on TikTok video categories. Drawing on established methodologies in data collection, processing, and stochastic modeling, we construct and analyze a discrete-time Markov chain describing transitions among six content categories; motivational, dance, comedy, lifestyle, educational, and food, based on an observed sequence of 65 videos. The study presents the corresponding 6×6 transition matrix and examines its structural properties and long-run behavior through the stationary distribution.
While Markov chains have been widely used in e-commerce and music recommendation systems [12], their application to short-form video platforms remains limited. Existing studies on short-form video consumption and recommendation tend to emphasize large-scale engagement metrics, feature-based modeling, or learning-based architectures, rather than analytically tractable stochastic models of category-level transition dynamics [15]. This gap motivates the present study, which provides a transparent Markovian framework for analyzing category transitions and long-run exposure behavior. Extensions to hybrid approaches combining Markov models with neural networks have been proposed in related contexts [17] and represent a natural direction for future work.
The mathematical framework adopted in this study is intentionally classical. Rather than introducing new Markov chain theory, the contribution lies in the rigorous translation of established stochastic process methodology to a short-form video context where formal category-level transition modeling remains underexplored. The emphasis is on analytical clarity, reproducibility, and structural insight, consistent with applied probability and mathematical modeling research.
Accordingly, the objective of this study is methodological rather than inferential. The dataset is not intended to support statistically representative conclusions about TikTok as a platform with billions of videos, but to demonstrate how a discrete-time Markov chain can be constructed, analyzed, and interpreted for category-level transitions in short-form video consumption. Within this scope, the analysis focuses on the structural properties of the induced stochastic process and its long-run behavior.
The remainder of the paper is organized as follows. Section 2 reviews the necessary preliminaries on Markov chains and their fundamental properties. Section 3 describes the dataset and experimental setup, including the construction of the transition matrix. It also presents the analysis of the resulting Markov chain, focusing on its structural properties and long-run behavior. Section 4 presents the numerical simulation. Finally, Section 5 discusses the implications of the findings, outlines limitations,

and suggests directions for future research.

2 Methodology

2.1 Stochastic Processes

Many problems in probability theory involve analysing how certain systems randomly evolve. In the context of social media, for example, the sequence of TikTok video categories that a user views can be regarded as a random process. For instance, after watching one video, the category of the next video is uncertain and influenced by some underlying probabilistic factors. Such systems, where outcomes evolve step by step with inherent randomness, are modelled by **stochastic processes**.

Definition 2.1. *A stochastic process is a collection of random variables*

$$\{X_t : t \in T\}$$

defined on a common probability space $(\Omega, \mathcal{F}, \mathbb{P})$*, with values in a state space* $\mathcal{X}$*. The index set* T *is called the parameter set, and is mostly used to represent time.*

The parameter set T may either be discrete or continuous. In the discrete case, T is countable, while in the continuous case, T is an interval of the real line. The state space $\mathcal{X}$ may also be finite, countable, or uncountable.
An important aspect of studying stochastic processes is understanding the distribution of the process at a given time t, as well as the **joint distributions** of $(X_{t_1}, \dots, X_{t_n})$ for finite sets of times $\{t_1, \dots, t_n\} \subseteq T$. Together, these finite-dimensional distributions describe the probabilistic structure of the process.

Definition 2.2. *A stochastic process* $\{X_t : t \in T\}$ *is said to be*

1. *stationary if its finite-dimensional distributions are invariant under changes in time;*
2. *independent increments if, for any disjoint time intervals, the increments of the process are independent;*
3. *Markovian if the conditional distribution of the future given the past depends only on the present.*

Markov chains, which we shall discuss next, form an important subclass of discrete-time stochastic processes. They are particularly useful in applications where the "memoryless" property is a reasonable assumption.

2.2 Markov Chains

Throughout this paper, we shall refer to Markov chains as discrete-time Markov chains.

Definition 2.3. *A sequence of random variables* $(X_0, X_1, X_2, \dots)$ *with state space* $\mathcal{X}$ *is called a (discrete-time) Markov chain if, for all* $t \in \mathbb{N}_0$ *and all* $x_t, y \in \mathcal{X}$*,*

$$\mathbb{P}\left(X_{t+1} = y \mid X_0 = x_0,\ X_1 = x_1,\ \dots,\ X_t = x_t\right) = \mathbb{P}\left(X_{t+1} = y \mid X_t = x_t\right). \tag{1}$$

Equation (1) is known as the Markov property, which states that the conditional probability of transitioning from state x_t to state y depends only on the current state x_t, and not on the preceding sequence of states $x_0, x_1, \dots, x_{t-1}$.

2.3 Transition Matrices

Consider the random variables X_t and X_{t+1}, which take values in the states x and y, respectively. We say that the process makes a transition from state x to state y between time t and time $t+1$, and we denote this transition by $x \to y$.

To represent the transition probabilities between all possible states in the state space $\mathcal{X}$, we define the transition matrix of the Markov chain.

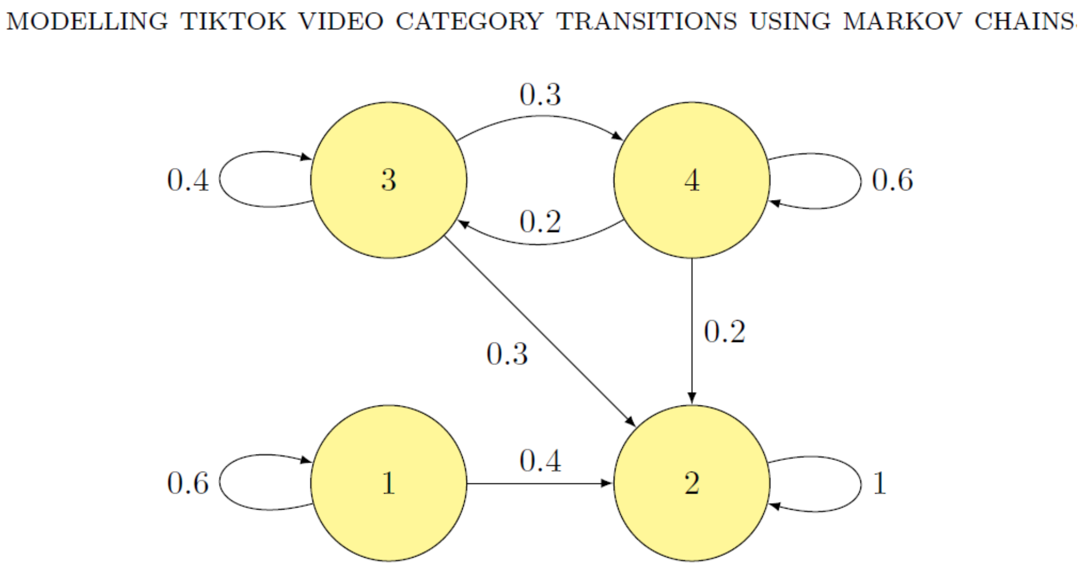
Definition 2.4. *The transition matrix, denoted by P, is a $|\mathcal{X}| \times |\mathcal{X}|$ matrix where each entry $P(x, y)$ represents the probability of moving from state x to state y in one time step. That is,*

$$P(x, y) = \mathbb{P}\left(X_{t+1} = y \mid X_t = x\right) \quad \textit{for all } x, y \in \mathcal{X}. \tag{2}$$

The x-th row of the transition matrix P corresponds to the probability distribution $P(x, \cdot)$. Therefore, P is a stochastic matrix, meaning all of its entries are non-negative and each row sums to 1. That is,

$$\sum_{y \in \mathcal{X}} P(x, y) = 1 \quad \text{for all } x \in \mathcal{X}.$$

For example, consider the state space $\mathcal{X} = \{1, 2, 3, 4\}$ with transition diagram



The corresponding transition matrix P for the Markov chain is given by

$$P = \begin{pmatrix} 0.6 & 0.4 & 0 & 0 \\ 0 & 1.0 & 0 & 0 \\ 0 & 0.3 & 0.4 & 0.3 \\ 0 & 0.2 & 0.2 & 0.6 \end{pmatrix}. \tag{3}$$

Each row of the matrix represents the transition probabilities from a given state to all possible states. For example, the third row shows that from state 3, the process moves to state 2 with probability 0.3, stays in state 3 with probability 0.4, and moves to state 4 with probability 0.3.

2.4 t-step Transition Probabilities

In many applications, we are not only interested in the immediate, 1-step transitions of a Markov chain, but also in the probability of moving between states over multiple time steps. These are called *t-step transition probabilities*, and they help us in understanding the long-term behavior of the chain.

Consider the Markov chain $(X_0, X_1, X_2, \dots)$ with finite state space $\mathcal{X}$. We want to find the 2-step transition probability

$$\mathbb{P}\left(X_2 = y \mid X_0 = x\right) \quad \text{where } x, y \in \mathcal{X}.$$

We have that

$$\begin{aligned}
\mathbb{P}\left(X_2 = y \mid X_0 = x\right) &= \sum_{z \in \mathcal{X}} \mathbb{P}\left(X_2 = y, X_1 = z \mid X_0 = x\right) \\
&= \sum_{z \in \mathcal{X}} \mathbb{P}\left(X_2 = y \mid X_1 = z, X_0 = x\right) \cdot \mathbb{P}\left(X_1 = z \mid X_0 = x\right) \\
&= \sum_{z \in \mathcal{X}} \mathbb{P}\left(X_2 = y \mid X_1 = z\right) \cdot \mathbb{P}\left(X_1 = z \mid X_0 = x\right) \\
&= \sum_{z \in \mathcal{X}} P(z, y) \cdot P(x, z) = (P^2)(x, y)
\end{aligned}$$

Therefore, the 2-step transition probability from state x to state y is given by the (x, y)-entry of the matrix P^2.
This can also be shown for the 3-step transition probability, and, in general, for the t-step transition probability. We shall state this result as a theorem and prove it in what follows.

Theorem 2.5 (t-step Transition Probability). *Let $(X_0, X_1, X_2, \ldots)$ be a Markov chain with finite state space $\mathcal{X}$ and transition matrix P. Then, for any $t \in \mathbb{N}$ and any $x, y \in \mathcal{X}$, the t-step transition probability is given by*

$$\mathbb{P}(X_t = y \mid X_0 = x) = (P^t)(x, y). \tag{4}$$

Proof. We prove the result by induction on t.
Base case: For $t = 1$, we have $\mathbb{P}(X_1 = y \mid X_0 = x) = P(x, y)$. Thus, by definition, the result holds for $t = 1$.
Inductive step: Assume the result holds for some $t = n \geq 1$, that is, $\mathbb{P}(X_n = y \mid X_0 = x) = (P^n)(x, y)$. We want to show it holds for $t = n+1$. Using the law of total probability and the Markov property,

$$\begin{aligned}
\mathbb{P}(X_{n+1} = y \mid X_0 = x) &= \sum_{z \in \mathcal{X}} \mathbb{P}(X_{n+1} = y \mid X_n = z) \cdot \mathbb{P}(X_n = z \mid X_0 = x) \\
&= \sum_{z \in \mathcal{X}} P(z, y) \cdot (P^n)(x, z) = (P^n \cdot P)(x, y) = (P^{n+1})(x, y).
\end{aligned}$$

Thus, by induction, the result holds for all $t \in \mathbb{N}$.

2.5 Distributions

Let $(X_0, X_1, X_2, \dots)$ be a Markov chain with finite state space $\mathcal{X}$ and transition matrix P. The distribution of X_t at time t is called the marginal distribution at time t, and is defined by $\mu_t(x) = \mathbb{P}(X_t = x)$ for all $x \in \mathcal{X}$. When $t = 0$, the distribution of X_0 is called the initial distribution, and we denote it by μ_0. In general, we represent the marginal distribution at time t as the vector

$$\mu_t = \begin{pmatrix} \mu_t(x_1) \\ \mu_t(x_2) \\ \vdots \\ \mu_t(x_n) \end{pmatrix} \quad \text{where } x_k \in \mathcal{X},\ k = 1, 2, \dots, n.$$

Subsequently, we shall represent the distributions as row vectors to omit the transpose symbol.Next, We present a result regarding how distributions evolve under a stochastic transition matrix.

Proposition 2.6 (Chapman-Kolmogorov). *Let $\mathcal{X}$ be a finite state space, let P be a stochastic matrix on $\mathcal{X}$, and let μ_0 be the initial distribution on $\mathcal{X}$. Define $\mu_t := \mu_0 P^t$ for $t \in \mathbb{N}$. Then, for all $s, t \geq 0$,*

$$\mu_{s+t} = \mu_s P^t.$$

Proof. The property is immediate since $\mu_{s+t} = \mu_0 P^{s+t} = \mu_0 P^s P^t = (\mu_0 P^s) P^t = \mu_s P^t$.

2.6 Properties of Markov Chains

We now define some important properties of Markov chains.

Definition 2.7 (Irreducible Chain). *A Markov chain is called irreducible if, for any two states $i, j \in \mathcal{X}$, there exists $t \geq 0$ such that $P^t(i, j) > 0$.*

Definition 2.8 (Period). *A state i has period d if d is the greatest common divisor of all $t \geq 1$ such that $P^t(i, i) > 0$. A chain is called aperiodic if all its states have period 1.*

Definition 2.9 (Recurrent and Transient States). *A state i is recurrent if, starting from i, the chain will return to i with probability 1. Otherwise it is* ***transient.***

Definition 2.10 (Absorbing State). *A state i is absorbing if $P(i, i) = 1$.*

Definition 2.11 (Ergodic Chain). *A Markov chain is called ergodic if it is irreducible and aperiodic.*

Definition 2.12 (Stationary Distribution). *Let P be the transition matrix of a Markov chain on a finite state space $\mathcal{X}$. A probability distribution π on $\mathcal{X}$ is called a stationary distribution if*

$$\pi P = \pi.$$

Theorem 2.13. *If the chain is ergodic (irreducible and aperiodic), then there exists a unique stationary distribution π, and for any initial distribution μ_0, the marginal distributions converge. That is,*

$$\lim_{t \to \infty} \mu_t = \pi.$$

The theoretical foundations and properties of discrete-time Markov chains used in this study follow standard treatments in the literature [3, 4, 5, 6, 7].

3 Experiment and Analysis

3.1 Experiment

The experiment is designed to model category-to-category transitions in a single observed viewing sequence, treating the order of videos as a realization of a stochastic process. Each video category is regarded as a discrete state, and successive videos define transitions between these states. This abstraction allows the viewing process to be represented as a finite-state Markov chain, where transition probabilities summarize observed navigation tendencies between content categories.

Although the dataset is limited in size, the experimental setup is sufficient to demonstrate the full modeling pipeline, including state definition, transition probability estimation, and structural analysis of the resulting stochastic process. The focus of the experiment is therefore not predictive accuracy, but the interpretability and analytical tractability of category-level transition dynamics in short-form video consumption.

To improve transparency and reproducibility, Table 1 summarizes the dataset used in this study, including category counts, data source, and collection methodology.

Table 1: Summary of the TikTok video dataset used in the experiment

Attribute	Description
Platform	TikTok
Data source	Publicly accessible video feed
Collection method	Manual sequential observation
Observation unit	Single continuous viewing session
Total number of videos	65
Number of categories	6
Categories	Motivational, Dance, Comedy, Lifestyle, Educational, Food
Category counts	Motivational (12), Dance (4), Comedy (15), Lifestyle (12), Educational (13), Food (8)
Temporal structure	Ordered sequence preserving viewing order
Purpose of dataset	Proof-of-concept modeling of category transitions
Representativeness	Illustrative; not platform-wide

The dataset represents a single viewing trajectory and is intentionally limited in scope, serving to demonstrate the construction and analysis of a finite-state Markov chain rather than to support large-scale statistical inference.

For the experiment, we collected a sequence of 65 TikTok videos, each assigned to one of six content categories. These categories, together with their abbreviations used throughout the paper, are summarized in Table 2.

Table 2: TikTok video categories and abbreviations

Category	Abbreviation
Motivational	M
Dance	D
Comedy	C
Lifestyle	L
Educational	E
Food	F

The sequence obtained is:

$$
\begin{aligned}
&M \to C \to E \to F \to C \to C \to M \to M \to E \to C \\
&\to D \to F \to C \to F \to C \to E \to F \to M \to C \to L \\
&\to E \to C \to F \to C \to D \to C \to D \to L \to L \to E \\
&\to L \to E \to L \to F \to C \to M \to M \to C \to M \to C \\
&\to E \to M \to F \to F \to L \to D \to C \to E \to M \to L \\
&\to E \to L \to L \to E \to L \to E \to M \to M \to L \\
&\to E \to C \to M \to L \to M
\end{aligned}
$$

We estimate the one-step transition probabilities by relative frequencies. For states $i, j \in \{M, D, C, L, E, F\}$, define

$$P(i \to j) = \frac{\#\{t : X_t = i, X_{t+1} = j\}}{\#\{t : X_t = i\}},$$

with frequencies M=12, D=4, C=15, L=12, E=13, F=8. Below is the table of transition probabilities.

	M	D	C	L	E	F
M	1/4	0	1/3	1/4	1/12	1/12
D	0	0	1/2	1/4	0	1/4
C	4/15	1/5	1/15	1/15	4/15	2/15
L	1/12	1/12	0	1/6	7/12	1/12
E	3/13	0	3/13	4/13	1/13	2/13
F	1/8	0	5/8	1/8	0	1/8

Table 3: Transition probabilities $P(i \to j)$.

Thus, we have the state space $\mathcal{X} = \{M, D, C, L, E, F\}$ with transition matrix

$$P = \begin{pmatrix} \frac{1}{4} & 0 & \frac{1}{3} & \frac{1}{4} & \frac{1}{12} & \frac{1}{12} \\ 0 & 0 & \frac{1}{2} & \frac{1}{4} & 0 & \frac{1}{4} \\ \frac{4}{15} & \frac{1}{5} & \frac{1}{15} & \frac{1}{15} & \frac{4}{15} & \frac{2}{15} \\ \frac{1}{12} & \frac{1}{12} & 0 & \frac{1}{6} & \frac{7}{12} & \frac{1}{12} \\ \frac{3}{13} & 0 & \frac{3}{13} & \frac{4}{13} & \frac{1}{13} & \frac{2}{13} \\ \frac{1}{8} & 0 & \frac{5}{8} & \frac{1}{8} & 0 & \frac{1}{8} \end{pmatrix},$$

and initial distribution

$$\mu_0 = (1,\, 0,\, 0,\, 0,\, 0,\, 0)\,.$$

The estimated transition probabilities reveal non-uniform navigation patterns between categories. In particular, certain categories exhibit higher self-transition probabilities, indicating persistence in viewing similar content types, while others show stronger cross-category transitions. These empirical patterns motivate the subsequent analysis of irreducibility, recurrence, and long-run behavior of the chain.

3.1.1 Sampling Variability and Potential Bias

The dataset consists of a single sequence of 65 consecutively viewed videos and therefore reflects observational trajectory. As such, the estimated transition probabilities are subject to sampling variability and may be influenced by manual data collection, temporal effects, and the aggregation of heterogeneous content into broad categories. No claim is made regarding the representativeness of these probabilities at the platform-wide level.

3.1.2 Statistical Reliability and Model Assumptions

Transition probabilities are estimated using relative frequencies, a standard approach for finite-state Markov chains. Given the limited sample size, formal statistical inference—such as confidence interval construction or goodness-of-fit testing—is not statistically meaningful in this setting. In larger datasets, uncertainty quantification could be achieved using multinomial confidence intervals or bootstrap methods, and model adequacy could be assessed via likelihood-based or chi-square tests.

The use of finite observational sequences for modeling social media dynamics has been adopted in related studies where interpretability and structural analysis are prioritized over large-scale inference [8].

3.2 Analysis

Given the state space $\mathcal{X}$ and transition matrix P as above, we shall now study some of its properties and compute the stationary distribution.

3.2.1 Irreducibility

The chain is irreducible, since every state can be reached from every other state. Equivalently, the communicating class of the chain is the whole state space $\mathcal{X}$.

3.2.2 Periodicity

Several states have positive self-transition probability, e.g. $P(M \to M) = 1/4 > 0$, $P(L \to L) = 1/6 > 0$, $P(F \to F) = 1/8 > 0$. Any state with a self-loop has period 1, and, in an irreducible chain, this implies every state has period 1. Hence the chain is aperiodic.

The established properties of irreducibility and aperiodicity imply that the viewing process does not become trapped within a subset of categories and does not exhibit cyclical behavior. From a behavioral perspective, this suggests that users are exposed to a diverse range of content categories over time, rather than repeatedly oscillating between a fixed subset. .

3.2.3 Recurrence

For a finite-state irreducible Markov chain, every state is positive recurrent. Thus all six states are recurrent, and are indeed, positive recurrent.

3.2.4 Absorbing States

There are no absorbing states. Consequently the chain is not an absorbing chain.
The absence of absorbing states indicates that no single content category permanently dominates the viewing process. From a behavioral perspective, this suggests that users do not become trapped in a single category, but continue to transition among multiple content types over time. In contrast to absorbing dynamics, where exposure would eventually concentrate entirely on one category, the present structure allows for sustained category diversity.

Moreover, since the chain is finite and irreducible, all states are positive recurrent. This implies that each category is revisited infinitely often in the long run, with a well-defined expected return time. Together, positive recurrence and the lack of absorbing states reinforce the interpretation that long-term viewing behavior is governed by stable equilibrium dynamics rather than terminal or degenerate outcomes.

3.2.5 Ergodicity

Since the chain is finite, irreducible, and aperiodic, it is ergodic. Therefore there exists a unique stationary distribution π and, for any initial distribution μ_0,

$$\mu_t = \mu_0 P^t \xrightarrow[t\to\infty]{} \pi.$$

Ergodicity further guarantees that long-run exposure patterns are well-defined and independent of the initial category viewed.

3.3 Stationary Distribution

The stationary distribution can be interpreted as the long-run proportion of time a user is expected to spend viewing each category, assuming the observed transition dynamics persist. Categories with higher stationary probabilities correspond to those that dominate long-term exposure, while lower probabilities indicate more transient or less persistent content types. Importantly, the stationary distribution summarizes cumulative viewing behavior rather than short-term fluctuations.
The stationary distribution π is the (unique) probability row vector satisfying $\pi P = \pi$ and $\sum_x \pi(x) = 1$. For P, the computed stationary distribution is

$$\begin{aligned}\pi &= \left(\frac{3}{16}, \frac{1}{16}, \frac{15}{64}, \frac{3}{16}, \frac{13}{64}, \frac{1}{8}\right)\\ &\approx (0.1875,\ 0.0625,\ 0.234375,\ 0.1875,\ 0.203125,\ 0.125).\end{aligned}$$

The stationary distribution matches the observed frequencies of each category when looking at the first 64 positions in the sequence. Since the chain is ergodic, if we keep following the same pattern, the

distribution of categories will always get closer to π over time, no matter where we start.
The stationary distribution is computed using direct linear algebraic methods and verified numerically via the power method. This choice is intentional: for finite-state ergodic Markov chains of moderate dimension, direct methods provide exact solutions, numerical stability, and full reproducibility. More advanced optimization-based or large-scale iterative techniques are typically motivated by high-dimensional or sparse state spaces, which are not present in the current setting.

3.4 Model Validation and Scope of Inference

The present analysis does not include validation on a held-out test set or comparison with independent user trajectories. Such validation procedures require larger datasets with multiple observation sequences and are not statistically meaningful for a single, short viewing trajectory. Accordingly, the model is not intended as a predictive tool for individual user behavior.

Instead, validation is performed at the structural level. By establishing irreducibility, aperiodicity, and ergodicity, we verify that the estimated transition matrix induces a well-defined stochastic process with a unique stationary distribution. This form of structural validation ensures internal mathematical consistency and is standard in applied stochastic modeling when the objective is to characterize equilibrium behavior rather than short-term prediction.

3.5 Sensitivity and Robustness of Long-Run Behavior

For finite-state ergodic Markov chains, the stationary distribution depends continuously on the entries of the transition matrix. Consequently, small perturbations in the estimated transition probabilities lead to bounded changes in the stationary distribution. This continuity property provides an inherent degree of robustness to sampling variability in empirical estimates derived from finite datasets.
Although a formal sensitivity analysis is not conducted in this study due to data limitations, the numerical convergence observed via the power method indicates stable equilibrium behavior under the estimated model. In particular, the qualitative ranking of categories in the stationary distribution appears resilient to minor fluctuations in transition probabilities. In larger datasets, robustness could be assessed more explicitly by perturbing transition probabilities within confidence bounds or by applying bootstrap-based resampling methods to evaluate the resulting variation in long-run category exposure.
Similar robustness considerations arise in hybrid and sequential modeling contexts, where Markov-based representations provide interpretable summaries of long-run behavior despite underlying variability in transition dynamics [17].

3.6 First-Order Markov Assumption

The model assumes a first-order Markov property, whereby the category of the next video depends only on the current category. This assumption is widely adopted due to its interpretability and analytical tractability, but it abstracts away potential longer-range dependencies in viewing behavior.

Formal testing of the Markov property—such as chi-square or likelihood ratio tests comparing first-order and higher-order transition structures—requires substantially larger samples to produce reliable results. The assumption is therefore stated explicitly, and its empirical validation is deferred to future work using richer datasets.

4 Numerical Simulations

To complement the analytical results, numerical simulations were carried out to illustrate the dynamic behavior of the proposed Markov chain model and to verify convergence toward the stationary distribution. The simulations are based on the empirically estimated 6×6 transition matrix obtained from the observed TikTok video sequence.
Starting from an initial probability distribution over the six content categories, the evolution of the

state probabilities was computed iteratively using the power method. Specifically, given an initial distribution vector $\boldsymbol{\mu}_0$, successive distributions were generated according to

$$\boldsymbol{\mu}_{n+1} = \boldsymbol{\mu}_n P,$$

where P denotes the transition matrix. This procedure was repeated over multiple iterations to examine convergence behavior.

The numerical results demonstrate rapid convergence of $\boldsymbol{\mu}_n$ to the stationary distribution, independent of the choice of initial distribution. This behavior is consistent with the theoretical properties established earlier—namely irreducibility and aperiodicity—which guarantee ergodicity and convergence to a unique stationary distribution.

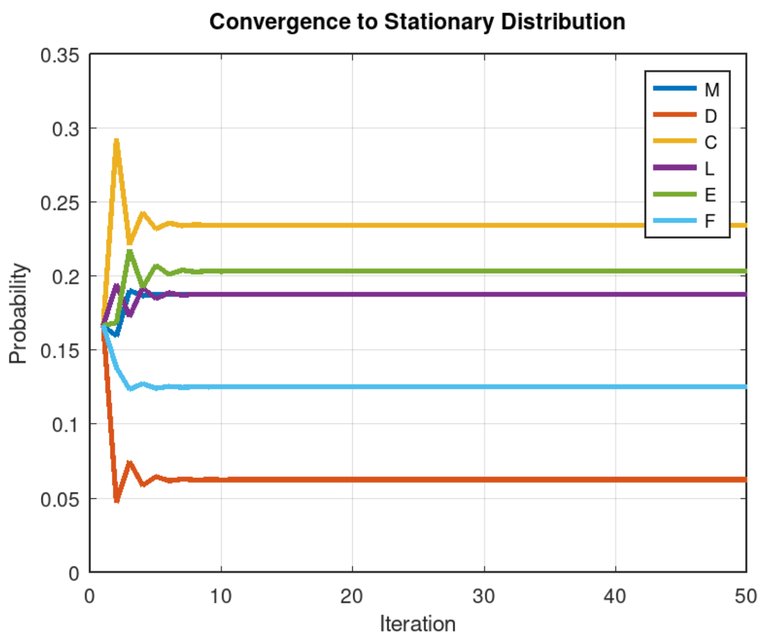


Figure 1: Convergence of category probability distributions over 50 iterations using the power method. The stabilization of the curves illustrates convergence to the stationary distribution.

Figure 1 illustrates the convergence of category probabilities over 50 iterations. Each curve represents the probability associated with a given content category as the number of iterations increases. The stabilization of all curves indicates that transient effects associated with the initial distribution diminish over time, and that the system converges toward its long-run equilibrium. Categories with higher stationary probabilities converge to higher limiting values, while those with lower stationary probabilities decay accordingly.

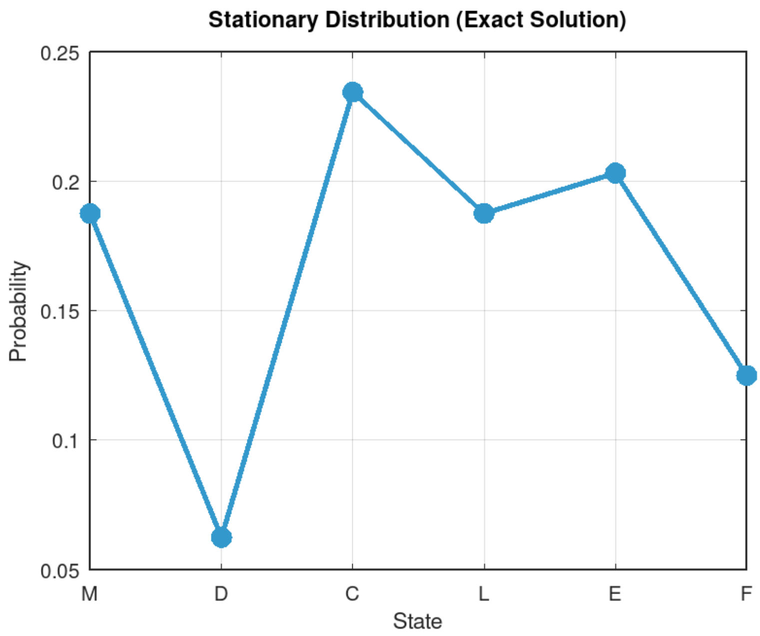


Figure 2: Stationary distribution of TikTok video categories obtained from the estimated transition matrix, representing long-run exposure proportions across categories.

Figure 2 displays the stationary distribution obtained numerically. This distribution represents the long-run proportion of time the viewing process is expected to spend in each category under the estimated transition dynamics. The relative magnitudes of the stationary probabilities provide a concise summary of long-term exposure patterns across content categories.

Overall, the numerical simulations provide computational validation of the analytical findings and offer an intuitive visualization of long-run exposure dynamics. They confirm that short-term fluctuations in category probabilities diminish over time and that the viewing process converges toward a stable equilibrium determined solely by the transition structure. These results further support the suitability of the Markov chain framework for modeling category-level transitions in short-form video consumption.

5 Discussion and Conclusion

This study does not aim to model or infer the internal mechanics of TikTok's proprietary recommendation algorithm. Instead, it abstracts observed category-level transitions in a viewing sequence into a stochastic process. The resulting Markov chain captures user navigation behavior at the categorical level, rather than the platform's algorithmic decision rules governing content ranking or personalization.

Despite this level of abstraction, the proposed framework yields insights that are relevant to the analysis of recommendation systems at an aggregate scale. In particular, the stationary distribution of the Markov chain characterizes long-run exposure shares across content categories, providing a principled means of examining content balance, dominance, and persistence under repeated viewing dynamics. Such equilibrium behavior complements short-term engagement metrics by revealing how local transition patterns accumulate into global exposure outcomes over time.

From a methodological perspective, category-level Markov models offer a transparent and analytically tractable baseline against which more complex recommendation models can be evaluated. Their interpretability makes them especially useful for exploratory analysis, system auditing, and fairness-oriented studies, where understanding long-run exposure dynamics is as important as predicting immediate user interactions.

In this paper, we analyzed a sequence of TikTok videos by modeling category transitions as a discrete-time Markov chain. Using the collected data, we constructed a transition matrix and examined key structural properties of the chain. The analysis showed that the chain is irreducible and aperiodic, and hence ergodic. Consequently, all states are positive recurrent, and the long-term behavior of the process is fully characterized by a unique stationary distribution. The stationary distribution was computed explicitly and found to be consistent with the empirical category frequencies observed in the dataset, demonstrating the suitability of Markov chains for capturing the probabilistic structure of category transitions in short-form video consumption.

Beyond the technical results, the analysis suggests that category transitions on TikTok exhibit stable long-run patterns. Regardless of the initial category, the viewing process converges toward a predictable equilibrium distribution across categories. This finding highlights how seemingly random user navigation can be shaped by underlying transition probabilities, offering insight into cumulative exposure dynamics on short-form video platforms.

Compared with data-intensive neural recommendation models [13, 14, 15], the Markov chain framework emphasizes analytical transparency and long-run interpretability. While such models may achieve higher predictive accuracy, classical Markov models remain valuable as baselines for auditing, exposure analysis, and fairness-oriented investigations [12].

The primary limitations are the modest dataset size and the first-order Markov assumption, which abstracts away personalization and longer-range dependencies. The dataset consists of only 65 videos grouped into six broad categories, which restricts statistical inference and external validity. Moreover, TikTok's recommendation system incorporates personalized features such as user interactions, watch time, and adaptive algorithmic feedback, none of which are captured by the simplified Markov chain model employed here. As a result, while the findings are informative at the categorical level, they do not reflect the full complexity of real-world recommendation mechanisms.

Future research may extend this framework in several directions. First, larger and more diverse datasets, potentially involving multiple users and sessions, would enable more robust statistical validation. Second, higher-order Markov chains or Hidden Markov Models could be employed to capture longer-range dependencies in viewing behavior. Third, hybrid approaches combining Markov models with learning-based architectures (e.g. machine learning and deep neural networks techniques), may offer improved descriptive and predictive performance in settings where contextual and personalized features play a central role [17]. These extensions would build on the foundation established in this study and contribute to a deeper understanding of user behavior on short-form video social media platforms. Future extensions may integrate stochastic transition models with learning-based architectures, following hybrid approaches proposed in related domains .

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