

Concentration Inequalities and Martingale Inequalities: A Survey

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Abstract. We examine a number of generalized and extended versions of concentration inequalities and martingale inequalities. These inequalities are effective for analyzing processes with quite general conditions as illustrated in an example for an infinite Polya process and web graphs.

1. Introduction

One of the main tools in probabilistic analysis is the concentration inequalities. Basically, the concentration inequalities are meant to give a sharp prediction of the actual value of a random variable by bounding the error term (from the expected value) with an associated probability. The classical concentration inequalities such as those for the binomial distribution have the best possible error estimates with exponentially small probabilistic bounds. Such concentration inequalities usually require certain independence assumptions (i.e., the random variable can be decomposed as a sum of independent random variables).

When the independence assumptions do not hold, it is still desirable to have similar, albeit slightly weaker, inequalities at our disposal. One approach is the martingale method. If the random variable and the associated probability space can be organized into a chain of events with modified probability spaces

and if the incremental changes of the value of the event is “small,” then the martingale inequalities provide very good error estimates. The reader is referred to numerous textbooks [Alon and Spencer 92, Janson et al. 00, McDiarmid 98] on this subject.

In the past few years, there has been a great deal of research in analyzing general random graph models for realistic massive graphs that have uneven degree distribution, such as the power law [Abello et al. 98, Aiello et al. 00, Aiello et al. 02, Albert and Barabási 02, Barabási and Albert 99]. The usual concentration inequalities and martingale inequalities have often been found to be inadequate and in many cases not feasible. The reasons are multifold: due to uneven degree distribution, the error bound of those very large degrees offset the delicate analysis in the sparse part of the graph. For the setup of the martingales, a uniform upper bound for the incremental changes are often too poor to be of any use. Furthermore, the graph is dynamically evolving, and therefore the probability space is changing at each tick of the time.

In spite of these difficulties, it is highly desirable to extend the classical concentration inequalities and martingale inequalities so that rigorous analysis for random graphs with general degree distributions can be carried out. Indeed, in the course of studying general random graphs, a number of variations and generalizations of concentration inequalities and martingale inequalities have been scattered around. It is the goal of this survey to put together these extensions and generalizations to present a more complete picture. We will examine and compare these inequalities, and complete proofs will be given. Needless to say, this survey is far from complete since all the work is quite recent and the selection is heavily influenced by our personal learning experience on this topic. Indeed, many of these inequalities have been included in our previous papers [Chung and Lu 02b, Chung and Lu 02a, Chung et al. 03b, Chung and Lu 04].

In addition to numerous variations of the inequalities, we also include an example of an application on a generalization of Polya’s urn problem. Due to the fundamental nature of these concentration inequalities and martingale inequalities, they may be useful for many other problems as well.

This paper is organized as follows:

1. Introduction: overview, recent developments and summary.
2. Binomial distribution and its asymptotic behavior: the normalized binomial distribution and Poisson distribution.
3. General Chernoff inequalities: sums of independent random variables in five different concentration inequalities.

4. More concentration inequalities: five more variations of the concentration inequalities.
5. Martingales and Azuma's inequality: basics for martingales and proofs for Azuma's inequality.
6. General martingale inequalities: four general versions of martingale inequalities with proofs.
7. Supermartingales and submartingales: modifying the definitions for martingale and still preserving the effectiveness of the martingale inequalities.
8. The decision tree and relaxed concentration inequalities: instead of the worst case incremental bound (the Lipschitz condition), only certain "local" conditions are required.
9. A generalized Polya's urn problem: an application for an infinite Polya process by using these general concentration and martingale inequalities. For web graphs generated by the preferential attachment scheme, the concentration for the power law degree distribution can be derived in a similar way.

2. The Binomial Distribution and Its Asymptotic Behavior

Bernoulli trials, named after James Bernoulli, can be thought of as a sequence of coin flips. For some fixed value p , where $0 \leq p \leq 1$, the outcome of the coin tossing process has probability p of getting a "head." Let S_n denote the number of heads after n tosses. We can write S_n as a sum of independent random variables X_i as follows:

$$S_n = X_1 + X_2 + \cdots + X_n,$$

where, for each i , the random variable X satisfies

$$\begin{aligned}\Pr(X_i = 1) &= p, \\ \Pr(X_i = 0) &= 1 - p.\end{aligned}\tag{2.1}$$

A classical question is to determine the distribution of S_n . It is not too difficult to see that S_n has the *binomial distribution* $B(n, p)$:

$$\Pr(S_n = k) = \binom{n}{k} p^k (1 - p)^{n-k}, \quad \text{for } k = 0, 1, 2, \dots, n.$$

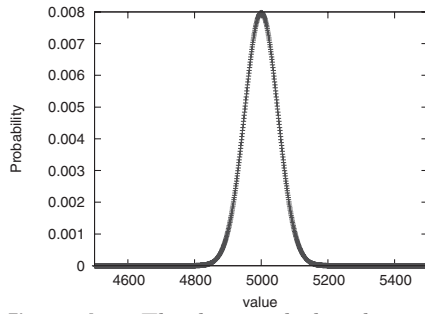


Figure 1. The binomial distribution $B(10000, 0.5)$.

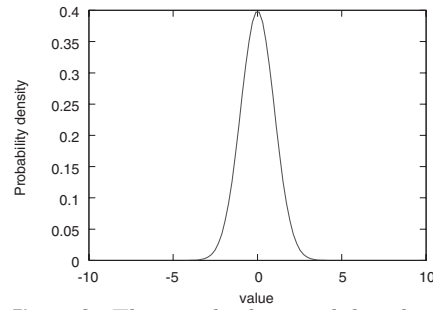


Figure 2. The standard normal distribution $N(0, 1)$.

The expectation and variance of $B(n, p)$ are

$$E(S_n) = np \quad \text{and} \quad \text{Var}(S_n) = np(1 - p),$$

respectively.

To better understand the asymptotic behavior of the binomial distribution, we compare it with the normal distribution $N(\alpha, \sigma)$, whose density function is given by

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\alpha)^2}{2\sigma^2}}, \quad -\infty < x < \infty,$$

where α denotes the expectation and σ^2 is the variance.

The case $N(0, 1)$ is called the *standard normal distribution* whose density function is given by

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, \quad -\infty < x < \infty.$$

When p is a constant, the limit of the binomial distribution, after scaling, is the standard normal distribution and can be viewed as a special case of the Central-Limit Theorem, sometimes called the DeMoivre-Laplace limit Theorem [Feller 71].

Theorem 2.1. *The binomial distribution $B(n, p)$ for S_n , as defined in (2.1), satisfies, for two constants a and b ,*

$$\lim_{n \rightarrow \infty} \Pr(a\sigma < S_n - np < b\sigma) = \int_a^b \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx,$$

where $\sigma = \sqrt{np(1-p)}$ provided that $np(1-p) \rightarrow \infty$ as $n \rightarrow \infty$.

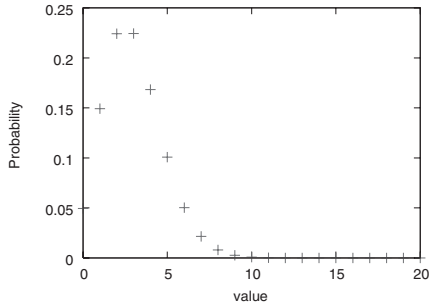


Figure 3. The binomial distribution $B(1000, 0.003)$.

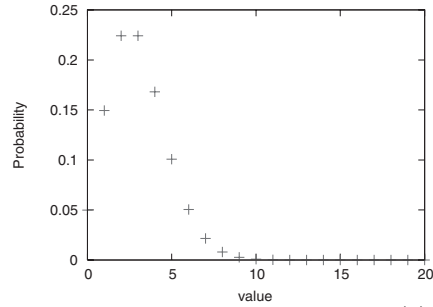


Figure 4. The Poisson distribution $P(3)$.

When np is upper bounded (by a constant), Theorem 2.1 is no longer true. For example, for $p = \frac{\lambda}{n}$, the limit distribution of $B(n, p)$ is the so-called *Poisson distribution* $P(\lambda)$:

$$\Pr(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}, \quad \text{for } k = 0, 1, 2, \dots$$

The expectation and variance of the Poisson distribution $P(\lambda)$ are given by

$$\mathbb{E}(X) = \lambda \quad \text{and} \quad \text{Var}(X) = \lambda.$$

Theorem 2.2. For $p = \frac{\lambda}{n}$, where λ is a constant, the limit distribution of binomial distribution $B(n, p)$ is the Poisson distribution $P(\lambda)$.

Proof. We consider

$$\begin{aligned} \lim_{n \rightarrow \infty} \Pr(S_n = k) &= \lim_{n \rightarrow \infty} \binom{n}{k} p^k (1-p)^{n-k} \\ &= \lim_{n \rightarrow \infty} \frac{\lambda^k \prod_{i=0}^{k-1} (1 - \frac{i}{n})}{k!} e^{-p(n-k)} \\ &= \frac{\lambda^k}{k!} e^{-\lambda}. \end{aligned}$$

□

As p decreases from $\Theta(1)$ to $\Theta(\frac{1}{n})$, the asymptotic behavior of the binomial distribution $B(n, p)$ changes from the normal distribution to the Poisson distribution. (Some examples are illustrated in Figures 5 and 6.) Theorem 2.1 states that the asymptotic behavior of $B(n, p)$ within the interval $(np - C\sigma, np + C\sigma)$ (for any constant C) is close to the normal distribution. In some applications, we might need asymptotic estimates beyond this interval.

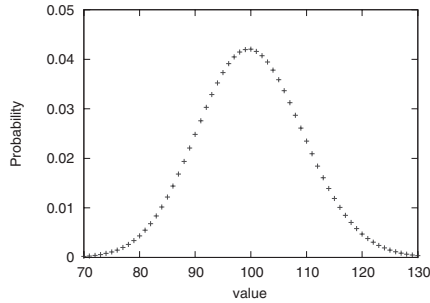


Figure 5. The binomial distribution $B(1000, 0.1)$.

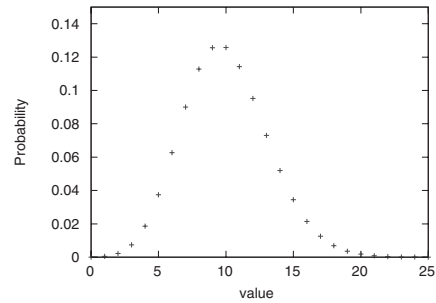


Figure 6. The binomial distribution $B(1000, 0.01)$.

3. General Chernoff Inequalities

If the random variable under consideration can be expressed as a sum of independent variables, it is possible to derive good estimates. The binomial distribution is one such example where $S_n = \sum_{i=1}^n X_i$ and the X_i are independent and identical. In this section, we consider sums of independent variables that are not necessarily identical. To control the probability of how close a sum of random variables is to the expected value, various concentration inequalities are in play. A typical version of the Chernoff inequalities, attributed to Herman Chernoff, can be stated as follows:

Theorem 3.1. [Chernoff 81] *Let X_1, \dots, X_n be independent random variables with $E(X_i) = 0$ and $|X_i| \leq 1$ for all i . Let $X = \sum_{i=1}^n X_i$, and let σ^2 be the variance of X_i . Then,*

$$\Pr(|X| \geq k\sigma) \leq 2e^{-k^2/4n},$$

for any $0 \leq k \leq 2\sigma$.

If the random variables X_i under consideration assume nonnegative values, the following version of Chernoff inequalities is often useful.

Theorem 3.2. [Chernoff 81] *Let X_1, \dots, X_n be independent random variables with*

$$\Pr(X_i = 1) = p_i, \quad \Pr(X_i = 0) = 1 - p_i.$$

We consider the sum $X = \sum_{i=1}^n X_i$, with expectation $E(X) = \sum_{i=1}^n p_i$. Then, we have

$$\begin{aligned} \text{(Lower tail)} \quad \Pr(X \leq E(X) - \lambda) &\leq e^{-\lambda^2/2E(X)}, \\ \text{(Upper tail)} \quad \Pr(X \geq E(X) + \lambda) &\leq e^{-\frac{\lambda^2}{2(E(X) + \lambda/3)}}. \end{aligned}$$

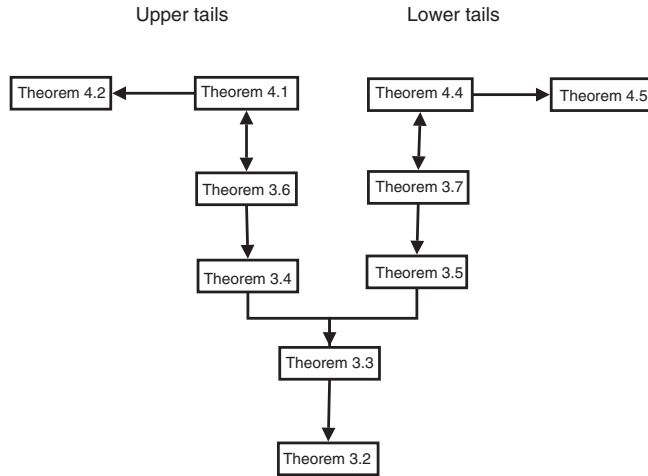


Figure 7. The flowchart for theorems on the sum of independent variables.

We remark that the term $\lambda/3$ appearing in the exponent of the bound for the upper tail is significant. This covers the case when the limit distribution is Poisson as well as normal.

There are many variations of the Chernoff inequalities. Due to the fundamental nature of these inequalities, we will state several versions and then prove the strongest version from which all the other inequalities can be deduced. (See Figure 7 for the flowchart of these theorems.) In this section, we will prove Theorem 3.6 and deduce Theorems 3.4 and 3.3. Theorems 4.1 and 4.2 will be stated and proved in the next section. Theorems 3.7, 3.5, 4.4, and 4.5 on the lower tail can be deduced by reflecting X to $-X$.

The following inequality is a generalization of the Chernoff inequalities for the binomial distribution:

Theorem 3.3. [Chung and Lu 02b] *Let X_1, \dots, X_n be independent random variables with*

$$\Pr(X_i = 1) = p_i, \quad \Pr(X_i = 0) = 1 - p_i.$$

For $X = \sum_{i=1}^n a_i X_i$ with $a_i > 0$, we have $E(X) = \sum_{i=1}^n a_i p_i$, and we define $\nu = \sum_{i=1}^n a_i^2 p_i$. Then, we have

$$\Pr(X \leq E(X) - \lambda) \leq e^{-\lambda^2/2\nu}, \tag{3.1}$$

$$\Pr(X \geq E(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\nu+a\lambda/3)}}, \tag{3.2}$$

where $a = \max\{a_1, a_2, \dots, a_n\}$.

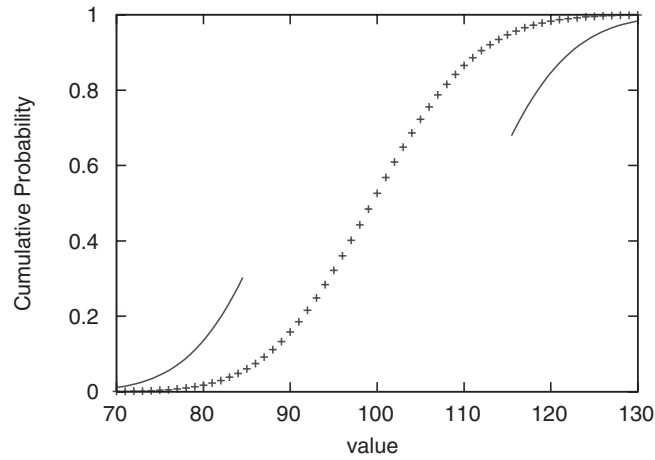


Figure 8. Chernoff inequalities.

To compare inequalities (3.1) to (3.2), we consider an example in Figure 8. The cumulative distribution is the function $\Pr(X > x)$. The dotted curve in Figure 8 illustrates the cumulative distribution of the binomial distribution $B(1000, 0.1)$, with the value ranging from 0 to 1 as x goes from $-\infty$ to ∞ . The solid curve at the lower-left corner is the bound $e^{-\lambda^2/2\nu}$ for the lower tail. The solid curve at the upper-right corner is the bound $1 - e^{-\frac{\lambda^2}{2(\nu+a\lambda/3)}}$ for the upper tail.

The inequality (3.2) in the Theorem 3.3 is a corollary of the following general concentration inequality (also see Theorem 2.7 in the survey paper by McDiarmid [McDiarmid 98]).

Theorem 3.4. [McDiarmid 98] *Let X_i ($1 \leq i \leq n$) be independent random variables satisfying $X_i \leq \mathbb{E}(X_i) + M$, for $1 \leq i \leq n$. We consider the sum $X = \sum_{i=1}^n X_i$ with expectation $\mathbb{E}(X) = \sum_{i=1}^n \mathbb{E}(X_i)$ and variance $\text{Var}(X) = \sum_{i=1}^n \text{Var}(X_i)$. Then, we have*

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + M\lambda/3)}}.$$

In the other direction, we have the following inequality.

Theorem 3.5. *If X_1, X_2, \dots, X_n are nonnegative independent random variables, we have the following bounds for the sum $X = \sum_{i=1}^n X_i$:*

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2 \sum_{i=1}^n \mathbb{E}(X_i^2)}}.$$

A strengthened version of Theorem 3.5 is as follows:

Theorem 3.6. *Suppose that the X_i are independent random variables satisfying $X_i \leq M$, for $1 \leq i \leq n$. Let $X = \sum_{i=1}^n X_i$ and $\|X\| = \sqrt{\sum_{i=1}^n \mathbb{E}(X_i^2)}$. Then, we have*

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\|X\|^2 + M\lambda/3)}}.$$

Replacing X by $-X$ in the proof of Theorem 3.6, we have the following theorem for the lower tail.

Theorem 3.7. *Let X_i be independent random variables satisfying $X_i \geq -M$, for $1 \leq i \leq n$. Let $X = \sum_{i=1}^n X_i$ and $\|X\| = \sqrt{\sum_{i=1}^n \mathbb{E}(X_i^2)}$. Then, we have*

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2(\|X\|^2 + M\lambda/3)}}.$$

Before we give the proof of Theorems 3.6, we will first show the implications of Theorems 3.6 and 3.7. Namely, we will show that the other concentration inequalities can be derived from Theorems 3.6 and 3.7.

Fact 3.8. *Theorem 3.6 \implies Theorem 3.4.*

Proof. Let $X'_i = X_i - \mathbb{E}(X_i)$ and $X' = \sum_{i=1}^n X'_i = X - \mathbb{E}(X)$. We have

$$X'_i \leq M \quad \text{for } 1 \leq i \leq n.$$

We also have

$$\begin{aligned} \|X'\|^2 &= \sum_{i=1}^n \mathbb{E}(X'^2_i) \\ &= \sum_{i=1}^n \text{Var}(X_i) \\ &= \text{Var}(X). \end{aligned}$$

Applying Theorem 3.6, we get

$$\begin{aligned} \Pr(X \geq \mathbb{E}(X) + \lambda) &= \Pr(X' \geq \lambda) \\ &\leq e^{-\frac{\lambda^2}{2(\|X'\|^2 + M\lambda/3)}} \\ &\leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + M\lambda/3)}}. \end{aligned}$$

□

Fact 3.9. *Theorem 3.7 \implies Theorem 3.5.*

The proof is straightforward by choosing $M = 0$.

Fact 3.10. *Theorems 3.4 and 3.5 \implies Theorem 3.3.*

Proof. We define $Y_i = a_i X_i$. Note that

$$\|X\|^2 = \sum_{i=1}^n \mathbb{E}(Y_i^2) = \sum_{i=1}^n a_i^2 p_i = \nu.$$

Equation (3.1) follows from Theorem 3.5 since the Y_i are nonnegatives.

For the other direction, we have

$$Y_i \leq a_i \leq a \leq \mathbb{E}(Y_i) + a.$$

Equation (3.2) follows from Theorem 3.4. □

Fact 3.11. *Theorem 3.6 and Theorem 3.7 \implies Theorem 3.1.*

The proof is by choosing $Y = X - \mathbb{E}(X)$ and $M = 1$ and applying Theorems 3.6 and 3.7 to Y .

Fact 3.12. *Theorem 3.3 \implies Theorem 3.2.*

The proof follows by choosing $a_1 = a_2 = \dots = a_n = 1$.

Finally, we give the complete proof of Theorem 3.6 and thus finish the proofs for all the theorems in this section on Chernoff inequalities.

Proof of Theorem 3.6. We consider

$$\mathbb{E}(e^{tX}) = \mathbb{E}(e^{t \sum_i X_i}) = \prod_{i=1}^n \mathbb{E}(e^{tX_i}),$$

since the X_i are independent.

We define

$$g(y) = 2 \sum_{k=2}^{\infty} \frac{y^{k-2}}{k!} = \frac{2(e^y - 1 - y)}{y^2}$$

and use the following facts about g :

- $g(0) = 1$.

- $g(y) \leq 1$, for $y < 0$.
- $g(y)$ is monotone increasing, for $y \geq 0$.
- For $y < 3$, we have

$$g(y) = 2 \sum_{k=2}^{\infty} \frac{y^{k-2}}{k!} \leq \sum_{k=2}^{\infty} \frac{y^{k-2}}{3^{k-2}} = \frac{1}{1 - y/3},$$

since $k! \geq 2 \cdot 3^{k-2}$.

Then we have, for $k \geq 2$,

$$\begin{aligned} \mathbf{E}(e^{tX}) &= \prod_{i=1}^n \mathbf{E}(e^{tX_i}) \\ &= \prod_{i=1}^n \mathbf{E} \left(\sum_{k=0}^{\infty} \frac{t^k X_i^k}{k!} \right) \\ &= \prod_{i=1}^n \mathbf{E} \left(1 + t\mathbf{E}(X_i) + \frac{1}{2}t^2 X_i^2 g(tX_i) \right) \\ &\leq \prod_{i=1}^n \left(1 + t\mathbf{E}(X_i) + \frac{1}{2}t^2 \mathbf{E}(X_i^2) g(tM) \right) \\ &\leq \prod_{i=1}^n e^{t\mathbf{E}(X_i) + \frac{1}{2}t^2 \mathbf{E}(X_i^2) g(tM)} \\ &= e^{t\mathbf{E}(X) + \frac{1}{2}t^2 g(tM) \sum_{i=1}^n \mathbf{E}(X_i^2)} \\ &= e^{t\mathbf{E}(X) + \frac{1}{2}t^2 g(tM) \|X\|^2}. \end{aligned}$$

Hence, for t satisfying $tM < 3$, we have

$$\begin{aligned} \Pr(X \geq \mathbf{E}(X) + \lambda) &= \Pr(e^{tX} \geq e^{t\mathbf{E}(X) + t\lambda}) \\ &\leq e^{-t\mathbf{E}(X) - t\lambda} \mathbf{E}(e^{tX}) \\ &\leq e^{-t\lambda + \frac{1}{2}t^2 g(tM) \|X\|^2} \\ &\leq e^{-t\lambda + \frac{1}{2}t^2 \|X\|^2 \frac{1}{1 - tM/3}}. \end{aligned}$$

To minimize the above expression, we choose $t = \frac{\lambda}{\|X\|^2 + M\lambda/3}$. Therefore, $tM < 3$, and we have

$$\begin{aligned} \Pr(X \geq \mathbf{E}(X) + \lambda) &\leq e^{-t\lambda + \frac{1}{2}t^2 \|X\|^2 \frac{1}{1 - tM/3}} \\ &= e^{-\frac{\lambda^2}{2(\|X\|^2 + M\lambda/3)}}. \end{aligned}$$

The proof is complete. \square

4. More Concentration Inequalities

Here we state several variations and extensions of the concentration inequalities in Theorem 3.6. We first consider the upper tail.

Theorem 4.1. *Let X_i denote independent random variables satisfying $X_i \leq \mathbb{E}(X_i) + a_i + M$, for $1 \leq i \leq n$. For $X = \sum_{i=1}^n X_i$, we have*

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + \sum_{i=1}^n a_i^2 + M\lambda/3)}}.$$

Proof. Let $X'_i = X_i - \mathbb{E}(X_i) - a_i$ and $X' = \sum_{i=1}^n X'_i$. We have

$$X'_i \leq M \quad \text{for } 1 \leq i \leq n.$$

$$\begin{aligned} X' - \mathbb{E}(X') &= \sum_{i=1}^n (X'_i - \mathbb{E}(X'_i)) \\ &= \sum_{i=1}^n (X'_i + a_i) \\ &= \sum_{i=1}^n (X_i - \mathbb{E}(X_i)) \\ &= X - \mathbb{E}(X). \end{aligned}$$

Thus,

$$\begin{aligned} \|X'\|^2 &= \sum_{i=1}^n \mathbb{E}(X'^2_i) \\ &= \sum_{i=1}^n \mathbb{E}((X_i - \mathbb{E}(X_i) - a_i)^2) \\ &= \sum_{i=1}^n \mathbb{E}((X_i - \mathbb{E}(X_i))^2 + a_i^2) \\ &= \text{Var}(X) + \sum_{i=1}^n a_i^2. \end{aligned}$$

By applying Theorem 3.6, the proof is finished. \square

Theorem 4.2. *Suppose that the X_i are independent random variables satisfying $X_i \leq \mathbb{E}(X_i) + M_i$, for $0 \leq i \leq n$. We order the X_i so that the M_i are in*

increasing order. Let $X = \sum_{i=1}^n X_i$. Then, for any $1 \leq k \leq n$, we have

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + \sum_{i=k}^n (M_i - M_k)^2 + M_k \lambda/3)}}.$$

Proof. For fixed k , we choose $M = M_k$ and

$$a_i = \begin{cases} 0 & \text{if } 1 \leq i \leq k, \\ M_i - M_k & \text{if } k \leq i \leq n. \end{cases}$$

We have

$$\begin{aligned} X_i - \mathbb{E}(X_i) &\leq M_i \leq a_i + M_k \quad \text{for } 1 \leq k \leq n, \\ \sum_{i=1}^n a_i^2 &= \sum_{i=k}^n (M_i - M_k)^2. \end{aligned}$$

Using Theorem 4.1, we have

$$\Pr(X_i \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + \sum_{i=k}^n (M_i - M_k)^2 + M_k \lambda/3)}}.$$

□

Example 4.3. Let X_1, X_2, \dots, X_n be independent random variables. For $1 \leq i \leq n-1$, suppose that the X_i follow the same distribution with

$$\Pr(X_i = 0) = 1 - p \quad \text{and} \quad \Pr(X_i = 1) = p$$

and that X_n follows the distribution with

$$\Pr(X_n = 0) = 1 - p \quad \text{and} \quad \Pr(X_n = \sqrt{n}) = p.$$

Consider the sum $X = \sum_{i=1}^n X_i$.

We have

$$\begin{aligned} \mathbb{E}(X) &= \sum_{i=1}^n \mathbb{E}(X_i) \\ &= (n-1)p + \sqrt{n}p. \end{aligned}$$

$$\begin{aligned} \text{Var}(X) &= \sum_{i=1}^n \text{Var}(X_i) \\ &= (n-1)p(1-p) + np(1-p) \\ &= (2n-1)p(1-p). \end{aligned}$$

Apply Theorem 3.4 with $M = (1-p)\sqrt{n}$. We have

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2((2n-1)p(1-p)+(1-p)\sqrt{n}\lambda/3)}}.$$

In particular, for constant $p \in (0, 1)$ and $\lambda = \Theta(n^{\frac{1}{2}+\epsilon})$, we have

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\Theta(n^\epsilon)}.$$

Now we apply Theorem 4.2 with $M_1 = \dots = M_{n-1} = (1-p)$ and $M_n = \sqrt{n}(1-p)$. Choosing $k = n-1$, we have

$$\begin{aligned} \text{Var}(X) + (M_n - M_{n-1})^2 &= (2n-1)p(1-p) + (1-p)^2(\sqrt{n}-1)^2 \\ &\leq (2n-1)p(1-p) + (1-p)^2n \\ &\leq (1-p^2)n. \end{aligned}$$

Thus,

$$\Pr(X_i \geq \mathbb{E}(X) + \lambda) \leq e^{-\frac{\lambda^2}{2((1-p^2)n+(1-p)^2\lambda/3)}}.$$

For constant $p \in (0, 1)$ and $\lambda = \Theta(n^{\frac{1}{2}+\epsilon})$, we have

$$\Pr(X \geq \mathbb{E}(X) + \lambda) \leq e^{-\Theta(n^{2\epsilon})}.$$

From the above examples, we note that Theorem 4.2 gives a significantly better bound than that in Theorem 3.4 if the random variables X_i have very different upper bounds.

For completeness, we also list the corresponding theorems for the lower tails. (These can be derived by replacing X by $-X$.)

Theorem 4.4. *Let X_i denote independent random variables satisfying $X_i \geq \mathbb{E}(X_i) - a_i - M$, for $0 \leq i \leq n$. For $X = \sum_{i=1}^n X_i$, we have*

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + \sum_{i=1}^n a_i^2 + M\lambda/3)}}.$$

Theorem 4.5. *Let X_i denote independent random variables satisfying $X_i \geq \mathbb{E}(X_i) - M_i$, for $0 \leq i \leq n$. We order the X_i so that the M_i are in increasing order. Let $X = \sum_{i=1}^n X_i$. Then, for any $1 \leq k \leq n$, we have*

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2(\text{Var}(X) + \sum_{i=k}^n (M_i - M_k)^2 + M_k\lambda/3)}}.$$

Continuing the above example, we choose $M_1 = M_2 = \dots = M_{n-1} = p$ and $M_n = \sqrt{np}$. We choose $k = n - 1$, so we have

$$\begin{aligned} \text{Var}(X) + (M_n - M_{n-1})^2 &= (2n - 1)p(1 - p) + p^2(\sqrt{n} - 1)^2 \\ &\leq (2n - 1)p(1 - p) + p^2n \\ &\leq p(2 - p)n. \end{aligned}$$

Using Theorem 4.5, we have

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2(p(2-p)n + p^2\lambda/3)}}.$$

For a constant $p \in (0, 1)$ and $\lambda = \Theta(n^{\frac{1}{2} + \epsilon})$, we have

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\Theta(n^{2\epsilon})}.$$

5. Martingales and Azuma's Inequality

A martingale is a sequence of random variables X_0, X_1, \dots with finite means such that the conditional expectation of X_{n+1} given X_0, X_1, \dots, X_n is equal to X_n .

The above definition is given in the classical book of Feller [Feller 71, p. 210]. However, the conditional expectation depends on the random variables under consideration and can be difficult to deal with in various cases. In this survey we will use the following definition, which is concise and basically equivalent for the finite cases.

Suppose that Ω is a probability space with a probability distribution p . Let \mathcal{F} denote a σ -field on Ω . (A σ -field on Ω is a collection of subsets of Ω that contains \emptyset and Ω and is closed under unions, intersections, and complementation.) In a σ -field \mathcal{F} of Ω , the smallest set in \mathcal{F} containing an element x is the intersection of all sets in \mathcal{F} containing x . A function $f : \Omega \rightarrow \mathbb{R}$ is said to be \mathcal{F} -measurable if $f(x) = f(y)$ for any y in the smallest set containing x . (For more terminology on martingales, the reader is referred to [Janson et al. 00].)

If $f : \Omega \rightarrow \mathbb{R}$ is a function, we define the *expectation* $\mathbb{E}(f) = \mathbb{E}(f(x) \mid x \in \Omega)$ by

$$\mathbb{E}(f) = \mathbb{E}(f(x) \mid x \in \Omega) := \sum_{x \in \Omega} f(x)p(x).$$

If \mathcal{F} is a σ -field on Ω , we define the *conditional expectation* $\mathbb{E}(f \mid \mathcal{F}) : \Omega \rightarrow \mathbb{R}$ by the formula

$$\mathbb{E}(f \mid \mathcal{F})(x) := \frac{1}{\sum_{y \in \mathcal{F}(x)} p(y)} \sum_{y \in \mathcal{F}(x)} f(y)p(y),$$

where $\mathcal{F}(x)$ is the smallest element of \mathcal{F} that contains x .

A *filter* \mathbf{F} is an increasing chain of σ -subfields

$$\{0, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F}.$$

A martingale (obtained from) X is associated with a filter \mathbf{F} and a sequence of random variables X_0, X_1, \dots, X_n satisfying $X_i = \mathbb{E}(X \mid \mathcal{F}_i)$ and, in particular, $X_0 = \mathbb{E}(X)$ and $X_n = X$.

Example 5.1. For given independent random variables Y_1, Y_2, \dots, Y_n , we can define a martingale $X = Y_1 + Y_2 + \cdots + Y_n$ as follows. Let \mathcal{F}_i be the σ -field generated by Y_1, \dots, Y_i . (In other words, \mathcal{F}_i is the minimum σ -field so that Y_1, \dots, Y_i are \mathcal{F}_i -measurable.) We have a natural filter \mathbf{F} :

$$\{0, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F}.$$

Let $X_i = \sum_{j=1}^i Y_j + \sum_{j=i+1}^n \mathbb{E}(Y_j)$. Then, $X_0, X_1, X_2, \dots, X_n$ forms a martingale corresponding to the filter \mathbf{F} .

For $\mathbf{c} = (c_1, c_2, \dots, c_n)$ a vector with positive entries, the martingale X is said to be \mathbf{c} -Lipschitz if

$$|X_i - X_{i-1}| \leq c_i \tag{5.1}$$

for $i = 1, 2, \dots, n$. The following theorem is a powerful tool for controlling martingales.

Theorem 5.2. (Azuma's inequality.) *If a martingale X is \mathbf{c} -Lipschitz, then*

$$\Pr(|X - \mathbb{E}(X)| \geq \lambda) \leq 2e^{-\frac{\lambda^2}{2 \sum_{i=1}^n c_i^2}}, \tag{5.2}$$

where $\mathbf{c} = (c_1, \dots, c_n)$.

Theorem 5.3. *Let X_1, X_2, \dots, X_n be independent random variables satisfying*

$$|X_i - \mathbb{E}(X_i)| \leq c_i \quad \text{for } 1 \leq i \leq n.$$

Then, we have the following bound for the sum $X = \sum_{i=1}^n X_i$:

$$\Pr(|X - \mathbb{E}(X)| \geq \lambda) \leq 2e^{-\frac{\lambda^2}{2 \sum_{i=1}^n c_i^2}}.$$

Proof of Azuma's inequality. For a fixed t , we consider the convex function $f(x) = e^{tx}$. For any $|x| \leq c$, $f(x)$ is below the line segment from $(-c, f(-c))$ to $(c, f(c))$. In other words, we have

$$e^{tx} \leq \frac{1}{2c}(e^{tc} - e^{-tc})x + \frac{1}{2}(e^{tc} + e^{-tc}).$$

Therefore, we can write

$$\begin{aligned} \mathbb{E}(e^{t(X_i - X_{i-1})} | \mathcal{F}_{i-1}) &\leq \mathbb{E}\left(\frac{1}{2c_i}(e^{tc_i} - e^{-tc_i})(X_i - X_{i-1}) + \frac{1}{2}(e^{tc_i} + e^{-tc_i}) | \mathcal{F}_{i-1}\right) \\ &= \frac{1}{2}(e^{tc_i} + e^{-tc_i}) \\ &\leq e^{t^2 c_i^2 / 2}. \end{aligned}$$

Here we apply the conditions $\mathbb{E}(X_i - X_{i-1} | \mathcal{F}_{i-1}) = 0$ and $|X_i - X_{i-1}| \leq c_i$.

Hence,

$$\mathbb{E}(e^{tX_i} | \mathcal{F}_{i-1}) \leq e^{t^2 c_i^2 / 2} e^{tX_{i-1}}.$$

Inductively, we have

$$\begin{aligned} \mathbb{E}(e^{tX}) &= \mathbb{E}(\mathbb{E}(e^{tX_n} | \mathcal{F}_{n-1})) \\ &\leq e^{t^2 c_n^2 / 2} \mathbb{E}(e^{tX_{n-1}}) \\ &\quad \vdots \\ &\leq \prod_{i=1}^n e^{t^2 c_i^2 / 2} \mathbb{E}(e^{tX_0}) \\ &= e^{\frac{1}{2} t^2 \sum_{i=1}^n c_i^2} e^{t\mathbb{E}(X)}. \end{aligned}$$

Therefore,

$$\begin{aligned} \Pr(X \geq \mathbb{E}(X) + \lambda) &= \Pr(e^{t(X - \mathbb{E}(X))} \geq e^{t\lambda}) \\ &\leq e^{-t\lambda} \mathbb{E}(e^{t(X - \mathbb{E}(X))}) \\ &\leq e^{-t\lambda} e^{\frac{1}{2} t^2 \sum_{i=1}^n c_i^2} \\ &= e^{-t\lambda + \frac{1}{2} t^2 \sum_{i=1}^n c_i^2}. \end{aligned}$$

We choose $t = \frac{\lambda}{\sum_{i=1}^n c_i^2}$ (in order to minimize the previous expression). We have

$$\begin{aligned} \Pr(X \geq \mathbb{E}(X) + \lambda) &\leq e^{-t\lambda + \frac{1}{2} t^2 \sum_{i=1}^n c_i^2} \\ &= e^{-\frac{\lambda^2}{2 \sum_{i=1}^n c_i^2}}. \end{aligned}$$

To derive a similar lower bound, we consider $-X_i$ instead of X_i in the preceding proof. Then, we obtain the following bound for the lower tail:

$$\Pr(X \leq \mathbb{E}(X) - \lambda) \leq e^{-\frac{\lambda^2}{2 \sum_{i=1}^n c_i^2}}.$$

□

6. General Martingale Inequalities

Many problems that can be set up as a martingale do not satisfy the Lipschitz condition. It is desirable to be able to use tools similar to the Azuma inequality in such cases. In this section, we will first state and then prove several extensions of the Azuma inequality (see Figure 9).

Our starting point is the following well-known concentration inequality (see [McDiarmid 98]):

Theorem 6.1. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $|X_i - X_{i-1}| \leq M$, for $1 \leq i \leq n$.

Then, we have

$$\Pr(X - \mathbb{E}(X) \geq \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n \sigma_i^2 + M\lambda/3)}}.$$

Since the sum of independent random variables can be viewed as a martingale (see Example 5.1), Theorem 6.1 implies Theorem 3.4. In a similar way, the following theorem is associated with Theorem 4.1.

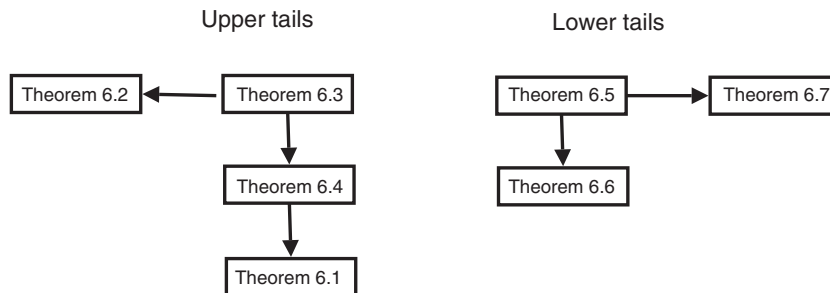


Figure 9. The flowchart for theorems on martingales.

Theorem 6.2. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_i - X_{i-1} \leq M_i$, for $1 \leq i \leq n$.

Then, we have

$$\Pr(X - \mathbb{E}(X) \geq \lambda) \leq e^{-\frac{\lambda^2}{2\sum_{i=1}^n(\sigma_i^2 + M_i^2)}}.$$

Theorem 6.2 can be further generalized:

Theorem 6.3. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_i - X_{i-1} \leq a_i + M$, for $1 \leq i \leq n$.

Then, we have

$$\Pr(X - \mathbb{E}(X) \geq \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n(\sigma_i^2 + a_i^2) + M\lambda/3)}}.$$

Theorem 6.3 implies Theorem 6.1 by choosing $a_1 = a_2 = \cdots = a_n = 0$.

We also have the following theorem corresponding to Theorem 4.2.

Theorem 6.4. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_i - X_{i-1} \leq M_i$, for $1 \leq i \leq n$.

Then, for any M , we have

$$\Pr(X - \mathbb{E}(X) \geq \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n \sigma_i^2 + \sum_{M_i > M} (M_i - M)^2 + M\lambda/3)}}.$$

Theorem 6.3 implies Theorem 6.4 by choosing

$$a_i = \begin{cases} 0 & \text{if } M_i \leq M, \\ M_i - M & \text{if } M_i \geq M. \end{cases}$$

It suffices to prove Theorem 6.3 so that all the above stated theorems hold.

Proof of Theorem 6.3. Recall that $g(y) = 2 \sum_{k=2}^{\infty} \frac{y^{k-2}}{k!}$ satisfies the following properties:

- $g(y) \leq 1$, for $y < 0$.
- $\lim_{y \rightarrow 0} g(y) = 1$.
- $g(y)$ is monotone increasing, for $y \geq 0$.
- When $b < 3$, we have $g(b) \leq \frac{1}{1-b/3}$.

Since $E(X_i | \mathcal{F}_{i-1}) = X_{i-1}$ and $X_i - X_{i-1} - a_i \leq M$, we have

$$\begin{aligned}
 E(e^{t(X_i - X_{i-1} - a_i)} | \mathcal{F}_{i-1}) &= E\left(\sum_{k=0}^{\infty} \frac{t^k}{k!} (X_i - X_{i-1} - a_i)^k | \mathcal{F}_{i-1}\right) \\
 &= 1 - ta_i + E\left(\sum_{k=2}^{\infty} \frac{t^k}{k!} (X_i - X_{i-1} - a_i)^k | \mathcal{F}_{i-1}\right) \\
 &\leq 1 - ta_i + E\left(\frac{t^2}{2} (X_i - X_{i-1} - a_i)^2 g(tM) | \mathcal{F}_{i-1}\right) \\
 &= 1 - ta_i + \frac{t^2}{2} g(tM) E((X_i - X_{i-1} - a_i)^2 | \mathcal{F}_{i-1}) \\
 &= 1 - ta_i + \frac{t^2}{2} g(tM) (E((X_i - X_{i-1})^2 | \mathcal{F}_{i-1}) + a_i^2) \\
 &\leq 1 - ta_i + \frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2) \\
 &\leq e^{-ta_i + \frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2)}.
 \end{aligned}$$

Thus,

$$\begin{aligned}
 E(e^{tX_i} | \mathcal{F}_{i-1}) &= E(e^{t(X_i - X_{i-1} - a_i)} | \mathcal{F}_{i-1}) e^{tX_{i-1} + ta_i} \\
 &\leq e^{-ta_i + \frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2)} e^{tX_{i-1} + ta_i} \\
 &= e^{\frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2)} e^{tX_{i-1}}.
 \end{aligned}$$

Inductively, we have

$$\begin{aligned}
 E(e^{tX}) &= E(E(e^{tX_n} | \mathcal{F}_{n-1})) \\
 &\leq e^{\frac{t^2}{2} g(tM) (\sigma_n^2 + a_n^2)} E(e^{tX_{n-1}}) \\
 &\quad \vdots \\
 &\leq \prod_{i=1}^n e^{\frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2)} E(e^{tX_0}) \\
 &= e^{\frac{1}{2} t^2 g(tM) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} e^{tE(X)}.
 \end{aligned}$$

Then for t satisfying $tM < 3$, we have

$$\begin{aligned}
\Pr(X \geq \mathbb{E}(X) + \lambda) &= \Pr(e^{tX} \geq e^{t\mathbb{E}(X) + t\lambda}) \\
&\leq e^{-t\mathbb{E}(X) - t\lambda} \mathbb{E}(e^{tX}) \\
&\leq e^{-t\lambda} e^{\frac{1}{2}t^2 g(tM) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\
&= e^{-t\lambda + \frac{1}{2}t^2 g(tM) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\
&\leq e^{-t\lambda + \frac{1}{2} \frac{t^2}{1-tM/3} \sum_{i=1}^n (\sigma_i^2 + a_i^2)}.
\end{aligned}$$

We choose $t = \frac{\lambda}{\sum_{i=1}^n (\sigma_i^2 + a_i^2) + M\lambda/3}$. Clearly $tM < 3$ and

$$\begin{aligned}
\Pr(X \geq \mathbb{E}(X) + \lambda) &\leq e^{-t\lambda + \frac{1}{2} \frac{t^2}{1-tM/3} \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\
&= e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + M\lambda/3)}}.
\end{aligned}$$

The proof of the theorem is complete. \square

For completeness, we state the following theorems for the lower tails. The proofs are almost identical and will be omitted.

Theorem 6.5. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_{i-1} - X_i \leq a_i + M$, for $1 \leq i \leq n$.

Then, we have

$$\Pr(X - \mathbb{E}(X) \leq -\lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + M\lambda/3)}}.$$

Theorem 6.6. *Let X be the martingale associated with a filter \mathbf{F} satisfying*

1. $\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_{i-1} - X_i \leq M_i$, for $1 \leq i \leq n$.

Then, we have

$$\Pr(X - \mathbb{E}(X) \leq -\lambda) \leq e^{-\frac{\lambda^2}{2 \sum_{i=1}^n (\sigma_i^2 + M_i^2)}}.$$

Theorem 6.7. Let X be the martingale associated with a filter \mathbf{F} satisfying

1. $\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2$, for $1 \leq i \leq n$;
2. $X_{i-1} - X_i \leq M_i$, for $1 \leq i \leq n$.

Then, for any M , we have

$$\Pr(X - \mathbb{E}(X) \leq -\lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n \sigma_i^2 + \sum_{M_i > M} (M_i - M)^2 + M\lambda/3)}}.$$

7. Supermartingales and Submartingales

In this section, we consider further-strengthened versions of the martingale inequalities that have been mentioned so far. Instead of a fixed upper bound for the variance, we will assume that the variance $\text{Var}(X_i | \mathcal{F}_{i-1})$ is upper bounded by a linear function of X_{i-1} . Here we assume this linear function is nonnegative for all values that X_{i-1} takes. We first need some terminology.

For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

a sequence of random variables X_0, X_1, \dots, X_n is called a *submartingale* if X_i is \mathcal{F}_i -measurable (i.e., $X_i(a) = X_i(b)$ if all elements of \mathcal{F}_i that contain a also contain b and vice versa) and $\mathbb{E}(X_i | \mathcal{F}_{i-1}) \leq X_{i-1}$, for $1 \leq i \leq n$.

A sequence of random variables X_0, X_1, \dots, X_n is said to be a *supermartingale* if X_i is \mathcal{F}_i -measurable and $\mathbb{E}(X_i | \mathcal{F}_{i-1}) \geq X_{i-1}$, for $1 \leq i \leq n$.

To avoid repetition, we will first state a number of useful inequalities for submartingales and supermartingales. Then, we will give the proof for the general inequalities in Theorem 7.3 for submartingales and in Theorem 7.5 for supermartingales. Furthermore, we will show that all the stated theorems follow from Theorems 7.3 and 7.5. (See Figure 10.) Note that the inequalities for submartingale and supermartingale are not quite symmetric.

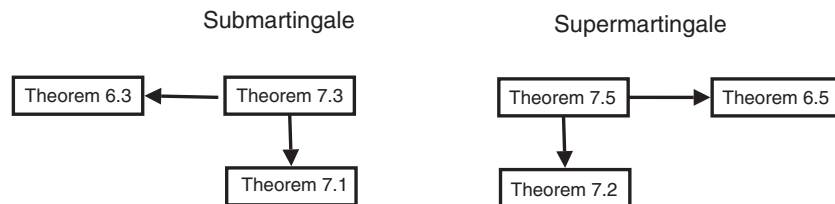


Figure 10. The flowchart for theorems on submartingales and supermartingales.

Theorem 7.1. *Suppose that a submartingale X , associated with a filter \mathbf{F} , satisfies*

$$\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \phi_i X_{i-1}$$

and

$$X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) \leq M$$

for $1 \leq i \leq n$. Then, we have

$$\Pr(X_n \geq X_0 + \lambda) \leq e^{-\frac{\lambda^2}{2((X_0+\lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3)}}.$$

Theorem 7.2. *Suppose that a supermartingale X , associated with a filter \mathbf{F} , satisfies, for $1 \leq i \leq n$,*

$$\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \phi_i X_{i-1}$$

and

$$\mathbf{E}(X_i|\mathcal{F}_{i-1}) - X_i \leq M.$$

Then, we have

$$\Pr(X_n \leq X_0 - \lambda) \leq e^{-\frac{\lambda^2}{2(X_0(\sum_{i=1}^n \phi_i) + M\lambda/3)}},$$

for any $\lambda \leq X_0$.

Theorem 7.3. *Suppose that a submartingale X , associated with a filter \mathbf{F} , satisfies*

$$\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \sigma_i^2 + \phi_i X_{i-1}$$

and

$$X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) \leq a_i + M$$

for $1 \leq i \leq n$. Here, σ_i , a_i , ϕ_i , and M are nonnegative constants. Then, we have

$$\Pr(X_n \geq X_0 + \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3)}}.$$

Remark 7.4. Theorem 7.3 implies Theorem 7.1 by setting all σ_i and a_i to zero. Theorem 7.3 also implies Theorem 6.3 by choosing $\phi_1 = \cdots = \phi_n = 0$.

The theorem for a supermartingale is slightly different due to the asymmetry of the condition on the variance.

Theorem 7.5. *Suppose that a supermartingale X , associated with a filter \mathbf{F} , satisfies, for $1 \leq i \leq n$,*

$$\text{Var}(X_i|\mathcal{F}_{i-1}) \leq \sigma_i^2 + \phi_i X_{i-1}$$

and

$$\mathbf{E}(X_i|\mathcal{F}_{i-1}) - X_i \leq a_i + M,$$

where M , a_i , σ_i , and ϕ_i are nonnegative constants. Then, we have

$$\Pr(X_n \leq X_0 - \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + X_0(\sum_{i=1}^n \phi_i) + M\lambda/3)},$$

for any $\lambda \leq 2X_0 + \frac{\sum_{i=1}^n (\sigma_i^2 + a_i^2)}{\sum_{i=1}^n \phi_i}$.

Remark 7.6. Theorem 7.5 implies Theorem 7.2 by setting all σ_i and a_i to zero. Theorem 7.5 also implies Theorem 6.5 by choosing $\phi_1 = \dots = \phi_n = 0$.

Proof of Theorem 7.3. For a positive t (to be chosen later), we consider

$$\begin{aligned} \mathbf{E}(e^{tX_i}|\mathcal{F}_{i-1}) &= e^{t\mathbf{E}(X_i|\mathcal{F}_{i-1}) + ta_i} \mathbf{E}(e^{t(X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)}|\mathcal{F}_{i-1}) \\ &= e^{t\mathbf{E}(X_i|\mathcal{F}_{i-1}) + ta_i} \sum_{k=0}^{\infty} \frac{t^k}{k!} \mathbf{E}((X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)^k|\mathcal{F}_{i-1}) \\ &\leq e^{t\mathbf{E}(X_i|\mathcal{F}_{i-1}) + \sum_{k=2}^{\infty} \frac{t^k}{k!} \mathbf{E}((X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)^k|\mathcal{F}_{i-1})} \end{aligned}$$

Recall that $g(y) = 2 \sum_{k=2}^{\infty} \frac{y^{k-2}}{k!}$ satisfies

$$g(y) \leq g(b) < \frac{1}{1 - b/3}$$

for all $y \leq b$ and $0 \leq b \leq 3$.

Since $X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i \leq M$, we have

$$\begin{aligned} \sum_{k=2}^{\infty} \frac{t^k}{k!} \mathbf{E}((X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)^k|\mathcal{F}_{i-1}) &\leq \frac{g(tM)}{2} t^2 \mathbf{E}((X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)^2|\mathcal{F}_{i-1}) \\ &= \frac{g(tM)}{2} t^2 (\text{Var}(X_i|\mathcal{F}_{i-1}) + a_i^2) \\ &\leq \frac{g(tM)}{2} t^2 (\sigma_i^2 + \phi_i X_{i-1} + a_i^2). \end{aligned}$$

Since $\mathbf{E}(X_i|\mathcal{F}_{i-1}) \leq X_{i-1}$, we have

$$\begin{aligned} \mathbf{E}(e^{tX_i}|\mathcal{F}_{i-1}) &\leq e^{t\mathbf{E}(X_i|\mathcal{F}_{i-1}) + \sum_{k=2}^{\infty} \frac{t^k}{k!} \mathbf{E}((X_i - \mathbf{E}(X_i|\mathcal{F}_{i-1}) - a_i)^k|\mathcal{F}_{i-1})} \\ &\leq e^{tX_{i-1} + \frac{g(tM)}{2} t^2 (\sigma_i^2 + \phi_i X_{i-1} + a_i^2)} \\ &= e^{(t + \frac{g(tM)}{2} \phi_i t^2) X_{i-1}} e^{\frac{t^2}{2} g(tM) (\sigma_i^2 + a_i^2)}. \end{aligned}$$

We define $t_i \geq 0$ for $0 < i \leq n$, satisfying

$$t_{i-1} = t_i + \frac{g(t_0 M)}{2} \phi_i t_i^2,$$

while t_0 will be chosen later. Then,

$$t_n \leq t_{n-1} \leq \cdots \leq t_0,$$

and

$$\begin{aligned} \mathbb{E}(e^{t_i X_i} | \mathcal{F}_{i-1}) &\leq e^{(t_i + \frac{g(t_0 M)}{2} \phi_i t_i^2) X_{i-1}} e^{\frac{t_i^2}{2} g(t_i M) (\sigma_i^2 + a_i^2)} \\ &\leq e^{(t_i + \frac{g(t_0 M)}{2} t_i^2 \phi_i) X_{i-1}} e^{\frac{t_i^2}{2} g(t_i M) (\sigma_i^2 + a_i^2)} \\ &= e^{t_{i-1} X_{i-1}} e^{\frac{t_i^2}{2} g(t_i M) (\sigma_i^2 + a_i^2)}, \end{aligned}$$

since $g(y)$ is increasing for $y > 0$.

By Markov's inequality, we have

$$\begin{aligned} \Pr(X_n \geq X_0 + \lambda) &\leq e^{-t_n(X_0 + \lambda)} \mathbb{E}(e^{t_n X_n}) \\ &= e^{-t_n(X_0 + \lambda)} \mathbb{E}(\mathbb{E}(e^{t_n X_n} | \mathcal{F}_{n-1})) \\ &\leq e^{-t_n(X_0 + \lambda)} \mathbb{E}(e^{t_{n-1} X_{n-1}}) e^{\frac{t_n^2}{2} g(t_n M) (\sigma_n^2 + a_n^2)} \\ &\quad \vdots \\ &\leq e^{-t_n(X_0 + \lambda)} \mathbb{E}(e^{t_0 X_0}) e^{\sum_{i=1}^n \frac{t_i^2}{2} g(t_i M) (\sigma_i^2 + a_i^2)} \\ &\leq e^{-t_n(X_0 + \lambda) + t_0 X_0 + \frac{t_0^2}{2} g(t_0 M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)}. \end{aligned}$$

Note that

$$\begin{aligned} t_n &= t_0 - \sum_{i=1}^n (t_{i-1} - t_i) \\ &= t_0 - \sum_{i=1}^n \frac{g(t_0 M)}{2} \phi_i t_i^2 \\ &\geq t_0 - \frac{g(t_0 M)}{2} t_0^2 \sum_{i=1}^n \phi_i. \end{aligned}$$

Hence,

$$\begin{aligned} \Pr(X_n \geq X_0 + \lambda) &\leq e^{-t_n(X_0 + \lambda) + t_0 X_0 + \frac{t_0^2}{2} g(t_0 M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\ &\leq e^{-(t_0 - \frac{g(t_0 M)}{2} t_0^2 \sum_{i=1}^n \phi_i)(X_0 + \lambda) + t_0 X_0 + \frac{t_0^2}{2} g(t_0 M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\ &= e^{-t_0 \lambda + \frac{g(t_0 M)}{2} t_0^2 (\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda) \sum_{i=1}^n \phi_i)}. \end{aligned}$$

Now we choose $t_0 = \frac{\lambda}{\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3}$. Using the fact that $t_0 M < 3$, we have

$$\begin{aligned} \Pr(X_n \geq X_0 + \lambda) &\leq e^{-t_0 \lambda + t_0^2 (\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda) \sum_{i=1}^n \phi_i) \frac{1}{2(1-t_0 M/3)}} \\ &= e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3)}}. \end{aligned}$$

The proof of the theorem is complete. \square

Proof of Theorem 7.5. The proof is quite similar to that of Theorem 7.3. The following inequality still holds:

$$\begin{aligned} \mathbb{E}(e^{-tX_i} | \mathcal{F}_{i-1}) &= e^{-t\mathbb{E}(X_i | \mathcal{F}_{i-1}) + ta_i} \mathbb{E}(e^{-t(X_i - \mathbb{E}(X_i | \mathcal{F}_{i-1}) + a_i)} | \mathcal{F}_{i-1}) \\ &= e^{-t\mathbb{E}(X_i | \mathcal{F}_{i-1}) + ta_i} \sum_{k=0}^{\infty} \frac{t^k}{k!} \mathbb{E}((\mathbb{E}(X_i | \mathcal{F}_{i-1}) - X_i - a_i)^k | \mathcal{F}_{i-1}) \\ &\leq e^{-t\mathbb{E}(X_i | \mathcal{F}_{i-1}) + \sum_{k=2}^{\infty} \frac{t^k}{k!} \mathbb{E}((\mathbb{E}(X_i | \mathcal{F}_{i-1}) - X_i - a_i)^k | \mathcal{F}_{i-1})} \\ &\leq e^{-t\mathbb{E}(X_i | \mathcal{F}_{i-1}) + \frac{g(tM)}{2} t^2 \mathbb{E}((X_i - \mathbb{E}(X_i | \mathcal{F}_{i-1}) - a_i)^2)} \\ &\leq e^{-t\mathbb{E}(X_i | \mathcal{F}_{i-1}) + \frac{g(tM)}{2} t^2 (\text{Var}(X_i | \mathcal{F}_{i-1}) + a_i^2)} \\ &\leq e^{-(t - \frac{g(tM)}{2} t^2 \phi_i) X_{i-1}} e^{\frac{g(tM)}{2} t^2 (\sigma_i^2 + a_i^2)}. \end{aligned}$$

We now define $t_i \geq 0$, for $0 \leq i < n$, satisfying

$$t_{i-1} = t_i - \frac{g(t_n M)}{2} \phi_i t_i^2;$$

t_n will be defined later. Then, we have

$$t_0 \leq t_1 \leq \dots \leq t_n,$$

and

$$\begin{aligned} \mathbb{E}(e^{-t_i X_i} | \mathcal{F}_{i-1}) &\leq e^{-(t_i - \frac{g(t_i M)}{2} t_i^2 \phi_i) X_{i-1}} e^{\frac{g(t_i M)}{2} t_i^2 (\sigma_i^2 + a_i^2)} \\ &\leq e^{-(t_i - \frac{g(t_n M)}{2} t_i^2 \phi_i) X_{i-1}} e^{\frac{g(t_n M)}{2} t_i^2 (\sigma_i^2 + a_i^2)} \\ &= e^{-t_{i-1} X_{i-1}} e^{\frac{g(t_n M)}{2} t_i^2 (\sigma_i^2 + a_i^2)}. \end{aligned}$$

By Markov's inequality, we have

$$\begin{aligned}
\Pr(X_n \leq X_0 - \lambda) &= \Pr(-t_n X_n \geq -t_n(X_0 - \lambda)) \\
&\leq e^{t_n(X_0 - \lambda)} \mathbf{E}(e^{-t_n X_n}) \\
&= e^{t_n(X_0 - \lambda)} \mathbf{E}(\mathbf{E}(e^{-t_n X_n} | \mathcal{F}_{n-1})) \\
&\leq e^{t_n(X_0 - \lambda)} \mathbf{E}(e^{-t_{n-1} X_{n-1}}) e^{\frac{g(t_n M)}{2} t_n^2 (\sigma_n^2 + a_n^2)} \\
&\quad \vdots \\
&\leq e^{t_n(X_0 - \lambda)} \mathbf{E}(e^{-t_0 X_0}) e^{\sum_{i=1}^n \frac{g(t_n M)}{2} t_i^2 (\sigma_i^2 + a_i^2)} \\
&\leq e^{t_n(X_0 - \lambda) - t_0 X_0 + \frac{t_n^2}{2} g(t_n M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)}.
\end{aligned}$$

We note that

$$\begin{aligned}
t_0 &= t_n + \sum_{i=1}^n (t_{i-1} - t_i) \\
&= t_n - \sum_{i=1}^n \frac{g(t_n M)}{2} \phi_i t_i^2 \\
&\geq t_n - \frac{g(t_n M)}{2} t_n^2 \sum_{i=1}^n \phi_i.
\end{aligned}$$

Thus, we have

$$\begin{aligned}
\Pr(X_n \leq X_0 - \lambda) &\leq e^{t_n(X_0 - \lambda) - t_0 X_0 + \frac{t_n^2}{2} g(t_n M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\
&\leq e^{t_n(X_0 - \lambda) - (t_n - \frac{g(t_n M)}{2} t_n^2) X_0 + \frac{t_n^2}{2} g(t_n M) \sum_{i=1}^n (\sigma_i^2 + a_i^2)} \\
&= e^{-t_n \lambda + \frac{g(t_n M)}{2} t_n^2 (\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (\sum_{i=1}^n \phi_i) X_0)}.
\end{aligned}$$

We choose $t_n = \frac{\lambda}{\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (\sum_{i=1}^n \phi_i) X_0 + M\lambda/3}$. We have $t_n M < 3$ and

$$\begin{aligned}
\Pr(X_n \leq X_0 - \lambda) &\leq e^{-t_n \lambda + t_n^2 (\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (\sum_{i=1}^n \phi_i) X_0) \frac{1}{2(1-t_n M/3)}} \\
&\leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + X_0 (\sum_{i=1}^n \phi_i) + M\lambda/3)}}.
\end{aligned}$$

It remains to verify that all t_i are nonnegative. Indeed,

$$\begin{aligned}
 t_i &\geq t_0 \\
 &\geq t_n - \frac{g(t_n M)}{2} t_n^2 \sum_{i=1}^n \phi_i \\
 &\geq t_n \left(1 - \frac{1}{2(1 - t_n M/3)} t_n \sum_{i=1}^n \phi_i \right) \\
 &= t_n \left(1 - \frac{\lambda}{2X_0 + \frac{\sum_{i=1}^n (\sigma_i^2 + a_i^2)}{\sum_{i=1}^n \phi_i}} \right) \\
 &\geq 0.
 \end{aligned}$$

The proof of the theorem is complete. \square

8. The Decision Tree and Relaxed Concentration Inequalities

In this section, we will extend and generalize previous theorems to a martingale that is not strictly Lipschitz but is *nearly* Lipschitz. Namely, the (Lipschitz-like) assumptions are allowed to fail for relatively small subsets of the probability space, and we can still have similar but weaker concentration inequalities. Similar techniques have been introduced by Kim and Vu in their important work on deriving concentration inequalities for multivariate polynomials [Kim and Vu 00]. The basic setup for decision trees can be found in [Alon and Spencer 92] and has been used in the work of Alon, Kim, and Spencer [Alon et al. 97]. Wormald [Wormald 99] considers martingales with a “stopping time” that has a similar flavor. Here we use a rather general setting, and we shall give a complete proof.

We are only interested in finite probability spaces, and we use the following computational model. The random variable X can be evaluated by a sequence of decisions Y_1, Y_2, \dots, Y_n . Each decision has finitely many outputs. The probability that an output is chosen depends on the previous history. We can describe the process by a decision tree T , a complete rooted tree with depth n . Each edge uv of T is associated with a probability p_{uv} depending on the decision made from u to v . Note that for any node u , we have

$$\sum_v p_{u,v} = 1.$$

We allow p_{uv} to be zero and thus include the case of having fewer than r outputs, for some fixed r . Let Ω_i denote the probability space obtained after the first i decisions. Suppose that $\Omega = \Omega_n$ and X is the random variable on Ω . Let

$\pi_i: \Omega \rightarrow \Omega_i$ be the projection mapping each point to the subset of points with the same first i decisions. Let \mathcal{F}_i be the σ -field generated by Y_1, Y_2, \dots, Y_i . (In fact, $\mathcal{F}_i = \pi_i^{-1}(2^{\Omega_i})$ is the full σ -field via the projection π_i .) The \mathcal{F}_i form a natural filter:

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \dots \subset \mathcal{F}_n = \mathcal{F}.$$

The leaves of the decision tree are exactly the elements of Ω . Let $X_0, X_1, \dots, X_n = X$ denote the sequence of decisions to evaluate X . Note that X_i is \mathcal{F}_i -measurable and can be interpreted as a labeling on nodes at depth i .

There is one-to-one correspondence between the following:

- A sequence of random variables X_0, X_1, \dots, X_n satisfying X_i is \mathcal{F}_i -measurable, for $i = 0, 1, \dots, n$.
- A vertex labeling of the decision tree T , $f: V(T) \rightarrow \mathbb{R}$.

In order to simplify and unify the proofs for various general types of martingales, here we introduce a definition for a function $f: V(T) \rightarrow \mathbb{R}$. We say f satisfies an *admissible* condition P if $P = \{P_v\}$ holds for every vertex v .

Here are examples of admissible conditions:

1. **Supermartingale:** For $1 \leq i \leq n$, we have

$$\mathbb{E}(X_i | \mathcal{F}_{i-1}) \geq X_{i-1}.$$

Thus, the admissible condition P_u holds if

$$f(u) \leq \sum_{v \in C(u)} p_{uv} f(v),$$

where $C(u)$ is the set of all children nodes of u and p_{uv} is the transition probability at the edge uv .

2. **Submartingale:** For $1 \leq i \leq n$, we have

$$\mathbb{E}(X_i | \mathcal{F}_{i-1}) \leq X_{i-1}.$$

In this case, the admissible condition of the submartingale is

$$f(u) \geq \sum_{v \in C(u)} p_{uv} f(v).$$

3. **Martingale:** For $1 \leq i \leq n$, we have

$$\mathbb{E}(X_i | \mathcal{F}_{i-1}) = X_{i-1}.$$

The admissible condition of the martingale is then

$$f(u) = \sum_{v \in C(u)} p_{uv} f(v).$$

4. **c-Lipschitz:** For $1 \leq i \leq n$, we have

$$|X_i - X_{i-1}| \leq c_i.$$

The admissible condition of the **c-Lipschitz** property can be described as follows:

$$|f(u) - f(v)| \leq c_i, \quad \text{for any child } v \in C(u),$$

where the node u is at level i of the decision tree.

5. **Bounded variance:** For $1 \leq i \leq n$, we have

$$\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2$$

for some constants σ_i .

The admissible condition of the bounded variance property can be described as

$$\sum_{v \in C(u)} p_{uv} f^2(v) - \left(\sum_{v \in C(u)} p_{uv} f(v) \right)^2 \leq \sigma_i^2.$$

6. **General bounded variance:** For $1 \leq i \leq n$, we have

$$\text{Var}(X_i | \mathcal{F}_{i-1}) \leq \sigma_i^2 + \phi_i X_{i-1},$$

where σ_i and ϕ_i are nonnegative constants and $X_i \geq 0$. The admissible condition of the general bounded variance property can be described as follows:

$$\sum_{v \in C(u)} p_{uv} f^2(v) - \left(\sum_{v \in C(u)} p_{uv} f(v) \right)^2 \leq \sigma_i^2 + \phi_i f(u), \quad \text{for } f(u) \geq 0,$$

where i is the depth of the node u .

7. **Upper-bound:** For $1 \leq i \leq n$, we have

$$X_i - \mathbf{E}(X_i | \mathcal{F}_{i-1}) \leq a_i + M,$$

where a_i and M are nonnegative constants. The admissible condition of the upper bounded property can be described as follows:

$$f(v) - \sum_{v \in C(u)} p_{uv} f(v) \leq a_i + M, \quad \text{for any child } v \in C(u),$$

where i is the depth of the node u .

8. Lower-bound: For $1 \leq i \leq n$, we have

$$E(X_i | \mathcal{F}_{i-1}) - X_i \leq a_i + M,$$

where a_i and M are nonnegative constants. The admissible condition of the lower bounded property can be described as follows:

$$\sum_{v \in C(u)} p_{uv} f(v) - f(v) \leq a_i + M, \quad \text{for any child } v \in C(u),$$

where i is the depth of the node u .

For any labeling f on T and fixed vertex r , we can define a new labeling f_r as follows:

$$f_r(u) = \begin{cases} f(r) & \text{if } u \text{ is a descendant of } r, \\ f(u) & \text{otherwise.} \end{cases}$$

A property P is said to be *invariant* under subtree-unification if for a vertex r and any tree labeling f satisfying P , f_r satisfies P .

We have the following theorem.

Theorem 8.1. *The eight properties as stated in the preceding examples—supermartingale, submartingale, martingale, \mathbf{c} -Lipschitz, bounded variance, general bounded variance, upper-bounded, and lower-bounded properties—are all invariant under subtree-unification.*

Proof. We note that these properties are all admissible conditions. Let P denote any one of these. For any node u , if u is not a descendant of r , then f_r and f have the same value on v and its children nodes. Hence, P_u holds for f_r since P_u does for f .

If u is a descendant of r , then $f_r(u)$ takes the same value as $f(r)$ as well as its children nodes. We verify P_u in each case. Assume that u is at level i of the decision tree T .

1. For supermartingale, submartingale, and martingale properties, we have

$$\begin{aligned}
 \sum_{v \in C(u)} p_{uv} f_r(v) &= \sum_{v \in C(u)} p_{uv} f(r) \\
 &= f(r) \sum_{v \in C(u)} p_{uv} \\
 &= f(r) \\
 &= f_r(u).
 \end{aligned}$$

Hence, P_u holds for f_r .

2. For the \mathbf{c} -Lipschitz property, we have

$$|f_r(u) - f_r(v)| = 0 \leq c_i, \quad \text{for any child } v \in C(u).$$

Again, P_u holds for f_r .

3. For the bounded variance property, we have

$$\begin{aligned}
 \sum_{v \in C(u)} p_{uv} f_r^2(v) - \left(\sum_{v \in C(u)} p_{uv} f_r(v) \right)^2 & \\
 &= \sum_{v \in C(u)} p_{uv} f^2(r) - \left(\sum_{v \in C(u)} p_{uv} f(r) \right)^2 \\
 &= f^2(r) - f^2(r) \\
 &= 0 \\
 &\leq \sigma_i^2.
 \end{aligned}$$

4. For the second bounded variance property, we have

$$f_r(u) = f(r) \geq 0.$$

$$\begin{aligned}
 \sum_{v \in C(u)} p_{uv} f_r^2(v) - \left(\sum_{v \in C(u)} p_{uv} f_r(v) \right)^2 & \\
 &= \sum_{v \in C(u)} p_{uv} f^2(r) - \left(\sum_{v \in C(u)} p_{uv} f(r) \right)^2 \\
 &= f^2(r) - f^2(r) \\
 &= 0 \\
 &\leq \sigma_i^2 + \phi_i f_r(u).
 \end{aligned}$$

5. For the upper-bounded property, we have

$$\begin{aligned} f_r(v) - \sum_{v \in C(u)} p_{uv} f_r(v) &= f(r) - \sum_{v \in C(u)} p_{uv} f(r) \\ &= f(r) - f(r) \\ &= 0 \\ &\leq a_i + M, \end{aligned}$$

for any child v of u .

6. For the lower-bounded property, we have

$$\begin{aligned} \sum_{v \in C(u)} p_{uv} f_r(v) - f_r(v) &= \sum_{v \in C(u)} p_{uv} f(r) - f(r) \\ &= f(r) - f(r) \\ &= 0 \\ &\leq a_i + M, \end{aligned}$$

for any child v of u .

Therefore, P_v holds for f_r and any vertex v . \square

For two admissible conditions P and Q , we define PQ to be the property that is only true when both P and Q are true. If both admissible conditions P and Q are invariant under subtree-unification, then PQ is also invariant under subtree-unification.

For any vertex u of the tree T , an ancestor of u is a vertex lying on the unique path from the root to u . For an admissible condition P , the associated *bad* set B_i over the X_i is defined to be

$$B_i = \{v \mid \text{the depth of } v \text{ is } i, \text{ and } P_u \text{ does not hold for some ancestor } u \text{ of } v\}.$$

Lemma 8.2. *For a filter \mathbf{F} ,*

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \dots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that each random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. For any admissible condition P , let B_i be the associated bad set of P over X_i . There are random variables Y_0, \dots, Y_n satisfying

- (1) Y_i is \mathcal{F}_i -measurable.
- (2) Y_0, \dots, Y_n satisfy condition P .
- (3) $\{x : Y_i(x) \neq X_i(x)\} \subset B_i$, for $0 \leq i \leq n$.

Proof. We modify f and define f' on T as follows. For any vertex u ,

$$f'(u) = \begin{cases} f(u) & \text{if } f \text{ satisfies } P_v \text{ for every ancestor } v \text{ of } u \text{ including } u \text{ itself,} \\ f(v) & v \text{ is the ancestor with smallest depth so that } f \text{ fails } P_v. \end{cases}$$

Let S be the set of vertices u satisfying

- f fails P_u ,
- f satisfies P_v for every ancestor v of u .

It is clear that f' can be obtained from f by a sequence of subtree-unifications, where S is the set of the roots of subtrees. Furthermore, the order of subtree-unifications does not matter. Since P is invariant under subtree-unifications, the number of vertices that P fails decreases. Now we will show that f' satisfies P .

Suppose to the contrary that f' fails P_u for some vertex u . Since P is invariant under subtree-unifications, f also fails P_u . By the definition, there is an ancestor v (of u) in S . After the subtree-unification on the subtree rooted at v , P_u is satisfied. This is a contradiction.

Let Y_0, Y_1, \dots, Y_n be the random variables corresponding to the labeling f' . The Y_i satisfy the desired properties in (1)–(3). \square

The following theorem generalizes Azuma's inequality. A similar but more restricted version can be found in [Kim and Vu 00].

Theorem 8.3. *For a filter \mathbf{F} ,*

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \dots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that the random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let $B = B_n$ denote the bad set associated with the following admissible condition:

$$\begin{aligned} \mathbb{E}(X_i | \mathcal{F}_{i-1}) &= X_{i-1}, \\ |X_i - X_{i-1}| &\leq c_i, \end{aligned}$$

for $1 \leq i \leq n$ where c_1, c_2, \dots, c_n are nonnegative numbers. Then, we have

$$\Pr(|X_n - X_0| \geq \lambda) \leq 2e^{-\frac{\lambda^2}{2\sum_{i=1}^n c_i^2}} + \Pr(B).$$

Proof. We use Lemma 8.2, which gives random variables Y_0, Y_1, \dots, Y_n satisfying properties (1)–(3) in the statement of Lemma 8.2. Then, it satisfies

$$\begin{aligned} \mathbb{E}(Y_i | \mathcal{F}_{i-1}) &= Y_{i-1}, \\ |Y_i - Y_{i-1}| &\leq c_i. \end{aligned}$$

In other words, Y_0, \dots, Y_n form a martingale that is (c_1, \dots, c_n) -Lipschitz. By Azuma's inequality, we have

$$\Pr(|Y_n - Y_0| \geq \lambda) \leq 2e^{-\frac{\lambda^2}{2\sum_{i=1}^n c_i^2}}.$$

Since $Y_0 = X_0$ and $\{x : Y_n(x) \neq X_n(x)\} \subset B_n = B$, we have

$$\begin{aligned} \Pr(|X_n - X_0| \geq \lambda) &\leq \Pr(|Y_n - Y_0| \geq \lambda) + \Pr(X_n \neq Y_n) \\ &\leq 2e^{-\frac{\lambda^2}{2\sum_{i=1}^n c_i^2}} + \Pr(B). \end{aligned}$$

□

For $\mathbf{c} = (c_1, c_2, \dots, c_n)$, a vector with positive entries, a martingale is said to be near- \mathbf{c} -Lipschitz with an exceptional probability η if

$$\sum_i \Pr(|X_i - X_{i-1}| \geq c_i) \leq \eta. \quad (8.1)$$

Theorem 8.3 can be restated as follows:

Theorem 8.4. *For nonnegative values c_1, c_2, \dots, c_n , suppose that a martingale X is near- \mathbf{c} -Lipschitz with an exceptional probability η . Then, X satisfies*

$$\Pr(|X - \mathbb{E}(X)| < a) \leq 2e^{-\frac{a^2}{2\sum_{i=1}^n c_i^2}} + \eta.$$

Now, we can apply the same technique to relax all the theorems in the previous sections.

Here are the relaxed versions of Theorems 6.3, 7.1, and 7.3.

Theorem 8.5. *For a filter \mathbf{F} ,*

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \dots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \sigma_i^2, \\ X_i - \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq a_i + M, \end{aligned}$$

for some nonnegative constants σ_i and a_i . Then, we have

$$\Pr(X_n \geq X_0 + \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + M\lambda/3)}} + \Pr(B).$$

Theorem 8.6. For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a nonnegative random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \phi_i X_{i-1}, \\ X_i - \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq M, \end{aligned}$$

for some nonnegative constants ϕ_i and M . Then, we have

$$\Pr(X_n \geq X_0 + \lambda) \leq e^{-\frac{\lambda^2}{2((X_0 + \lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3)}} + \Pr(B).$$

Theorem 8.7. For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a nonnegative random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \sigma_i^2 + \phi_i X_{i-1}, \\ X_i - \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\leq a_i + M, \end{aligned}$$

for some nonnegative constants σ_i , ϕ_i , a_i and M . Then, we have

$$\Pr(X_n \geq X_0 + \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + (X_0 + \lambda)(\sum_{i=1}^n \phi_i) + M\lambda/3)}} + \Pr(B).$$

For supermartingales, we have the following relaxed versions of Theorems 6.5, 7.2, and 7.5.

Theorem 8.8. For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbb{E}(X_i | \mathcal{F}_{i-1}) &\geq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \sigma_i^2, \\ \mathbb{E}(X_i | \mathcal{F}_{i-1}) - X_i &\leq a_i + M, \end{aligned}$$

for some nonnegative constants σ_i , a_i , and M . Then, we have

$$\Pr(X_n \leq X_0 - \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + M\lambda/3)}} + \Pr(B).$$

Theorem 8.9. For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbf{E}(X_i | \mathcal{F}_{i-1}) &\geq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \phi_i X_{i-1}, \\ \mathbf{E}(X_i | \mathcal{F}_{i-1}) - X_i &\leq M, \end{aligned}$$

for some nonnegative constants ϕ_i and M . Then, we have

$$\Pr(X_n \leq X_0 - \lambda) \leq e^{-\frac{\lambda^2}{2(X_0(\sum_{i=1}^n \phi_i) + M\lambda/3)}} + \Pr(B),$$

for all $\lambda \leq X_0$.

Theorem 8.10. For a filter \mathbf{F} ,

$$\{\emptyset, \Omega\} = \mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_n = \mathcal{F},$$

suppose that a nonnegative random variable X_i is \mathcal{F}_i -measurable, for $0 \leq i \leq n$. Let B be the bad set associated with the following admissible conditions:

$$\begin{aligned} \mathbf{E}(X_i | \mathcal{F}_{i-1}) &\geq X_{i-1}, \\ \text{Var}(X_i | \mathcal{F}_{i-1}) &\leq \sigma_i^2 + \phi_i X_{i-1}, \\ \mathbf{E}(X_i | \mathcal{F}_{i-1}) - X_i &\leq a_i + M, \end{aligned}$$

for some nonnegative constants σ_i , ϕ_i , a_i , and M . Then, we have

$$\Pr(X_n \leq X_0 - \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^n (\sigma_i^2 + a_i^2) + X_0(\sum_{i=1}^n \phi_i) + M\lambda/3)}} + \Pr(B),$$

for $\lambda < X_0$.

9. A Generalized Polya's Urn Problem

To see the powerful effect of the concentration and martingale inequalities in the previous sections, the best way is to check out some interesting applications. In this section we give the probabilistic analysis of the following process involving balls and bins:

For a fixed $0 \leq p < 1$ and a positive integer $\kappa > 1$, begin with κ bins, each containing one ball and then introduce balls one at a time. For each new ball, with probability p , create a new bin and place the ball in that bin; otherwise, place the ball in an existing bin, such that the probability that the ball is placed in a bin is proportional to the number of balls in that bin.

Polya's urn problem (see [Johnson and Kotz 77]) is a special case of the above process with $p = 0$ so new bins are never created. For the case of $p > 0$, this infinite Polya process has a similar flavor as the *preferential attachment* scheme, one of the main models for generating the web graph among other information networks (see [Albert and Barabási 02, Barabási and Albert 99]).

In Section 9.1, we will show that the infinite Polya process generates a power law distribution so that the expected fraction of bins having k balls is asymptotic to $ck^{-\beta}$, where $\beta = 1 + 1/(1 - p)$ and c is a constant. Then, the concentration result on the probabilistic error estimates for the power law distribution will be given in Section 9.2.

9.1. The Expected Number of Bins with k Balls

To analyze the infinite Polya process, we let n_t denote the number of bins at time t and let e_t denote the number of balls at time t . We have

$$e_t = t + \kappa.$$

The number of bins n_t , however, is a sum of t random indicator variables,

$$n_t = \kappa + \sum_{i=1}^t s_i,$$

where

$$\begin{aligned} \Pr(s_j = 1) &= p, \\ \Pr(s_j = 0) &= 1 - p. \end{aligned}$$

It follows that

$$\mathbb{E}(n_t) = \kappa + pt.$$

To get a handle on the actual value of n_t , we use the binomial concentration inequality as described in Theorem 3.2. Namely,

$$\Pr(|n_t - \mathbb{E}(n_t)| > a) \leq e^{-a^2/(2pt+2a/3)}.$$

Thus, n_t is exponentially concentrated around $\mathbb{E}(n_t)$.

The problem of interest is the distribution of sizes of bins in the infinite Polya process.

Let $m_{k,t}$ denote the number of bins with k balls at time t . First, we note that

$$m_{1,0} = \kappa \quad \text{and} \quad m_{0,k} = 0.$$

We wish to derive the recurrence for the expected value $\mathbb{E}(m_{k,t})$. Note that a bin with k balls at time t could have come from two cases, either it was a bin with k balls at time $t-1$ and no ball was added to it, or it was a bin with $k-1$ balls at time $t-1$ and a new ball was put in. Let \mathcal{F}_t be the σ -algebra generated by all the possible outcomes at time t .

$$\begin{aligned} \mathbb{E}(m_{k,t}|\mathcal{F}_{t-1}) &= m_{k,t-1} \left(1 - \frac{(1-p)k}{t+\kappa}\right) + m_{k-1,t-1} \left(\frac{(1-p)(k-1)}{t+\kappa-1}\right) \\ \mathbb{E}(m_{k,t}) &= \mathbb{E}(m_{k,t-1}) \left(1 - \frac{(1-p)k}{t+\kappa-1}\right) + \mathbb{E}(m_{k-1,t-1}) \left(\frac{(1-p)(k-1)}{t+\kappa-1}\right). \end{aligned} \tag{9.1}$$

For $t > 0$ and $k = 1$, we have

$$\begin{aligned} \mathbb{E}(m_{1,t}|\mathcal{F}_{t-1}) &= m_{1,t-1} \left(1 - \frac{(1-p)}{t+\kappa-1}\right) + p, \\ \mathbb{E}(m_{1,t}) &= \mathbb{E}(m_{1,t-1}) \left(1 - \frac{(1-p)}{t+\kappa-1}\right) + p. \end{aligned} \tag{9.2}$$

To solve this recurrence, we use the following fact (see [Chung and Lu 04]):

Fact 9.1. For a sequence $\{a_t\}$ satisfying the recursive relation $a_{t+1} = (1 - \frac{b_t}{t})a_t + c_t$, $\lim_{t \rightarrow \infty} \frac{a_t}{t}$ exists and

$$\lim_{t \rightarrow \infty} \frac{a_t}{t} = \frac{c}{1+b},$$

provided that $\lim_{t \rightarrow \infty} b_t = b > 0$ and $\lim_{t \rightarrow \infty} c_t = c$.

We proceed by induction on k to show that $\lim_{t \rightarrow \infty} \mathbb{E}(m_{k,t})/t$ has a limit M_k for each k .

The first case is $k = 1$. In this case, we apply Fact 9.1 with $b_t = b = 1 - p$ and $c_t = c = p$ to deduce that $\lim_{t \rightarrow \infty} E(m_{1,t})/t$ exists and

$$M_1 = \lim_{t \rightarrow \infty} \frac{E(m_{1,t})}{t} = \frac{p}{2-p}.$$

Now we assume that $\lim_{t \rightarrow \infty} E(m_{k-1,t})/t$ exists, and we apply the fact again with $b_t = b = k(1-p)$ and $c_t = E(m_{k-1,t-1})(1-p)(k-1)/(t+\kappa-1)$, so $c = M_{k-1}(1-p)(k-1)$. Thus, the limit $\lim_{t \rightarrow \infty} E(m_{k,t})/t$ exists and is equal to

$$M_k = M_{k-1} \frac{(1-p)(k-1)}{1+k(1-p)} = M_{k-1} \frac{k-1}{k + \frac{1}{1-p}}. \quad (9.3)$$

Thus, we can write

$$M_k = \frac{p}{2-p} \prod_{j=2}^k \frac{j-1}{j + \frac{1}{1-p}} = \frac{p}{2-p} \frac{\Gamma(k)\Gamma(2 + \frac{1}{1-p})}{\Gamma(k+1 + \frac{1}{1-p})},$$

where $\Gamma(k)$ is the Gamma function.

We wish to show that the distribution of the bin sizes follows a power law with $M_k \propto k^{-\beta}$ (where \propto means “is proportional to”) for large k . If $M_k \propto k^{-\beta}$, then

$$\frac{M_k}{M_{k-1}} = \frac{k^{-\beta}}{(k-1)^{-\beta}} = \left(1 - \frac{1}{k}\right)^{\beta} = 1 - \frac{\beta}{k} + O\left(\frac{1}{k^2}\right).$$

From (9.3) we have

$$\frac{M_k}{M_{k-1}} = \frac{k-1}{k + \frac{1}{1-p}} = 1 - \frac{1 + \frac{1}{1-p}}{k + \frac{1}{1-p}} = 1 - \frac{1 + \frac{1}{1-p}}{k} + O\left(\frac{1}{k^2}\right).$$

Thus, we have an approximate power-law with

$$\beta = 1 + \frac{1}{1-p} = 2 + \frac{p}{1-p}.$$

9.2. Concentration on the Number of Bins with k Balls

Since the expected value can be quite different from the actual number of bins with k balls at time t , we give a (probabilistic) estimate of the difference.

We will prove the following theorem.

Theorem 9.2. *For the infinite Polya process, asymptotically almost surely the number of bins with k balls at time t is*

$$M_k(t + \kappa) + O(2\sqrt{k^3(t + \kappa)\ln(t + \kappa)}).$$

Recall that $M_1 = \frac{p}{2-p}$ and

$$M_k = \frac{p}{2-p} \frac{\Gamma(k)\Gamma(2 + \frac{1}{1-p})}{\Gamma(k+1 + \frac{1}{1-p})} = O(k^{-(1 + \frac{1}{1-p})}),$$

for $k \geq 2$. In other words, almost surely the distribution of the bin sizes for the infinite Polya process follows a power law with the exponent $\beta = 1 + \frac{1}{1-p}$.

Proof. We have shown that

$$\lim_{t \rightarrow \infty} \frac{\mathbb{E}(m_{k,t})}{t} = M_k,$$

where M_k is defined recursively in (9.3). It is sufficient to show that $m_{k,t}$ concentrates on the expected value. \square

We shall prove the following claim.

Claim 9.3. For any fixed $k \geq 1$ and for any $c > 0$ with probability at least $1 - 2(t + \kappa + 1)^{k-1}e^{-c^2}$, we have

$$|m_{k,t} - M_k(t + \kappa)| \leq 2kc\sqrt{t + \kappa}.$$

To see that the claim implies Theorem 9.2, we choose $c = \sqrt{k \ln(t + \kappa)}$. Note that

$$2(t + \kappa)^{k-1}e^{-c^2} = 2(t + \kappa + 1)^{k-1}(t + \kappa)^{-k} = o(1).$$

From Claim 9.3, with probability $1 - o(1)$, we have

$$|m_{k,t} - M_k(t + \kappa)| \leq 2\sqrt{k^3(t + \kappa) \ln(t + \kappa)},$$

as desired.

It remains to prove the claim.

Proof of Claim 9.3. We shall prove it by induction on k .

The base case of $k = 1$. For $k = 1$, from equation (9.2), we have

$$\begin{aligned} & \mathbb{E}(m_{1,t} - M_1(t + \kappa) | \mathcal{F}_{t-1}) \\ &= \mathbb{E}(m_{1,t} | \mathcal{F}_{t-1}) - M_1(t + \kappa) \\ &= m_{1,t-1} \left(1 - \frac{1-p}{t + \kappa - 1} \right) + p - M_1(t + \kappa - 1) - M_1 \\ &= (m_{1,t-1} - M_1(t + \kappa - 1)) \left(1 - \frac{1-p}{t + \kappa - 1} \right) + p - M_1(1-p) - M_1 \\ &= (m_{1,t-1} - M_1(t + \kappa - 1)) \left(1 - \frac{1-p}{t + \kappa - 1} \right), \end{aligned}$$

since $p - M_1(1-p) - M_1 = 0$.

Let $X_{1,t} = \frac{m_{1,t} - M_1(t+\kappa)}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})}$. We consider the martingale formed by $1 = X_{1,0}, X_{1,1}, \dots, X_{1,t}$. We have

$$\begin{aligned} X_{1,t} - X_{1,t-1} &= \frac{m_{1,t} - M_1(t+\kappa)}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})} - \frac{m_{1,t-1} - M_1(t+\kappa-1)}{\prod_{j=1}^{t-1} (1 - \frac{1-p}{j+\kappa-1})} \\ &= \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})} \\ &\quad \times \left[(m_{1,t} - M_1(t+\kappa)) - (m_{1,t-1} - M_1(t+\kappa-1)) \left(1 - \frac{1-p}{t+\kappa-1} \right) \right] \\ &= \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})} \\ &\quad \times \left[(m_{1,t} - m_{1,t-1}) + \frac{1-p}{t+\kappa-1} (m_{1,t-1} - M_1(t+\kappa-1)) - M_1 \right]. \end{aligned}$$

We note that $|m_{1,t} - m_{1,t-1}| \leq 1$, $m_{1,t-1} \leq t$ and $M_1 = \frac{p}{2-p} < 1$. We have

$$|X_{1,t} - X_{1,t-1}| \leq \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})}. \quad (9.4)$$

Since $|m_{1,t} - m_{1,t-1}| \leq 1$, we have

$$\begin{aligned} \text{Var}(m_{1,t} | \mathcal{F}_{t-1}) &\leq \text{E}((m_{1,t} - m_{1,t-1})^2 | \mathcal{F}_{t-1}) \\ &\leq 1. \end{aligned}$$

Therefore, we have the following upper bound for $\text{Var}(X_{1,t} | \mathcal{F}_{t-1})$:

$$\begin{aligned} \text{Var}(X_{1,t} | \mathcal{F}_{t-1}) &= \text{Var} \left((m_{1,t} - M_1(t+\kappa)) \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})} \middle| \mathcal{F}_{t-1} \right) \\ &= \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})^2} \text{Var}(m_{1,t} - M_1(t+\kappa) | \mathcal{F}_{t-1}) \\ &= \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})^2} \text{Var}(m_{1,t} | \mathcal{F}_{t-1}) \\ &\leq \frac{1}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})^2}. \end{aligned} \quad (9.5)$$

We apply Theorem 6.2 on the martingale $\{X_{1,t}\}$ with $\sigma_i^2 = \frac{4}{\prod_{j=1}^i (1 - \frac{1-p}{j+\kappa-1})^2}$, $M = \frac{4}{\prod_{j=1}^t (1 - \frac{1-p}{j+\kappa-1})}$, and $a_i = 0$. We have

$$\Pr(X_{1,t} \geq \text{E}(X_{1,t}) + \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^t \sigma_i^2 + M\lambda/3)}}.$$

Here, $E(X_{1,t}) = X_{1,0} = 1$. We will use the following approximation:

$$\begin{aligned} \prod_{j=1}^i \left(1 - \frac{1-p}{j+\kappa-1}\right) &= \prod_{j=1}^i \frac{j+\kappa-2+p}{j+\kappa-1} \\ &= \frac{\Gamma(\kappa)\Gamma(i+\kappa-1+p)}{\Gamma(\kappa-1+p)\Gamma(i+\kappa)} \\ &\approx C(i+\kappa)^{-1+p}, \end{aligned}$$

where $C = \frac{\Gamma(\kappa)}{\Gamma(\kappa-1+p)}$ is a constant depending only on p and κ .

For any $c > 0$, we choose $\lambda = \frac{4c\sqrt{t+\kappa}}{\prod_{j=1}^t (1-\frac{1-p}{j})} \approx 4C^{-1}ct^{3/2-2p}$. We have

$$\begin{aligned} \sum_{i=1}^t \sigma_i^2 &= \sum_{i=1}^t \frac{4}{\prod_{j=1}^i (1-\frac{1-p}{j})^2} \\ &\approx \sum_{i=1}^t 4C^{-2}(i+\kappa)^{2-2p} \\ &\approx \frac{4C^{-2}}{3-2p}(t+\kappa)^{3-2p} \\ &< 4C^{-2}(t+\kappa)^{3-2p}. \end{aligned}$$

We note that

$$M\lambda/3 \approx \frac{8}{3}C^{-2}ct^{5/2-2p} < 2C^{-2}t^{3-2p},$$

provided that $4c/3 < \sqrt{t+\kappa}$. We have

$$\begin{aligned} \Pr(X_{1,t} \geq 1 + \lambda) &\leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^t \sigma_i^2 + M\lambda/3)}} \\ &< e^{-\frac{16C^{-2}c^2t^{3-2p}}{8C^{-2}t^{3-2p} + 2C^{-2}(t+\kappa)^{3-2p}}} \\ &< e^{-c^2}. \end{aligned}$$

Since 1 is much smaller than λ , we can replace $1 + \lambda$ by λ without loss of generality. Thus, with probability at least $1 - e^{-c^2}$, we have

$$X_{1,t} \leq \lambda.$$

Similarly, with probability at least $1 - e^{-c^2}$, we have

$$m_{1,t} - M_1(t+\kappa) \leq 2c\sqrt{t+\kappa}. \quad (9.6)$$

We remark that inequality (9.6) holds for any $c > 0$. In fact, it is trivial when $4c/3 > \sqrt{t+\kappa}$, since $|m_{1,t} - M_1(t+\kappa)| \leq 2t$ always holds.

Similarly, by applying Theorem 6.6 on the martingale, the lower bound

$$m_{1,t} - M_1(t + \kappa) \geq -2c\sqrt{t + \kappa} \quad (9.7)$$

holds with probability at least $1 - e^{-c^2}$.

We have proved the claim for $k = 1$.

The inductive step. Suppose that the claim holds for $k - 1$. For k , we define

$$X_{k,t} = \frac{m_{k,t} - M_k(t + \kappa) - 2(k-1)c\sqrt{t + \kappa}}{\prod_{j=1}^t \left(1 - \frac{(1-p)k}{j + \kappa - 1}\right)}.$$

We have

$$\begin{aligned} & \mathbb{E}(m_{k,t} - M_k(t + \kappa) - 2(k-1)c\sqrt{t + \kappa} | \mathcal{F}_{t-1}) \\ &= \mathbb{E}(m_{k,t} | \mathcal{F}_{t-1}) - M_k(t + \kappa) - 2(k-1)c\sqrt{t + \kappa} \\ &= m_{k,t-1} \left(1 - \frac{(1-p)k}{t + \kappa - 1}\right) + m_{k-1,t-1} \left(\frac{(1-p)(k-1)}{t + \kappa - 1}\right) \\ & \quad - M_k(t + \kappa) - 2(k-1)c\sqrt{t + \kappa}. \end{aligned}$$

By the induction hypothesis, with probability at least $1 - 2t^{k-2}e^{-c^2}$, we have

$$|m_{k-1,t-1} - M_{k-1}(t + \kappa)| \leq 2(k-1)c\sqrt{t + \kappa}.$$

By using this estimate, with probability at least $1 - 2t^{k-2}e^{-c^2}$, we have

$$\begin{aligned} & \mathbb{E}(m_{k,t} - M_k(t + \kappa) - 2(k-1)c\sqrt{t + \kappa} | \mathcal{F}_{t-1}) \\ & \leq \left(1 - \frac{(1-p)k}{t}\right) (m_{k,t-1} - M_k(t + \kappa - 1) - 2(k-1)c\sqrt{t + \kappa - 1}), \end{aligned}$$

by using the fact that $M_k \leq M_{k-1}$ as seen in (9.3).

Therefore, $0 = X_{k,0}, X_{k,1}, \dots, X_{k,t}$ forms a submartingale with failure probability at most $2t^{k-2}e^{-c^2}$.

Similar to inequalities (9.4) and (9.5), it can be easily shown that

$$|X_{k,t} - X_{k,t-1}| \leq \frac{4}{\prod_{j=1}^t \left(1 - \frac{(1-p)k}{j + \kappa - 1}\right)} \quad (9.8)$$

and

$$\text{Var}(X_{k,t} | \mathcal{F}_{t-1}) \leq \frac{4}{\prod_{j=1}^t \left(1 - \frac{(1-p)k}{j + \kappa - 1}\right)^2}.$$

We apply Theorem 8.6 on the submartingale with $\sigma_i^2 = \frac{4}{\prod_{j=1}^i (1 - \frac{(1-p)k}{j+\kappa-1})^2}$, $M = \frac{4}{\prod_{j=1}^t (1 - \frac{(1-p)k}{j+\kappa-1})}$, and $a_i = 0$. We have

$$\Pr(X_{k,t} \geq \mathbb{E}(X_{k,t}) + \lambda) \leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^t \sigma_i^2 + M\lambda/3)}} + \Pr(B),$$

where $\Pr(B) \leq t^{k-1}e^{-c^2}$ by the induction hypothesis.

Here, $\mathbb{E}(X_{k,t}) = X_{k,0} = 0$. We will use the following approximation:

$$\begin{aligned} \prod_{j=1}^i \left(1 - \frac{(1-p)k}{j+\kappa-1}\right) &= \prod_{j=1}^i \frac{j - (1-p)k}{j + \kappa - 1} \\ &= \frac{\Gamma(\kappa)}{\Gamma(1 - (1-p)k)} \frac{\Gamma(i+1 - (1-p)k)}{\Gamma(i + \kappa)} \\ &\approx C_k (i + \kappa)^{-(1-p)k}, \end{aligned}$$

where $C_k = \frac{\Gamma(\kappa)}{\Gamma(1 - (1-p)k)}$ is a constant depending only on k , p , and κ .

For any $c > 0$, we choose $\lambda = \frac{4c\sqrt{t+\kappa}}{\prod_{j=1}^t (1 - \frac{(1-p)k}{j})} \approx 4C_k^{-1}ct^{3/2-p}$. We have

$$\begin{aligned} \sum_{i=1}^t \sigma_i^2 &= \sum_{i=1}^t \frac{4}{\prod_{j=1}^i (1 - \frac{(1-p)k}{j})^2} \\ &\approx \sum_{i=1}^t 4C_k^{-2}(i + \kappa)^{2k(1-p)} \\ &\approx \frac{4C_k^{-2}}{1 + 2k(1-p)} (t + \kappa)^{1+2k(1-p)} \\ &< 4C_k^{-2}(t + \kappa)^{1+2k(1-p)}. \end{aligned}$$

We note that

$$M\lambda/3 \approx \frac{8}{3}C_k^{-2}c(t + \kappa)^{1/2+2(1-p)} < 2C_k^{-2}(t + \kappa)^{1+2(1-p)},$$

provided that $4c/3 < \sqrt{t + \kappa}$. We have

$$\begin{aligned} \Pr(X_{k,t} \geq \lambda) &\leq e^{-\frac{\lambda^2}{2(\sum_{i=1}^t \sigma_i^2 + M\lambda/3)}} + \Pr(B) \\ &< e^{-\frac{16C_k^{-2}c^2(t+\kappa)^{1+2k(1-p)}}{8C_k^{-2}(t+\kappa)^{1+2(1-p)} + 2C_k^{-2}(t+\kappa)^{1+2(1-p)}}} + \Pr(B) \\ &< e^{-c^2} + (t + \kappa)^{k-1}e^{-c^2} \\ &\leq (t + \kappa + 1)^{k-1}e^{-c^2}. \end{aligned}$$

With probability at least $1 - (t + \kappa + 1)^{k-1}e^{-c^2}$, we have

$$X_{k,t} \leq \lambda.$$

Equivalently, with probability at least $1 - (t + \kappa + 1)^{k-1}e^{-c^2}$, we have

$$m_{k,t} - M_k(t + \kappa) \leq 2ck\sqrt{t + \kappa}. \quad (9.9)$$

We remark that inequality (9.9) holds for any $c > 0$. In fact, it is trivial when $4c/3 > \sqrt{t + \kappa}$, since $|m_{k,t} - M_k(t + \kappa)| \leq 2(t + \kappa)$ always holds.

To obtain the lower bound, we consider

$$X'_{k,t} = \frac{m_{k,t} - M_k(t + \kappa) + 2(k-1)c\sqrt{t + \kappa}}{\prod_{j=1}^t (1 - \frac{(1-p)k}{j+\kappa-1})}.$$

It can be shown easily that $X'_{k,t}$ is nearly a supermartingale. Similarly, by applying Theorem 8.9 to $X'_{k,t}$, the lower bound

$$m_{k,t} - M_k(t + \kappa) \geq -2kc\sqrt{t + \kappa} \quad (9.10)$$

holds with probability at least $1 - (t + \kappa + 1)^{k-1}e^{-c^2}$.

Together these prove the statement for k . The proof of Theorem 9.2 is complete. \square

The above methods for proving concentration of the power law distribution for the infinite Polya process can easily be carried out for many other problems. One of the most popular models for generating random graphs (which simulate web graphs and various information networks) is the so-called *preferential attachment scheme*. The problem on the degree distribution of the preferential attachment scheme can be viewed as a variation of the Polya process as we will see. Before we proceed, we first give a short description for the preferential attachment scheme [Aiello et al. 02, Mitzenmacher 04]:

- With probability p , for some fixed p , add a new vertex v , and add an edge $\{u, v\}$ from v by randomly and independently choosing u in proportion to the degree of u in the current graph. The initial graph, say, is one single vertex with a loop.
- Otherwise, add a new edge $\{r, s\}$ by independently choosing vertices r and s with probability proportional to their degrees. Here, r and s could be the same vertex.

The above preferential attachment scheme can be rewritten as the following variation of the Polya process:

- Start with one bin containing one ball.
- At each step, with probability p , add two balls, one to a new bin and one to an existing bin with probability proportional to the bin size. With probability $1 - p$, add two balls, each of which is independently placed in an existing bin with probability proportional to the bin size.

As we can see, the bins are the vertices; at each time step the bins that the two balls are placed are associated with an edge; the bin size is exactly the degree of the vertex.

It is not difficult to show the expected degrees of the preferential attachment model satisfy a power law distribution with exponent $1 + 2/(2 - p)$ (see [Aiello et al. 02, Mitzenmacher 04]). The concentration results for the power law degree distribution of the preferential attachment scheme can be proved in a very similar way as what we have done in this section for the Polya process. The details of the proof can be found in a forthcoming book [Chung and Lu 06].

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