

An introduction to the Probabilistic Method

Martín Ugarte

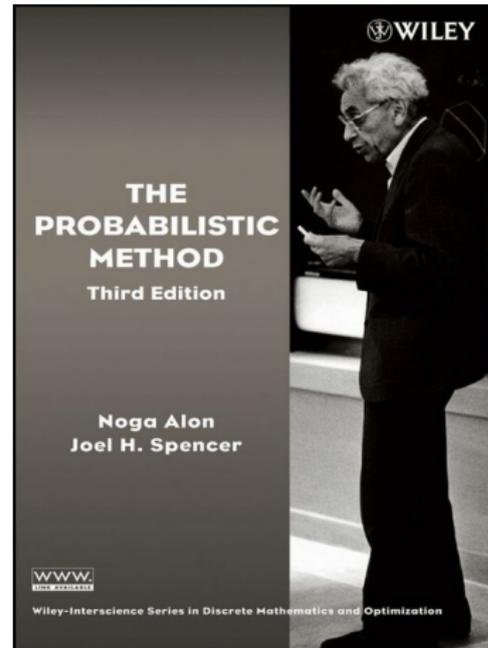
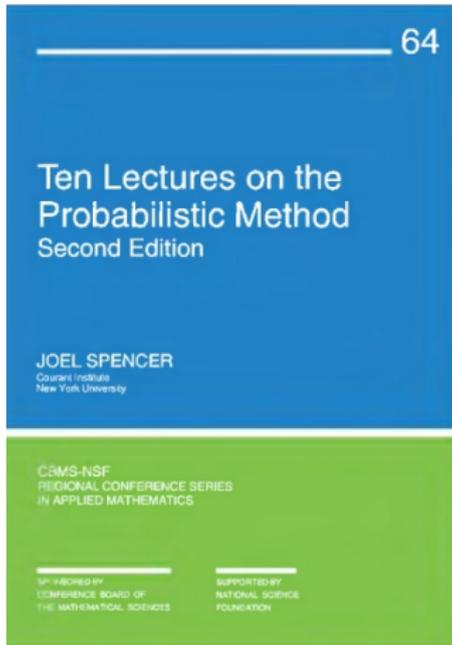
September 6, 2011

The first words about induction

“Even though this proposition may have an infinite number of cases, I shall give a very short proof of it assuming two lemmas. The first, which is self evident, is that the proposition is valid for the second row. The second is that if the proposition is valid for any row then it must necessarily be valid for the following row.”

Blaise Pascal, 17th century.

Standard references



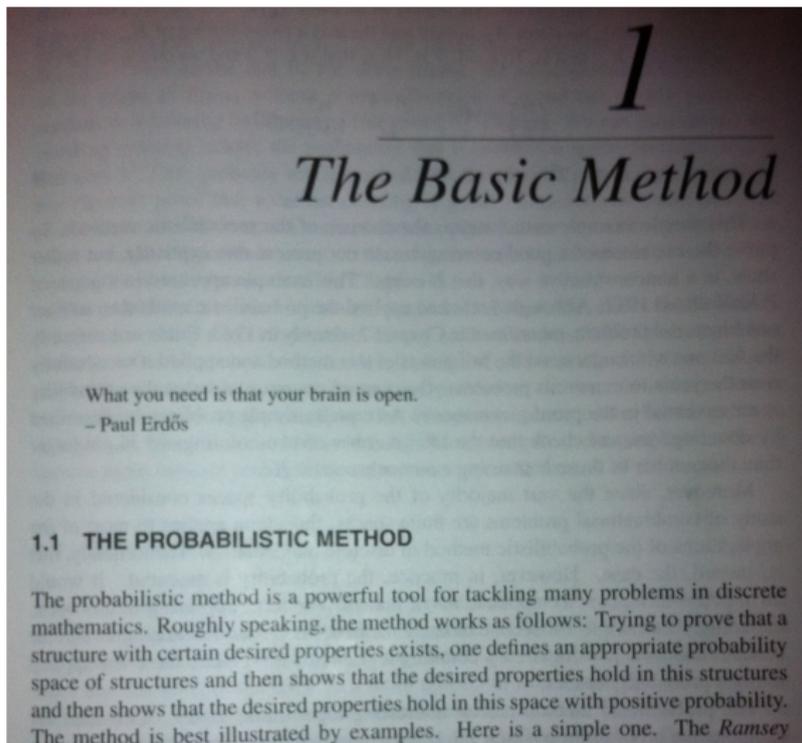
And the first pages...

LECTURE 1

The Probabilistic Method

Ramsey $R(k, k)$. The probabilistic method is best described by examples. Let us plunge right in. Let $R(k, t)$ denote the Ramsey function, i.e., the minimal n so that if the edges of K_n are two-colored Red and Blue then either there is a Red K_k or a Blue K_t . That $R(k, t)$ is well defined, i.e., its holding, for n sufficiently large, is Ramsey's Theorem, which will not be our concern here. Rather, we shall examine *lower bounds* to the Ramsey function. By simple logic:

And the first pages...



The first example

Definition

Given a positive integer k , the *Ramsey number* $R(k)$ is the smallest integer n such that in any two-coloring of the edges of K_n , there is a monochromatic K_k .

The first example

Definition

Given a positive integer k , the *Ramsey number* $R(k)$ is the smallest integer n such that in any two-coloring of the edges of K_n , there is a monochromatic K_k .

(Natural) question:

The first example

Definition

Given a positive integer k , the *Ramsey number* $R(k)$ is the smallest integer n such that in any two-coloring of the edges of K_n , there is a monochromatic K_k .

(Natural) question:

Given any k , how big is $R(k)$?

The Ramsey Numbers

We will use the basic method to give a lower bound for $R(k)$:

The Ramsey Numbers

We will use the basic method to give a lower bound for $R(k)$:

- Find an upper bound for the probability of randomly obtain a two-coloring of K_n with a red K_k or a blue K_k .

The Ramsey Numbers

We will use the basic method to give a lower bound for $R(k)$:

- Find an upper bound for the probability of randomly obtain a two-coloring of K_n with a red K_k or a blue K_k .

What if such an upper bound is less than 1?

The Ramsey Numbers (cont.)

Consider a random two-coloring of the edges of K_n where every edge is independently uniformly colored.

The Ramsey Numbers (cont.)

Consider a random two-coloring of the edges of K_n where every edge is independently uniformly colored.

Given any k -subset R of K_n , let A_R be the event of R being *monochromatic*.

What is the probability of A_R ?

The Ramsey Numbers (cont.)

Consider a random two-coloring of the edges of K_n where every edge is independently uniformly colored.

Given any k -subset R of K_n , let A_R be the event of R being *monochromatic*.

What is the probability of A_R ?

$$P[A_R] = 2^{1-\binom{k}{2}}.$$

The Ramsey Numbers (cont.)

Consider a random two-coloring of the edges of K_n where every edge is independently uniformly colored.

Given any k -subset R of K_n , let A_R be the event of R being *monochromatic*.

What is the probability of A_R ?

$$P[A_R] = 2^{1-\binom{k}{2}}.$$

Then the probability that at least one A_R occurs is at most $\binom{n}{k} 2^{1-\binom{k}{2}}$.

The Ramsey Numbers (cont.)

Corollary

If $\binom{n}{k} 2^{1-\binom{k}{2}} < 1$ then $R(k) > n$.

The Ramsey Numbers (cont.)

Corollary

If $\binom{n}{k} 2^{1-\binom{k}{2}} < 1$ then $R(k) > n$.

Let $f(k, n) = \binom{n}{k} 2^{1-\binom{k}{2}}$.

Here are some sample values:

k	n	$\approx f(n, k)$
4	6	0.46875
6	17	0.75537
10	100	0.98397
18	2639	0.99488
34	1225000	0.89015

A little look back

- 1) Define a probability space.

A little look back

- 1) Define a probability space.
- 2) Some structures with the desired property must be part of the space.

A little look back

- 1) Define a probability space.
- 2) Some structures with the desired property must be part of the space.
- 3) Choose a random structure in the space.

A little look back

- 1) Define a probability space.
- 2) Some structures with the desired property must be part of the space.
- 3) Choose a random structure in the space.
- 4) Prove that the property holds with strictly positive probability.

Tournaments

Definition

A tournament is a directed graph $G = (V, E)$ such that for every $x, y \in V$ with $x \neq y$, either $(x, y) \in E$ or $(y, x) \in E$ but not both.

Tournaments

Definition

A tournament is a directed graph $G = (V, E)$ such that for every $x, y \in V$ with $x \neq y$, either $(x, y) \in E$ or $(y, x) \in E$ but not both.

Definition

We say a tournament $G = (V, E)$ has the property S_k if for every k -subset A of V exists a vertex $v_A \notin A$ such that for every vertex $x \in A$, $(v_A, x) \in E$.

Tournaments

Definition

A tournament is a directed graph $G = (V, E)$ such that for every $x, y \in V$ with $x \neq y$, either $(x, y) \in E$ or $(y, x) \in E$ but not both.

Definition

We say a tournament $G = (V, E)$ has the property S_k if for every k -subset A of V exists a vertex $v_A \notin A$ such that for every vertex $x \in A$, $(v_A, x) \in E$.

Any existential questions?

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The probability space:

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The probability space:

- The set of tournaments with n nodes. Every tournament is equally likely.

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The probability space:

- The set of tournaments with n nodes. Every tournament is equally likely.

How to proceed:

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The probability space:

- The set of tournaments with n nodes. Every tournament is equally likely.

How to proceed:

- Find an upper bound $M = f(n, k)$ for the probability of randomly choose a tournament with n nodes without the property S_k .

The property S_k

Given a positive integer k we want to find n such that there is a tournament with n vertices satisfying S_k .

The probability space:

- The set of tournaments with n nodes. Every tournament is equally likely.

How to proceed:

- Find an upper bound $M = f(n, k)$ for the probability of randomly choose a tournament with n nodes without the property S_k .
- Find restrictions for n and k such that $M < 1$.

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

What is the probability of A_R ?

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

What is the probability of A_R ?

$$P[A_R] = (1 - 2^{-k})^{n-k}$$

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

What is the probability of A_R ?

$$P[A_R] = (1 - 2^{-k})^{n-k}$$

Now we want an upper bound for

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

What is the probability of A_R ?

$$P[A_R] = (1 - 2^{-k})^{n-k}$$

Now we want an upper bound for

$$P \left[\bigcup_{\substack{R \subset V \\ |R|=k}} A_R \right]$$

The property S_k (cont.)

Consider a random tournament $T = (V, E)$ with n nodes. For every k -subset R of V , let A_R be the event that there is no vertex in $V \setminus R$ that beats every node on R .

What is the probability of A_R ?

$$P[A_R] = (1 - 2^{-k})^{n-k}$$

Now we want an upper bound for

$$P \left[\bigcup_{\substack{R \subset V \\ |R|=k}} A_R \right] \leq \binom{n}{k} (1 - 2^{-k})^{n-k}$$

The property S_k (cont.)

Corollary

If $\binom{n}{k}(1 - 2^{-k})^{n-k} < 1$ then there is a tournament with n nodes and the property S_k .

The property S_k (cont.)

Corollary

If $\binom{n}{k}(1 - 2^{-k})^{n-k} < 1$ then there is a tournament with n nodes and the property S_k .

Let $g(k, n) = \binom{n}{k}(1 - 2^{-k})^{n-k}$.

Some sample values:

k	n	$\approx g(n, k)$
4	311	0.94973
5	931	0.98388
6	2581	0.99850

The property S_k (cont.)

Corollary

If $\binom{n}{k}(1 - 2^{-k})^{n-k} < 1$ then there is a tournament with n nodes and the property S_k .

Let $g(k, n) = \binom{n}{k}(1 - 2^{-k})^{n-k}$.

Some sample values:

k	n	$\approx g(n, k)$
4	311	0.94973
5	931	0.98388
6	2581	0.99850

How can we find a tournament satisfying S_4 ?

The algorithmic point of view

The corollary above seems to be useless if we want to find a tournament satisfying S_k .

The algorithmic point of view

The corollary above seems to be useless if we want to find a tournament satisfying S_k .

Anyway, we can use the meaning of $g(n, k)$ in the opposite sense.

The algorithmic point of view

The corollary above seems to be useless if we want to find a tournament satisfying S_k .

Anyway, we can use the meaning of $g(n, k)$ in the opposite sense.

Recall $g(n, k)$ is an upper bound for the probability of randomly finding a tournament with n nodes without the property S_k :

What if $g(n, k) \approx 0$?

The algorithmic point of view

The corollary above seems to be useless if we want to find a tournament satisfying S_k .

Anyway, we can use the meaning of $g(n, k)$ in the opposite sense.

Recall $g(n, k)$ is an upper bound for the probability of randomly finding a tournament with n nodes without the property S_k :

What if $g(n, k) \approx 0$?

k	n	$\approx g(n, k)$
4	500	0.00003
5	1200	0.00068
6	5000	$1,5 \cdot 10^{-15}$

The algorithmic point of view

The corollary above seems to be useless if we want to find a tournament satisfying S_k .

Anyway, we can use the meaning of $g(n, k)$ in the opposite sense.

Recall $g(n, k)$ is an upper bound for the probability of randomly finding a tournament with n nodes without the property S_k :

What if $g(n, k) \approx 0$?

k	n	$\approx g(n, k)$	k	n	$\approx g(n, k)$
4	500	0.00003	4	311	≈ 0.94973
5	1200	0.00068	5	931	≈ 0.98388
6	5000	$1,5 \cdot 10^{-15}$	6	2581	≈ 0.99850

The algorithmic point of view (cont.)

In the same way, we can use the bound for the Ramsey Numbers.

The algorithmic point of view (cont.)

In the same way, we can use the bound for the Ramsey Numbers.

Recall:

$f(k, n) = \binom{n}{k} 2^{1-\binom{k}{2}}$ is an upper bound for the probability of randomly finding a two-coloring of K_n with at least one monochromatic K_k .

The algorithmic point of view (cont.)

In the same way, we can use the bound for the Ramsey Numbers.

Recall:

$f(k, n) = \binom{n}{k} 2^{1-\binom{k}{2}}$ is an upper bound for the probability of randomly finding a two-coloring of K_n with at least one monochromatic K_k .

What if $f(n, k) \approx 0$?

The algorithmic point of view (cont.)

In the same way, we can use the bound for the Ramsey Numbers.

Recall:

$f(k, n) = \binom{n}{k} 2^{1-\binom{k}{2}}$ is an upper bound for the probability of randomly finding a two-coloring of K_n with at least one monochromatic K_k .

What if $f(n, k) \approx 0$?

Then it is very likely to randomly find a two-coloring of the edges of K_n with no monochromatic K_k .

The algorithmic point of view (cont.)

Surprisingly, for not so large k , there are large n for which it is very likely to find such colorings:

k	n	$\approx f(n, k)$	k	n	$\approx f(n, k)$
4	6	0.46875	4	5	0.15625
6	17	0.75537	6	10	0.01281
10	100	0.98397	10	50	0.00058
18	2639	0.99488	18	1500	0.00003
34	1225000	0.89015	34	600000	$2,5 \cdot 10^{-11}$

Expected value

Another way to use the probabilistic method is through the expected value.

Expected value

Another way to use the probabilistic method is through the expected value.

Definition

Let X be a random variable that can take value x_1 with probability p_1 , x_2 with probability p_2 , \dots , and x_n with probability p_n .

Expected value

Another way to use the probabilistic method is through the expected value.

Definition

Let X be a random variable that can take value x_1 with probability p_1 , x_2 with probability p_2 , \dots , and x_n with probability p_n . Then the expected value of X is

$$E[X] = \sum_{i=1}^n x_i \cdot p_i$$

Properties of expected value

Let X be a random variable.

Properties of expected value

Let X be a random variable.

- If $E[X] = m$, then X can take a value $x_1 \geq m$.

Properties of expected value

Let X be a random variable.

- If $E[X] = m$, then X can take a value $x_1 \geq m$.
- If $X = \sum_{i=1}^n X_i$, then $E[X] = \sum_{i=1}^n E[X_i]$.

Properties of expected value

Let X be a random variable.

- If $E[X] = m$, then X can take a value $x_1 \geq m$.
- If $X = \sum_{i=1}^n X_i$, then $E[X] = \sum_{i=1}^n E[X_i]$.

Example

Let σ be a permutation on the set $\{1, 2, \dots, n\}$.
What is the expected value for

$$X = |\{a \in \{1, \dots, n\} \mid \sigma(a) = a\}|?$$

Expected value applications

The probabilistic method can use the properties mentioned before.

Expected value applications

The probabilistic method can use the properties mentioned before. If we want to prove a “quantifiable” property, we can use it’s expected value.

Expected value applications

The probabilistic method can use the properties mentioned before. If we want to prove a “quantifiable” property, we can use it’s expected value.

Here is an example:

Theorem

Let $G = (V, E)$ be a graph with e edges. Then G contains a bipartite subgraph with at least $e/2$ edges.

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent.

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent. Define

$$X = \left| \left\{ \{x, y\} \in E \mid |\{x, y\} \cap R| = 1 \right\} \right|$$

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent. Define

$$X = \left| \left\{ \{x, y\} \in E \mid |\{x, y\} \cap R| = 1 \right\} \right|$$

Let $X_{\{x,y\}}$ be the indicator variable for $|\{x, y\} \cap R| = 1$.

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent. Define

$$X = \left| \left\{ \{x, y\} \in E \mid |\{x, y\} \cap R| = 1 \right\} \right|$$

Let $X_{\{x,y\}}$ be the indicator variable for $|\{x, y\} \cap R| = 1$.

$$X = \sum_{\{x,y\} \in E} X_{\{x,y\}}$$

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent. Define

$$X = \left| \left\{ \{x, y\} \in E \mid |\{x, y\} \cap R| = 1 \right\} \right|$$

Let $X_{\{x,y\}}$ be the indicator variable for $|\{x, y\} \cap R| = 1$.

$$X = \sum_{\{x,y\} \in E} X_{\{x,y\}} \Rightarrow E[X] = \sum_{\{x,y\} \in E} E[X_{\{x,y\}}]$$

Splitting graphs

Proof

Let $R \subseteq V$ where for every node x in V , $P[x \in R] = 1/2$, this choices being mutually independent. Define

$$X = \left| \left\{ \{x, y\} \in E \mid |\{x, y\} \cap R| = 1 \right\} \right|$$

Let $X_{\{x,y\}}$ be the indicator variable for $|\{x, y\} \cap R| = 1$.

$$X = \sum_{\{x,y\} \in E} X_{\{x,y\}} \Rightarrow E[X] = \sum_{\{x,y\} \in E} E[X_{\{x,y\}}]$$

As $E[X_{\{x,y\}}] = 1/2$ for every $\{x, y\} \in E$, we conclude there is a bipartite subgraph with at least $e/2$ edges.



The first application

The next theorem is considered the first application of the probabilistic method in combinatorics.

The first application

The next theorem is considered the first application of the probabilistic method in combinatorics.

Theorem (Szele 1943)

For every n , there is a tournament T with n players and at least $n!2^{1-n}$ Hamiltonian paths.

The first application

The next theorem is considered the first application of the probabilistic method in combinatorics.

Theorem (Szele 1943)

For every n , there is a tournament T with n players and at least $n!2^{1-n}$ Hamiltonian paths.

Here we say there exists a tournament, so it will be randomly chosen.

The first application (cont.)

Proof

Let $T = (V, E)$ be a tournament with n nodes. Let X be the number of Hamiltonian paths on T .

The first application (cont.)

Proof

Let $T = (V, E)$ be a tournament with n nodes. Let X be the number of Hamiltonian paths on T .

For every strict total order $<$ of the n nodes, let $X_{<}$ be the indicator random variable for $<$ giving an ordered hamiltonian path.

The first application (cont.)

Proof

Let $T = (V, E)$ be a tournament with n nodes. Let X be the number of Hamiltonian paths on T .

For every strict total order $<$ of the n nodes, let $X_{<}$ be the indicator random variable for $<$ giving an ordered hamiltonian path.

$$E[X] = \sum_{< \text{ order for } V} E[X_{<}]$$

The first application (cont.)

Proof

Let $T = (V, E)$ be a tournament with n nodes. Let X be the number of Hamiltonian paths on T .

For every strict total order $<$ of the n nodes, let $X_{<}$ be the indicator random variable for $<$ giving an ordered hamiltonian path.

$$E[X] = \sum_{< \text{ order for } V} E[X_{<}]$$

As $E[X_{<}] = 2^{1-n}$ for every linear order, and there are $n!$ orders for the n nodes, we conclude there is a tournament with $n!2^{1-n}$ Hamiltonian paths.



A lower bound for independent sets

The following theorem was proved independently by Caro (1979) and Wei (1981).

Theorem (Caro and Wei)

Let $G = (V, E)$ be a graph with n vertices. Then

$$\alpha(G) \geq \sum_{v \in V} \frac{1}{\deg(v) + 1}$$

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V .

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V . Define

$$I_{<} = \{v \in V \mid \{v, w\} \in E \Rightarrow v < w\}.$$

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V . Define

$$I_{<} = \{v \in V \mid \{v, w\} \in E \Rightarrow v < w\}.$$

Let $X_v = \mathbb{1}_{v \in I_{<}}$. As $v \in I_{<}$ iff it is the least element among v and its neighbors, $I_{<}$ is independent

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V . Define

$$I_{<} = \{v \in V \mid \{v, w\} \in E \Rightarrow v < w\}.$$

Let $X_v = \mathbb{1}_{v \in I_{<}}$. As $v \in I_{<}$ iff it is the least element among v and its neighbors, $I_{<}$ is independent and $E[X_v] = \frac{1}{\deg(v)+1}$.

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V . Define

$$I_{<} = \{v \in V \mid \{v, w\} \in E \Rightarrow v < w\}.$$

Let $X_v = \mathbb{1}_{v \in I_{<}}$. As $v \in I_{<}$ iff it is the least element among v and its neighbors, $I_{<}$ is independent and $E[X_v] = \frac{1}{\deg(v)+1}$.

Let $X_{<} = |I_{<}| = \sum_{v \in V} X_v$.

$$E[X_{<}] = \sum_{v \in V} E[X_v] = \sum_{v \in V} \frac{1}{\deg(v) + 1}.$$

A lower bound for independent sets (cont.)

Proof

Let $<$ be an uniformly chosen order for V . Define

$$I_{<} = \{v \in V \mid \{v, w\} \in E \Rightarrow v < w\}.$$

Let $X_v = \mathbb{1}_{v \in I_{<}}$. As $v \in I_{<}$ iff it is the least element among v and its neighbors, $I_{<}$ is independent and $E[X_v] = \frac{1}{\deg(v)+1}$.

Let $X_{<} = |I_{<}| = \sum_{v \in V} X_v$.

$$E[X_{<}] = \sum_{v \in V} E[X_v] = \sum_{v \in V} \frac{1}{\deg(v) + 1}.$$

Thus, for some order $<$, $I_{<}$ has at least $\sum_{v \in V} \frac{1}{\deg(v)+1}$ nodes. □

Crossing Numbers

Definition

An embedding of a graph $G = (V, E)$ on a surface Σ is a pair (f, g) where $f : V \rightarrow \Sigma$, $g : E \rightarrow A(\Sigma)$ (where $A(\Sigma)$ is the set of simple arcs on Σ) such that for every $\{x, y\} \in E$, $g(\{x, y\})$ starts in x and ends at y .

Crossing Numbers

Definition

An embedding of a graph $G = (V, E)$ on a surface Σ is a pair (f, g) where $f : V \rightarrow \Sigma$, $g : E \rightarrow A(\Sigma)$ (where $A(\Sigma)$ is the set of simple arcs on Σ) such that for every $\{x, y\} \in E$, $g(\{x, y\})$ starts in x and ends at y .

A planar representation is an embedding on \mathbb{R}^2 .

Crossing Numbers

Definition

An embedding of a graph $G = (V, E)$ on a surface Σ is a pair (f, g) where $f : V \rightarrow \Sigma$, $g : E \rightarrow A(\Sigma)$ (where $A(\Sigma)$ is the set of simple arcs on Σ) such that for every $\{x, y\} \in E$, $g(\{x, y\})$ starts in x and ends at y .

A planar representation is an embedding on \mathbb{R}^2 .

Definition

The crossing number of a planar representation is the number of pairs of intersecting curves on $g(E)$ with no common endpoints.

Crossing Numbers

Definition

An embedding of a graph $G = (V, E)$ on a surface Σ is a pair (f, g) where $f : V \rightarrow \Sigma$, $g : E \rightarrow A(\Sigma)$ (where $A(\Sigma)$ is the set of simple arcs on Σ) such that for every $\{x, y\} \in E$, $g(\{x, y\})$ starts in x and ends at y .

A planar representation is an embedding on \mathbb{R}^2 .

Definition

The crossing number of a planar representation is the number of pairs of intersecting curves on $g(E)$ with no common endpoints. The crossing number of a graph G , $cr(G)$, is the minimum possible crossing number in a planar representation of G . If $cr(G) = 0$, G is said to be planar.

Crossing Numbers (cont.)

Lemma

The crossing number of any simple graph $G = (V, E)$ is at least $|E| - 3|V|$.

Crossing Numbers (cont.)

Lemma

The crossing number of any simple graph $G = (V, E)$ is at least $|E| - 3|V|$.

Proof

Euler's formula: If $G = (V, E)$ is a simple connected planar graph then $|V| - |E| + f = 2$ where f is the number of divisions of the plane in any planar representation of G .

Crossing Numbers (cont.)

Lemma

The crossing number of any simple graph $G = (V, E)$ is at least $|E| - 3|V|$.

Proof

Euler's formula: If $G = (V, E)$ is a simple connected planar graph then $|V| - |E| + f = 2$ where f is the number of divisions of the plane in any planar representation of G . It follows that $|E| \leq 3|V| - 6$, so $|E| < 3|V|$.

Crossing Numbers (cont.)

Lemma

The crossing number of any simple graph $G = (V, E)$ is at least $|E| - 3|V|$.

Proof

Euler's formula: If $G = (V, E)$ is a simple connected planar graph then $|V| - |E| + f = 2$ where f is the number of divisions of the plane in any planar representation of G . It follows that $|E| \leq 3|V| - 6$, so $|E| < 3|V|$. Then the crossing number of any connected planar graph is at least $|E| - 3|V|$.



Crossing Numbers (cont.)

Theorem (Ajtai, Chvátal, Newborn and Szemerédi (1982))

The crossing number of any simple graph $G = (V, E)$ with $|E| \geq 4|V|$ is at least $|E|^3/64|V|^2$.

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p .

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p . The expected number of vertices is $p|V|$,

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p . The expected number of vertices is $p|V|$, the expected number of edges is $p^2|E|$

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p . The expected number of vertices is $p|V|$, the expected number of edges is $p^2|E|$ and expected number of crossing edges in the planar representation of H obtained by the restriction of (f, g) to H is p^4t .

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p . The expected number of vertices is $p|V|$, the expected number of edges is $p^2|E|$ and expected number of crossing edges in the planar representation of H obtained by the restriction of (f, g) to H is p^4t .
By the above lemma $p^4t \geq p^2|E| - 3p|V|$, so

$$t \geq \frac{|E|}{p^2} - \frac{3|V|}{p^3}$$

Crossing Numbers (cont.)

Proof

Let $G = (V, E)$ be a graph with $|E| \geq 4|V|$ and (f, g) a planar representation of G with crossing number t . Let H be an induced subgraph obtained by choosing randomly and independently each vertex of G with probability p . The expected number of vertices is $p|V|$, the expected number of edges is $p^2|E|$ and expected number of crossing edges in the planar representation of H obtained by the restriction of (f, g) to H is p^4t .

By the above lemma $p^4t \geq p^2|E| - 3p|V|$, so

$$t \geq \frac{|E|}{p^2} - \frac{3|V|}{p^3}$$

Now substitute $p = 4|V|/|E|$ (≤ 1) to obtain the desired result.



- 1 Introduction
 - An analogy with mathematical induction
 - Standard references
- 2 The basic method
 - The Ramsey Numbers
 - Tournaments
 - The algorithmic point of view
- 3 Expected value
 - Properties
 - Splitting graphs
 - Hamiltonian paths on Tournaments
- 4 Further applications
 - A lower bound for independent sets
 - Crossing numbers