

- propositional logic**
- $P \Rightarrow Q$: False iff $F \Rightarrow T$
 - $P \Rightarrow Q$: True if P always False
 - $P \Rightarrow Q = \neg P \vee Q$
 - $P \Rightarrow Q = \neg Q \Rightarrow \neg P$

- planar graphs**
- Euler's Formula: for every connected planar G , $v + f = e + 2$
 - for planar G with k connected components, $v - e + f = k + 1$
 - faces of at least nine sides $\Rightarrow (nf \leq 2e) \Rightarrow (v(2e/n) \geq e + 2)$
 - $(n=3) \Rightarrow (e \leq 3v-6)$, $(n=4) \Rightarrow (e \leq 2v-4)$ (planar bipartite)
 - Kuratowski's Theorem: non-planar iff contains $K_5/K_{3,3}$
 - all planar G s are 4-colorable
 - $K_{3,3}$ is bipartite and 2-colorable
 - K_{ii} is 1-colorable
 - max deg 2 \Rightarrow planar

- hypercubes (HC)**
- bit string definition: $V = n$ string bit strings, $E = \{x, y \mid x \text{ and } y \text{ differ in exactly one position}\}$
 - recursive definition: n -dim $HC = (n-1)$ -dim HC (D subcube) + $(n-1)$ -dim HC with edges between each pair of vertices Dx in D subcube and Tx in 1 subcube
 - $(n$ -dim $HC) \Rightarrow (2^n \text{ vertices}) \Rightarrow (e = n \cdot 2^{n-1})$
 - $(n \text{ vertices}) = (\log_2(n) \text{-dim } HC) = (e = \log_2(2n) + 2 \log_2(n) - 1 \text{ edges})$

- Chinese Remainder Theorem (CRT)**
- given a system of k modular congruences, $x \equiv a_i \pmod{m_i}$ where m_i are all coprime ($\gcd = 1$), there exists a unique solution for x
- ex: $x \equiv 1 \pmod{3}$, $x \equiv 3 \pmod{7}$, $x \equiv 4 \pmod{11}$
- | | | |
|-----------------------|-----------------------|------------------------|
| $a \equiv 1 \pmod{3}$ | $a \equiv 0 \pmod{7}$ | $a \equiv 0 \pmod{11}$ |
| $b \equiv 0 \pmod{3}$ | $b \equiv 1 \pmod{7}$ | $b \equiv 0 \pmod{11}$ |
| $c \equiv 0 \pmod{3}$ | $c \equiv 0 \pmod{7}$ | $c \equiv 1 \pmod{11}$ |
- $a: \frac{22}{25} \frac{14}{15}$ $b: \frac{33}{18} \frac{19}{15}$ $c: \frac{11}{18} \frac{16}{15}$
- $x \equiv (a \cdot 77 + b \cdot 33 + c \cdot 11) \pmod{243}$
- $x \equiv 124 \pmod{243}$
- $x \equiv 136 \pmod{3 \cdot 7 \cdot 11}$

- modular arithmetic rules**
- if $a \equiv c \pmod{m}$ and $b \equiv d \pmod{m}$
 - $a + b \equiv c + d \pmod{m}$
 - $a \cdot b \equiv c \cdot d \pmod{m}$
 - $a \cdot k \equiv b \cdot k \pmod{m}$

- polynomials (P)**
- property 1: a non-zero P of deg d has at most d roots
 - property 2: given $d+1$ points $(x_1, y_1), \dots, (x_{d+1}, y_{d+1})$ with all x_i distinct, there is a unique P of deg at most d that goes through those points

- Galois Fields**
- a finite field modulo m
 - # of points: # of polynomials
- | | |
|---------|-----------|
| $d+1$ | 1 |
| d | m |
| $d-1$ | m^2 |
| \dots | \dots |
| $d-k$ | m^{k+1} |
| \dots | \dots |
| 0 | m^{d+1} |

- counting**
- permutations (ordered)
 - w/o replacement: $\frac{n!}{(n-k)!}$
 - w/ replacement: n^k

- halting problem**
- to show $Test(X, y)$ which determines whether Q does some task X on input y
- def $TestHalt(P, x)$
- ```
def Q(y)
 run P(x)
 return Test(X, y)
```

- quantifiers**
- De Morgan's
  - $\neg (P \wedge Q) \equiv (\neg P \vee \neg Q)$
  - $\neg (P \vee Q) \equiv (\neg P \wedge \neg Q)$
  - De Morgan's for Quantifiers
  - $\neg (\forall x P(x)) \equiv \exists x \neg P(x)$
  - $\neg (\exists x P(x)) \equiv \forall x \neg P(x)$

|       | no repeated vertices | no repeated edges | start = end |
|-------|----------------------|-------------------|-------------|
| walk  |                      |                   |             |
| path  | X                    | X                 |             |
| tour  |                      |                   | X           |
| cycle | X                    | X                 | X           |

- bipartite graphs**
- $G$  where vertices are split into two groups and edges only go between groups
  - $V = L \cup R$ ,  $E \subseteq L \times R$
  - always 2-colorable
  - any  $G$  is bipartite iff it has no tours of odd length

- GCD, MI, & euclid's algorithm**
- $\gcd(x, y) = \gcd(y, x \bmod y)$
  - if  $\gcd(x, m) = 1$ , the MI of  $x \bmod m$  exists and is unique

- extended euclid's algorithm**
- find  $a, b$  such that  $ax + by = 1$
  - $a = x \bmod y$ ,  $b = y \bmod x$

ex: find GCD of 17 and 39.

ex: find the MI of 17 mod 39.

- (1)  $39 = 2 \cdot 17 + 5$   
(2)  $17 = 3 \cdot 5 + 2$   
(3)  $5 = 2 \cdot 2 + 1$   
(4)  $2 = 2 \cdot 1 + 0$

- Euler's Totient Function & Theorem**
- totient function:  $\phi(n) = \{i \mid 1 \leq i \leq n, \gcd(n, i) = 1\}$
  - totient theorem:  $a^{\phi(n)} \equiv 1 \pmod{n}$
  - properties
  - $\phi(p^k) = p^k - p^{k-1}$  for prime  $p$
  - $\phi(p^k) = p^k - p^{k-1} = p^k \cdot (1 - 1/p)$
  - $\phi(ab) = \phi(a) \phi(b)$

- LaGrange Interpolation**
- create  $P$ s that go through  $(x, 1)$  and  $(x, 0)$  for all  $j \neq i$
  - add linear combination of sub  $P$ s to get desired  $P$
- ex:  $(1, 1), (2, 2), (3, 3)$
- $\Delta_1 = \frac{(x-2)(x-3)}{(1-2)(1-3)}$     $\Delta_2 = \frac{(x-1)(x-3)}{(2-1)(2-3)}$     $\Delta_3 = \frac{(x-1)(x-2)}{(3-1)(3-2)}$
- $P = \Delta_1 + 2\Delta_2 + 3\Delta_3$  do arithmetic mod  $p!!!$

- error correcting codes**
- erasure errors:  $k$  dropped
  - packets labelled so recipient knows exactly which packets are dropped
  - must send  $n+k$  packets, where each packet is  $m$  is a number in GF
  - general error:
  - $n$  packets,  $k$  corrupted, must send  $n+2k$  packets
  - when reconstructing, there is a unique polynomial  $P(x)$  of degree at most  $n-1$  such that  $P(i) = y_i$  for at least  $n+k$  of the received packets

- countability**
- set is countable if there exists a bijection between it and  $\mathbb{N}$
  - countable:  $\mathbb{Z}, \mathbb{Q}, \mathbb{N} \times \mathbb{N}$ , finite length strings from finite or infinite set of characters
  - non-countable:  $\mathbb{R}[0, 1]$ ,  $\mathbb{R}$ , infinite length strings

- Cantor's Diagonalization**
- change every value along diagonal
  - can apply to functions, which are uniquely defined by their outputs on each input

- trees (T)**
- iff:
  - connected & acyclic
  - connected +  $e = v - 1$
  - connected + remove edge disconnects
  - acyclic + adding edge creates cycle
  - $T$ s with  $> 2$  vertices must have at least 2 leaves
  - all  $T$ s with at least 2 vertices are bipartite
  - every connected component in an acyclic  $G$  is a  $T$
  - acyclic  $G$  with  $k$  CCs  $\Rightarrow e = v - k$
  - a graph with  $v$  edges contains a cycle

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- stable matching**
- matching is job optimal  $\Rightarrow$  it is also candidate pessimal
  - $P \&R$  with jobs proposing  $\Rightarrow$  job optimal matching
  - there is only ONE job/candidate optimal matching

- P&R algorithm**
- improvement lemma
  - every candidate will only accept a better job as time goes on
  - every job will only propose worse candidate as time goes on
  - terminates in at most  $(n-1)^2 + 1$  days
  - a candidate receives proposal on day  $i \Rightarrow$  they receive some proposal on every day thereafter until termination
  - a candidate receives NO proposal on day  $i \Rightarrow$  they receive no proposal on any previous day  $j$
  - through a complete execution of the algorithm, there is at least 1 candidate who receives exactly 1 proposal

- Fermat's Little Theorem**
- for any prime  $p$  and any  $a \in \{0, 1, \dots, N-1\}$ ,  $a^{p-1} \equiv 1 \pmod{p}$
  - tells us that exponentiation is  $(p-1)$ -periodic when modulo  $p$

- one-to-one**
- $f: A \rightarrow B$  is a bijection iff it is onto and one-to-one
  - one-to-one (injective): every element in  $A$  has a mapping to a distinct element in  $B$
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- hamiltonian tour (HT)**
- tour that visits every vertex exactly once
  - every hypercube has a HT
- eulerian walk (EW)**
- walk that visits every edge exactly once
  - undirected  $G$  has an EW iff connected and has 0 or 2 odd degree vertices
  - undirected  $G$  has an EW with  $v.1 = v$  iff connected and has EXACTLY 2 odd degree vertices
- eulerian tour (ET)**
- a closed EW
  - undirected  $G$  has an ET iff  $G$  is connected and even degree

- handshaking lemma**
- sum of degrees =  $2e$
  - there must be even number of odd degree vertices

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- RSA**
- variables:
  - $x$  (mod  $N$ ): message
  - $y$  (mod  $N$ ): encrypted,  $\equiv x^e \pmod{N}$
  - $E(x) \equiv x^e \pmod{N}$
  - $D(y) \equiv y^d \pmod{N} \equiv x^{ed} \pmod{N} \equiv x \pmod{N}$  by FLT & CRT
  - private variables:
  - $p, q$ : 2 large primes
  - $d$ : private key,  $\equiv e^{-1} \pmod{(p-1)(q-1)}$
  - public:
  - $N$ : public key =  $pq$
  - $e$ : public key, arbitrarily chosen & is relatively prime to  $(p-1)(q-1)$

- Berlekamp-Welch Algorithm**
- $E(x) = (x-a_1)(x-a_2)\dots(x-a_k)$ : error locator  $P$
  - $Q(x) = P(x)E(x)$ .  $Q(i) = P(i)E(i) = n E(i)$
- ex: received  $(0, 1, 4, 0, 4)$  w/ one error
- $Q(0) = 0E(0)$     $a_0 = 0$
- $Q(1) = 1E(1)$     $a_3 + a_2 + a_1 = 1 - e$
- $Q(2) = 4E(2)$     $8a_3 + 4a_2 + 2a_1 = 8 - 4e$
- $Q(3) = 0E(3)$     $27a_3 + 9a_2 + 3a_1 = 0$
- $Q(4) = 4E(4)$     $64a_3 + 16a_2 + 4a_1 = 16 - 4e$

- bijections**
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| <b>probability and inference formulas</b><br>- conditional probability: $P(A B) = \frac{P(A \cap B)}{P(B)}$<br>- total probability: $P(A) = \sum_{i=1}^n P(B A_i)P(A_i)$<br>- Bayes Theorem: $P(A B) = \frac{P(B A)P(A)}{P(B)}$<br>- product rule: $P(A \cap B) = P(A)P(B A)$<br>- pairwise independence: $P(A B) = P(A)$<br>- pairwise independence: $P(A \cap B) = P(A)P(B)$<br>- mutual independence: $P(\bigcap_{i \in I} A_i) = \prod_{i \in I} P(A_i)$<br>pairwise I does not imply mutual I<br>- union bound: $P(\bigcup_{i=1}^n A_i) \leq \sum_{i=1}^n P(A_i)$ | <b>expected value formulas</b><br>- $E[X] = \sum k \cdot P(X=k)$<br>- linearity of expectation:<br>- $E[X+Y] = E[X] + E[Y]$<br>- $E[cX] = c E[X]$<br>- LOTUS: $E[f(X)] = \sum f(k) P(X=k)$                                                                                                                                                                                                                | <b>variance formulas</b><br><div><math>\begin{matrix} \text{O} \\ \text{for I.V} \end{matrix}</math><div><math>\text{Var}(X) = E[(X-E[X])^2]</math><math>\text{Var}(X) = E[X^2] - (E[X])^2</math></div><div><math>\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X,Y)</math><math>\text{Var}(cX) = c \cdot \text{Var}(X)</math></div><div><math>\text{Cov}(X,Y) = E[(X-E[X])(Y-E[Y])]</math><math>\text{Cov}(X,Y) = E[XY] - E[X]E[Y]</math><math>\text{Cov}(X,X) = \text{Var}(X)</math></div></div> <div>- Independent <math>\Rightarrow \text{Cov}(X,Y) = 0</math><br/>- <math>\text{Cov}(X,Y) = 0 \nRightarrow</math> Independent<br/>- <math>\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y}</math></div> | <b>bernoulli distribution</b><br>- Bern(p)<br>- $\Pr(X=0) = 1-p$<br>- $\Pr(X=1) = p$<br>- $E[X] = p$<br>- $\text{Var}(X) = p(1-p)$<br><b>binomial distribution</b><br>- Binom(n, p)<br>- $\Pr(X=k) = \binom{n}{k} p^k (1-p)^{n-k}$<br>- $E[X] = np$<br>- $\text{Var}(X) = np(1-p)$                                                                                                                          | <b>geometric distribution</b><br>- Geom(p)<br>- $\Pr(X=k) = p(1-p)^{k-1}$<br>- $E[X] = \frac{1}{p}$<br>- $\text{Var}(X) = \frac{1-p}{p^2}$<br><b>poisson distribution</b><br>- Poiss( $\lambda$ )<br>- $\Pr(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}$<br>- $E[X] = \lambda$<br>- $\text{Var}(X) = \lambda$<br><div><math>X \sim \text{Pois}(\lambda) + Y \sim \text{Pois}(\lambda_2) = \text{Pois}(\lambda + \lambda_2)</math></div> |
|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | <b>Markov's Inequality</b><br>- $P(X \geq c) \leq \frac{E(X)}{c}$                                                                                                                                                                                                                                                                                                                                         | <b>Chebyshev's Inequality</b><br>- $P( X-\mu  \geq c) \leq \frac{\text{Var}(X)}{c^2} = \frac{\sigma^2}{c^2} < \delta$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | <b>Central Limit Theorem</b><br><div><math>c \cdot \sigma \rightarrow 1 \quad c \cdot \sigma \rightarrow \frac{1}{2}</math></div> $P\left[\frac{S_n - n\mu}{\sigma/\sqrt{n}} \leq c\right] \rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^c e^{-x^2/2} dx \text{ as } n \rightarrow \infty \text{ where}$                                                                                                 |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>Probability Density Function (<math>f_X(x)</math>)</b><br>- $f_X(x) > 0$ for all x<br>- $\int_{-\infty}^{\infty} f_X(x) dx = 1$<br>- $P[a \leq X \leq b] = \int_a^b f_X(x) dx$                                                                                                                                                                                                                                                                                                                                                                                      | $Y = X_1 + \dots + X_N$ N is a RV<br>$E[Y] = E[E(Y N)]$<br>$= \sum_n E(Y N=n) P(N=n)$<br>$= \sum_n n E[X_i] P(N=n)$<br>$= E[X_i] E[N]$                                                                                                                                                                                                                                                                    | <b>Wald's Identity</b><br><b>Mean Squared Error</b><br>- $E[f(X)]$ where f is estimator<br><b>Ideal Estimation</b><br>- $E[Y X=x]$<br><b>Linear Least Squares Estimate</b><br>- $\text{LLSE}(Y X) = \frac{\text{Cov}(X,Y)}{\text{Var}(X)} (X - E[X]) + E[Y]$                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | $X_i$ has mean $\mu$ and variance $\sigma^2$ and<br>$S_n = \sum_{i=1}^n X_i, A_n = \frac{1}{n} \sum_{i=1}^n X_i$ $E[A_n] = \mu, \text{Var}(A_n) = \frac{\sigma^2}{n}$<br>as $n \rightarrow \infty, A_n \rightarrow N(\mu, \frac{\sigma^2}{n}), S_n \rightarrow N(n\mu, n\sigma^2)$<br>$\frac{A_n - \mu}{\sigma/\sqrt{n}} \rightarrow N(0, 1)$ , and $\frac{S_n - n\mu}{\sigma\sqrt{n}} \rightarrow N(0, 1)$ |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>Cumulative Density Function (<math>F_X(x)</math>)</b><br>- $F_X(x) = P[X \leq a] = \int_{-\infty}^a f_X(x) dx$<br>- $f_X(x) = \frac{d}{dx} F_X(x)$                                                                                                                                                                                                                                                                                                                                                                                                                  | <b>independence for continuous RVs</b><br>$P[a \leq X \leq b, c \leq Y \leq d]$<br>$= P[a \leq X \leq b] P[c \leq Y \leq d]$                                                                                                                                                                                                                                                                              | <b>bias- variance decomposition of MSE</b><br>- $E[(X - \hat{X})^2] = E[\delta^2 + 2\delta(\mu - \alpha) + (\mu - \alpha)^2]$<br>where $\delta = X - E[X]$<br>$= E[\delta^2] + 2(\mu - \alpha)E[\delta] + (\mu - \alpha)^2$<br>$= \text{Var}(X) + (\mu - \alpha)^2$                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | gives the <b>generalized Markov's inequality</b><br>$P( X - \alpha  \geq \epsilon) \leq \frac{\text{Var}(X) + (E[X] - \alpha)^2}{\epsilon^2}$                                                                                                                                                                                                                                                               |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>expected value</b><br>- $E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$<br><b>variance</b><br>- $\text{Var}(X) = E[(X - E[X])^2]$<br>$= E[X^2] - E[X]^2$<br>$= \int_{-\infty}^{\infty} x^2 f_X(x) dx - \left(\int_{-\infty}^{\infty} x f_X(x) dx\right)^2$<br><b>LOTUS</b><br>- $E[g(X)] = \int_{-\infty}^{\infty} g(x) f_X(x) dx$<br><b>Total Probability</b><br>- $P[A] = \int_{-\infty}^{\infty} P[A X=x] f_X(x) dx$                                                                                                                                                | <b>joint density</b><br>- $P[a \leq X \leq b, c \leq Y \leq d] = \int_c^d \int_a^b f_{X,Y}(x,y) dx dy$<br>- for independent RVs $f_{X,Y} = f_X(x) f_Y(y)$<br><b>marginal density</b><br>- $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$<br><b>conditional density</b><br>- $f_{Y X}(x,y) = \frac{f_{X,Y}(x,y)}{f_X(x)}$                                                                              | <b>invariant distribution</b>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | <b>Markov Chains</b>                                                                                                                                                                                                                                                                                                                                                                                        |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>uniform distribution</b><br>- Unif(a,b)<br>- pdf: $f_X(x) = \frac{1}{b-a}$ [a,b], 0 otherwise<br>- cdf: $F_X(x) = \frac{x-a}{b-a}$ [a,b], 0 otherwise<br>- $E[X] = \frac{1}{2}(a+b)$<br>- $\text{Var}(X) = \frac{1}{12}(b-a)^2$                                                                                                                                                                                                                                                                                                                                     | <b>normal distribution properties</b><br>$X \sim N(\mu, \sigma^2) \Rightarrow \frac{X-\mu}{\sigma} \sim N(0, 1)$<br>$\Rightarrow aX + b \sim N(a\mu + b, a^2\sigma^2)$<br>$aX + bY \sim N(a\mu_X + b\mu_Y, a^2\sigma_X^2 + b^2\sigma_Y^2)$<br>$\text{Var}(S_n) = E[S_n^2] - E[S_n]^2$<br>$= \sum_i E[X_i^2] + \sum_{i \neq j} E[X_i X_j] - E[nX_i]^2$<br>$= n E[X_i^2] + n(n-1)E[X_i X_j] - (n E[X_i])^2$ |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |                                                                                                                                                                                                                                                                                                                                                                                                             |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>normal distribution</b><br>- $N(\mu, \sigma^2)$<br>- pdf: $\frac{1}{\sqrt{2\pi}\sigma^2} e^{-(x-\mu)^2/(2\sigma^2)}$<br>- cdf: $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt$ for $N(0,1)$<br>- $E[X] = \mu$<br>- $\text{Var}(X) = \sigma^2$                                                                                                                                                                                                                                                                                                                |                                                                                                                                                                                                                                                                                                                                                                                                           |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |                                                                                                                                                                                                                                                                                                                                                                                                             |                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| <b>exponential distribution</b><br>- Exp( $\lambda$ )<br>- pdf: $f_X(x) = \lambda e^{-\lambda x}$ $x \geq 0$ , 0 otherwise<br>- cdf: $F_X(x) = 1 - e^{-\lambda x}$ $x \geq 0$ , 0 otherwise<br>- $E[X] = \frac{1}{\lambda}$<br>- $\text{Var}(X) = \frac{1}{\lambda^2}$                                                                                                                                                                                                                                                                                                 |                                                                                                                                                                                                                                                                                                                                                                                                           |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |                                                                                                                                                                                                                                                                                                                                                                                                             |                                                                                                                                                                                                                                                                                                                                                                                                                                      |