

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

### 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
  - $\neg(\forall x P(x)) \equiv \exists x \neg P(x)$
  - $\neg(\exists x P(x)) \equiv \forall x \neg P(x)$

### 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  $\Rightarrow (n \leq 2e) \Rightarrow (v/(2e/n) \geq e/2)$
- $(n=3) \Rightarrow (v \geq 3v-6)$ ,  $(n=4) \Rightarrow (e \leq 2v-4)$  (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
- $K_i$  is  $i$  colorable
- max deg 2  $\Rightarrow$  planar

### trees ( $T$ )

- iff:
  - connected + acyclic
  - connected +  $e = v-1$
  - connected + remove edge disconnects
  - acyclic + adding edge creates cycle
- Ts with  $\geq 2$  vertices must have at least 2 leaves
- all Ts 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  $v, r$  edges contains a cycle

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

### 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  $v, l = v, n$  iff connected and has EXACTLY 2 odd degree vertices

### eulerian tour (ET)

- 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

### stable matching

- matching is job optimal  $\Rightarrow$  it is also candidate pessimist
- PBR with jobs proposing  $\Rightarrow$  job optimal matching
- there is only ONE job/candidate optimal matching

### hypercubes (HC)

- bit string definition:  $V = n$  string bit strings,  $E = \{x, y \mid x$  and  $y$  differ in exactly one position)
- recursive definition:  $n$ -dim HC =  $(n-1)$ -dim HC (0 subcube) +  $(n-1)$ -dim HC with edges between each pair of vertices  $Dx$  in  $0$  subcube and  $Tx$  in  $1$  subcube
- $(n\text{-dim HC}) = (2^n \text{ vertices}) \Rightarrow (e = n \cdot 2^{n-1})$
- $(n \text{ vertices}) = (\log_2(n) \text{-dim HC}) = (e = \log_2(n) \cdot 2^{\log_2(n)-1} \text{ edges})$

### Chinese Remainder Theorem (CRT)

- given a system of  $k$  modular congruences,  $x \equiv a_i \pmod{m_i}$  where  $m_i$  are all coprime ( $\gcd(m_i) = 1$ ), there exists a unique solution for  $x$

$$\text{ex: } x \equiv 1 \pmod{3}, x \equiv 3 \pmod{7}, x \equiv 4 \pmod{11}.$$

$$\begin{array}{ll} a: 77 \pmod{147} & b: 33 \pmod{49} \\ \begin{matrix} 55 \\ 28 \\ 2 \end{matrix} & \begin{matrix} 14 \\ 10 \\ 15 \end{matrix} \\ c \equiv 0 \pmod{33} & c \equiv 0 \pmod{77} \\ \begin{matrix} 2 \\ 1 \end{matrix} & \begin{matrix} 1 \\ 1 \end{matrix} \\ x = (1 \cdot a + (5)(b) + (4)(c)) \pmod{147} & \\ \equiv [24] & \end{array}$$

### modular arithmetic rules

- if  $a \equiv c \pmod{m}$  &  $b \equiv d \pmod{m}$
- $a+b \equiv c+d \pmod{m}$
- $a \cdot b \equiv c \cdot d \pmod{m}$
- $a \cdot k \equiv b \cdot k \pmod{m}$

$$\text{if } a \equiv c \pmod{m};$$

you can divide by both sides AND  $m$  by  $k$

$$\text{ex: } 2x \equiv 4 \pmod{12} \Rightarrow x \equiv 2 \pmod{6}$$

you can also multiply both sides by a MI

$$\text{ex: } 8x \equiv 4 \pmod{16} \Rightarrow x \equiv 18 \equiv 3 \pmod{5}$$

$$\gcd(x,y) = 1 \wedge xy \neq 0 \Rightarrow x \equiv 1$$

- 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 polynomials
- |         |           |
|---------|-----------|
| $d+1$   | 1         |
| 4       | $m$       |
| $d-1$   | $m^2$     |
| $\dots$ | $\dots$   |
| $d-k$   | $m^{d+1}$ |
| $\dots$ | $m^{d+1}$ |
| 0       | $m^{d+1}$ |
- error correcting codes**
- erasure errors:
    - $n$  packets,  $k$  dropped
    - packets labelled so recipient knows exactly which packets are dropped
    - must send  $n$  packets, where each packet is  $n$  is a number in GF
    - general error:
      - $n$  packets,  $k$  corrupted, must send  $n+k$  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

### bi-partite 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 bi-partite 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.

$$(17, 39) \rightarrow (17, 12) \rightarrow (5, 12) \rightarrow (5, 7) \rightarrow (1, 7) \rightarrow (1, 1)$$

**ex:** find the MI of 17 mod 39.

$$\begin{array}{l} (1) 39 : (0) 17 = 39 \\ (0) 39 : (1) 17 = 17 \\ (0) 39 : (0) 17 = 17 \\ (0) 39 : (0) 17 = 17 \\ (0) 39 : (0) 17 = 17 \\ (0) 39 : (0) 17 = 17 \end{array}$$

$$17^{-1} \equiv -16 \pmod{39}$$

### Euler's Totient Function & Theorem

- totient function:  $\phi(n) = \#\{1 \leq i \leq n, \gcd(n, i) = 1\}$
- totient theorem:  $a^{\phi(n)} \equiv 1 \pmod{n}$

properties:

- $\phi(p) = p-1$  for prime  $p$
- $\phi(p^k) = p^k - p^{k-1}$
- $\phi(ab) = \phi(a)\phi(b)$

$$\phi(p^k) = p^k - p^{k-1}$$

### LaGrange Interpolation

- create  $P$ s that go through  $(x_1, y_1)$  and  $(x_j, y_j)$  for all  $j = i$
- add linear combination of sub  $P$ s to get desired  $P$

ex:  $(1, 1), (2, 2), (3, 3)$

$$\Delta_1 = \frac{(x-2)(x-3)}{(1-2)(1-3)}, \Delta_2 = \frac{(x-1)(x-3)}{(2-1)(2-3)}, \Delta_3 = \frac{(x-1)(x-2)}{(3-1)(3-2)}$$

$$P = \Delta_1 + 2\Delta_2 + 3\Delta_3 \quad \text{do arithmetic mod } p!!!$$

### RSA

- variables:
  - $x$  (mod  $N$ ): message
  - $y$  (mod  $N$ ): encrypted,  $\equiv x^e \pmod{N}$
  - $E(x) \equiv x^e \pmod{N}$
  - $D(y) \equiv D(x) \equiv x^{\phi(N)} \pmod{N}$  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 & relatively prime to  $(p-1)(q-1)$

### Berlekamp-Massey Algorithm

- $E(x) = (x-e_1)(x-e_2) \dots (x-e_d)$  error locator  $P$
- $Q(x) = P(x)E(x)$ ,  $Q(i) = P(i)E(i) = N \equiv E(i)$

ex: received  $(0, 1, 4, 0, 4)$  w/ one error

$$Q(0) = 0E(0) \quad a_0 = 0$$

$$Q(1) = 1E(1) \quad a_3 + a_2 + a_1 = 1 - e$$

$$Q(2) = 4E(2) \quad 8a_3 + 4a_2 + 1a_1 = 8 - 4e$$

$$Q(3) = 0E(3) \quad 27a_3 + 9a_2 + 3a_1 = 0$$

$$Q(4) = 4E(4) \quad 64a_3 + 16a_2 + 4a_1 = 16 - 4e$$

### halting problem

- to show  $\text{TestX}(Q, y)$  which determines whether  $Q$  does some task  $X$  on input  $y$

```
def TestXhalt(P, x)
  def Q(y)
    run P(x)
    do X
  return TestX(Q, y)
```

### 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

### bijections

- $f: A \rightarrow B$  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  $B$
- onto (surjective): every element in  $B$  has a pre-image in  $A$

one-to-one



onto



<b>probability and independence formulas</b> <ul style="list-style-type: none"> <li>- conditional probability: <math>P[A B] = \frac{P[A \cap B]}{P[B]}</math></li> <li>- total probability: <math>P[A] = \sum_{i=0}^n P[B_i A] P[A]</math></li> <li>- Bayes Theorem: <math>P[A B] = \frac{P[B A] P[A]}{P[B]}</math></li> <li>- product rule: <math>P[A \cap B] = P[A] P[B A]</math></li> <li>- pairwise independence: <math>P[A B] = P[A]</math></li> <li>- pairwise independence: <math>P[A \cap B] = P[A] P[B]</math></li> <li>- mutual independence: <math>P[\bigcap_{i \in I} A_i] = \prod_{i \in I} P[A_i]</math> pairwise I does not imply mutual I</li> <li>- union bound: <math>P[\bigcup_{i=1}^n A_i] \leq \sum_{i=1}^n P[A_i]</math></li> </ul>	<b>expected value formulas</b> <ul style="list-style-type: none"> <li>- <math>E[X] = \sum k \cdot P(X=k)</math></li> <li>- linearity of expectation:       <ul style="list-style-type: none"> <li>- <math>E[X+Y] = E[X] + E[Y]</math></li> <li>- <math>E[EX] = E[X]</math></li> </ul> </li> <li>- LOTUS: <math>E[fc(x)] = \sum f(k) P(X=k)</math></li> </ul> <b>Markov's Inequality</b> <ul style="list-style-type: none"> <li>- <math>P(X \geq c) \leq \frac{E(X)}{c}</math></li> </ul> <b>Chebyshev's Inequality</b> <ul style="list-style-type: none"> <li>- <math>P[ X-\mu  \geq c] \leq \frac{\text{Var}(X)}{c^2} = \frac{\sigma^2}{c^2} &lt; \delta</math></li> </ul>	<b>variance formulas</b> <ul style="list-style-type: none"> <li>- <math>\text{Var}(X) = E[(X-E[X])^2]</math></li> <li>- <math>\text{Var}(X) = E[X^2] - (E[X])^2</math></li> <li>- <math>\text{Var}(X+Y) = V(X)+V(Y)+2\text{Cov}(X,Y)</math></li> <li>- <math>\text{Var}(cX) = c^2 \text{Var}(X)</math></li> <li>- <math>\text{Cov}(X,Y) = E[(X-E[X])(Y-E[Y])]</math></li> <li>- <math>\text{Cov}(X,Y) = E[XY] - E[X]E[Y]</math></li> <li>- <math>\text{Cov}(X,X) = \text{Var}(X)</math></li> <li>- Independent <math>\Rightarrow \text{Cov}(X,Y) = 0</math></li> <li>- <math>\text{Cov}(X,Y) = 0 \not\Rightarrow \text{Independent}</math></li> <li>- <math>\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y}</math></li> </ul> <b>bernoulli distribution</b> <ul style="list-style-type: none"> <li>- Bern(p)</li> <li>- <math>\Pr(X=0) = 1-p</math></li> <li>- <math>\Pr(X=1) = p</math></li> <li>- <math>E[X] = p</math></li> <li>- <math>\text{Var}(X) = p(1-p)</math></li> </ul> <b>binomial distribution</b> <ul style="list-style-type: none"> <li>- Binom(n, p)</li> <li>- <math>\Pr(X=k) = \binom{n}{k} p^k (1-p)^{n-k}</math></li> <li>- <math>E[X] = np</math></li> <li>- <math>\text{Var}(X) = np(1-p)</math></li> </ul>		<b>geometric distribution</b> <ul style="list-style-type: none"> <li>- Geom(p)</li> <li>- <math>\Pr(X=k) = p(1-p)^{k-1}</math></li> <li>- <math>E[X] = \frac{1-p}{p}</math></li> <li>- <math>\text{Var}(X) = \frac{1-p}{p^2}</math></li> </ul> <b>poisson distribution</b> <ul style="list-style-type: none"> <li>- Poiss(λ)</li> <li>- <math>\Pr(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}</math></li> <li>- <math>E[X] = \lambda</math></li> <li>- <math>\text{Var}(X) = \lambda</math></li> </ul>
<b>Probability Density Function (<math>f_n(x)</math>)</b> <ul style="list-style-type: none"> <li>- <math>f_n(x) &gt; 0</math> for all x</li> <li>- <math>\int_{-\infty}^{\infty} f_n(x) dx = 1</math></li> <li>- <math>P[a \leq X \leq b] = \int_a^b f_n(x) dx</math></li> </ul> <b>Cumulative Density Function (<math>F_n(x)</math>)</b> <ul style="list-style-type: none"> <li>- <math>F_n(x) = P[X \leq x] = \int_{-\infty}^x f_n(t) dt</math></li> <li>- <math>F_n(x) = \frac{d}{dx} F_n(x)</math></li> </ul>	<b>Wald's Identity</b> <ul style="list-style-type: none"> <li><math>Y = X_1 + \dots + X_N</math> <math>N</math> is a RV</li> <li><math>E[Y] = E[E[Y N]]</math></li> <li><math>= \sum_n E[Y N=n] P(N=n)</math></li> <li><math>= \sum_n n E[X] P(N=n)</math></li> <li><math>= E[X] E[N]</math></li> </ul> <b>Independence for continuous RVs</b> <ul style="list-style-type: none"> <li><math>P[a \leq X \leq b, c \leq Y \leq d] = P[a \leq X \leq b] P[c \leq Y \leq d]</math></li> </ul>	<b>Mean Squared Error</b> <ul style="list-style-type: none"> <li>- <math>E[f(X) - f(\bar{X})]</math> where f is estimator</li> <li>- <math>E[Y X=x]</math></li> </ul> <b>Linear Least Squares Estimate</b> <ul style="list-style-type: none"> <li>- LLSE(<math>\hat{Y}</math>) = <math>\frac{\text{Cov}(X,Y)}{\text{Var}(X)} (X - E[X]) + E[Y]</math></li> </ul> <b>bias-variance decomposition of MSE</b> <ul style="list-style-type: none"> <li>- <math>E[(X-\alpha)^2] = E[\delta^2 + 2\delta(\mu-\alpha) + (\mu-\alpha)^2]</math> where <math>\delta = X - E[X]</math></li> <li>- <math>= E[\delta^2] + 2(\mu-\alpha)E[\delta] + (\mu-\alpha)^2</math></li> <li>- <math>= \text{Var}(X) + (\mu-\alpha)^2</math></li> </ul>	$X_i$ has mean $\mu$ and variance $\sigma^2$ and $S_n = \frac{1}{n} \sum_{i=1}^n X_i$ , $A_n = \frac{1}{n} \sum_{i=1}^n A_i$ , $E[A_n] = \mu$ , $\text{Var}(A_n) = \frac{\sigma^2}{n}$ as $n \rightarrow \infty$ , $A_n \rightarrow N(\mu, \frac{\sigma^2}{n})$ , $S_n \rightarrow N(\mu, n \sigma^2)$ $A_n - \mu \over \sigma/\sqrt{n} \rightarrow N(0, 1)$ , and $S_n - n\mu \over \sigma\sqrt{n} \rightarrow N(0, 1)$ gives the generalized Markov's inequality	
<b>expected value</b> <ul style="list-style-type: none"> <li>- <math>E[X] = \int_{-\infty}^{\infty} x f(x) dx</math></li> </ul> <b>variance</b> <ul style="list-style-type: none"> <li>- <math>\text{Var}(X) = E[(X-E[X])^2] = E[X^2] - (E[X])^2</math></li> <li>- <math>= \int_{-\infty}^{\infty} x^2 f(x) dx - (\int_{-\infty}^{\infty} x f(x) dx)^2</math></li> </ul> <b>LOTUS</b> <ul style="list-style-type: none"> <li>- <math>E[g(X)] = \int_{-\infty}^{\infty} g(x) f_X(x) dx</math></li> </ul> <b>Total Probability</b> <ul style="list-style-type: none"> <li>- <math>P[A] = \int_{-\infty}^{\infty} P[A X=x] f_X(x) dx</math></li> </ul>	<b>joint density</b> <ul style="list-style-type: none"> <li>- <math>P[a \leq X \leq b, c \leq Y \leq d] = \int_c^d \int_a^b f(x,y) dx dy</math></li> <li>- for independent RVs <math>f(x,y) = f_x(x) f_y(y)</math></li> </ul> <b>marginal density</b> <ul style="list-style-type: none"> <li>- <math>f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy</math></li> </ul> <b>conditional density</b> <ul style="list-style-type: none"> <li>- <math>f_{Y X}(x,y) = \frac{f_{X,Y}(x,y)}{f_X(x)}</math></li> </ul>	<b>invariant distribution</b>		
<b>uniform distribution</b> <ul style="list-style-type: none"> <li>- Unif(a,b)</li> <li>- pdf: <math>f_X(x) = \frac{1}{b-a}</math> <math>[a,b]</math>, 0 otherwise</li> <li>- cdf: <math>F_X(x) = \frac{x-a}{b-a}</math> <math>[a,b]</math>, 0 otherwise</li> <li>- <math>E[X] = \frac{1}{2}(a+b)</math></li> <li>- <math>\text{Var}(X) = \frac{1}{12}(b-a)^2</math></li> </ul> <b>normal distribution</b> <ul style="list-style-type: none"> <li>- <math>N(\mu, \sigma^2)</math></li> <li>- pdf: <math>\frac{1}{\sqrt{2\pi}\sigma^2} e^{-(x-\mu)^2/(2\sigma^2)}</math></li> <li>- cdf: <math>\frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt \sim N(0,1)</math> for <math>t = \frac{x-\mu}{\sigma}</math></li> <li>- <math>E[X] = \mu</math></li> <li>- <math>\text{Var}(X) = \sigma^2</math></li> </ul> <b>exponential distribution</b> <ul style="list-style-type: none"> <li>- <math>\text{Exp}(\lambda)</math></li> <li>- pdf: <math>f_X(x) = \lambda e^{-\lambda x}</math> <math>x \geq 0</math>, 0 otherwise</li> <li>- cdf: <math>F_X(x) = 1 - e^{-\lambda x}</math> <math>x \geq 0</math>, 0 otherwise</li> <li>- <math>E[X] = \frac{1}{\lambda}</math></li> <li>- <math>\text{Var}(X) = \frac{1}{\lambda^2}</math></li> </ul>	<b>normal distribution properties</b> <ul style="list-style-type: none"> <li>- <math>X \sim N(\mu, \sigma^2) \Rightarrow \frac{X-\mu}{\sigma} \sim N(0, 1)</math></li> <li>- <math>\Rightarrow \alpha X + b \sim N(\alpha\mu + b, \alpha^2 \sigma^2)</math></li> <li>- <math>\alpha X + b Y \sim N(\alpha\mu_X + b\mu_Y, \alpha^2 \sigma_X^2 + b^2 \sigma_Y^2)</math></li> </ul> $\text{Var}(S_n) = E[S_n^2] - E[S_n]^2$ <ul style="list-style-type: none"> <li>- <math>= \sum_i E[X_i^2] + \sum_{i,j} E[X_i X_j] \cdot E[n X_i]^2</math></li> <li>- <math>= n E[X_i^2] + n(n-1)E[X_i X_j] \cdot (n E[X_i])^2</math></li> </ul>	<b>Markov Chains</b>		