

# Optimal Gaussian Partitions with Application and Open Problems

Elchanan Mossel

UC Berkeley

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## Optimal Gaussian Partitions

How to partition

- $\mathbb{R}^n$  ( $n$  is unbounded)
- into  $r \times q$  parts  $f_i^{-1}(a)$  for  $1 \leq i \leq r$  and  $1 \leq a \leq q$ ,
- of prescribed Gaussian measures  $m_{i,a}$  with  $\sum_a m_{i,a} = 1$ ,
- such that  $r$  Gaussian vectors  $X_1, \dots, X_r \in \mathbb{R}^n$  with prescribed covariance structure  $\text{Cov}(X_i, X_j) = V_{i,j} I_n$
- maximize the expected value of "combinatorial quantity" depending only on  $(f_i(X_j))_{i=1}^r$ .

## Notes

- An asymptotic geometric problem (dimension is unbounded).
- value increases with dimension, maximum is supremum.

## Optimal Gaussian Partition

Given:

- $H : [q]^r \rightarrow \mathbb{R}$  (combinatorial weights)
- $m \in M_{r \times q}$  a stochastic matrix (parts sizes).
- $0 \leq V \in M_{r \times r}$  with  $V_{i,i} = 1$  for all  $i$  (covariance structure).

Define

$$M(H, m, V) := \sup \mathbb{E}[H(f_1(X_1), \dots, f_r(X_r))]$$

where the sup is taken over all

- dimensions  $n$ ,
- $f_i : \mathbb{R}^n \rightarrow [q]$  s.t.
- $\mathbb{P}[f_i(X) = a] = m_{i,a}$  for all  $1 \leq i \leq r$  and  $1 \leq a \leq q$ .
- $X_1, \dots, X_r \in \mathbb{R}^n$  are jointly Gaussian with  $\text{Cov}[X_i, X_j] = V_{i,j} I_n$ .

# What's known? $q = 2$ parts with $r = 2$

Thm: (C. Borell 1985)

When  $r = 2, q = 2$ , general  $m$  and

$$H(a, b) = 1(a = b), \quad V = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}, \rho > 0$$

Maximum is obtained in dimension  $n = 1$  and

$$f_i(x) = \begin{cases} 1 & x < t. \\ 2 & x \geq t. \end{cases}, \quad P[X > t] = m_{i,2}.$$

In words

Partition of  $\mathbb{R}^n$  into two parts of equal measure which maximizes the probability that two correlated Gaussians will fall in the same part is given by a half-space.

# What's known? $q = 2$ parts with general $r$

Thm: (Isaksson-M 2011)

When  $r \geq 2$ ,  $q = 2$ ,  $m = (m_1, m_2)$ ,  
 $H(a, b, c, \dots) = 1(a = b = c = \dots)$  and

$$V = \begin{pmatrix} 1 & \rho & \dots & \rho \\ \rho & 1 & \rho \dots & \\ \vdots & \ddots & \ddots & \dots \end{pmatrix}, \rho > 0$$

Maximum is obtained in dimension  $n = 1$  and

$$f_i(x) = \begin{cases} 1 & x < t. \\ 2 & x \geq t. \end{cases}, \quad P[X > t] = m_{i,2}.$$

What else is known?

Nothing.

## Borell's proof (1985)

Ehrhard symmetrization.

## Isaksson-M approach (2011)

- Formulate a spherical statement.
- Prove Spherical Statement using Rearrangement Inequalities.
- Project to a small number of coordinates to obtain Gaussian results

# Spherical Statement

## Spherical Partition Problem

Given  $n$ ,  $0 \leq \Sigma \in \mathbb{R}^{k \times k}$ ,  $(m_1, \dots, m_k) \in (0, 1)^k$ , Find  
 $\sup P(X_1 \in A_1, \dots, X_k \in A_k)$  where

- $X'_1, \dots, X'_k$  are jointly normal with  $\text{Cov}(X'_i, X'_j) = \Sigma_{i,j} I_n$
- $X_i = \frac{X'_i}{\|X'_i\|_2}$
- $\sup$  is over  $A_i$  with  $\mu(X_i \in A_i) = m_i$  where  $\mu$  is the Haar measure on the  $(n-1)$ -sphere.

## Thm: Optimal Spherical Partition

If  $\Sigma_{i,j}^{-1} \leq 0$  for all  $i \neq j$  then:

$$P(X_1 \in A_1, \dots, X_k \in A_k) \leq P(X_1 \in H_1, \dots, X_k \in H_k),$$

where  $H_i = \{x : x_1 \leq a_1\}$  with  $\mu(H_i) = \mu(A_i) = m_i$ .

# Optimal Spherical Partition - Proof Sketch

Express  $P(X_1 \in A_1, \dots, X_k \in A_k)$  in terms of independent normals  $Z_i \sim N(0, c_i I_n)$ . Writing  $W_i = Z_i / \|Z_i\|_2$  to obtain

$$C_1 \mathbb{E} \left[ \mathbf{1}_{\{W_1 \in A_1, \dots, W_k \in A_k\}} \prod_{1 \leq i < j \leq k} e^{-(\Sigma^{-1})_{i,j} \langle Z_i, Z_j \rangle} \right] =$$

$$C_1 \mathbb{E} \left[ \mathbf{1}_{\{W_1 \in A_1, \dots, W_k \in A_k\}} \prod_{1 \leq i < j \leq k} e^{-(\Sigma^{-1})_{i,j} \langle W_i, W_j \rangle \|Z_i\|_2 \|Z_j\|_2} \right]$$

Conditioned on  $\|Z_i\|_2$ ,  $W_i$  are uniformly distributed on the sphere and  $\langle W_i, W_j \rangle$  decreases in  $\|W_i - W_j\|$ .

Therefore can apply extended Riesz Inequality (Burchard-01, Morpurgo-02) to conclude maximum is obtained for half-spaces  $H_i$ .



# Optimal Gaussian Partitions

- Take  $n \leq m \rightarrow \infty$ .
- $X_i \in S^{m-1}$ ,  $Y_i \in R^n$  with the same covariance structure  $\Sigma$ .
- $Z_i =$  first  $n$  coordinates of  $X_i$ .
- $\sqrt{m}(Z_1, \dots, Z_k) \rightarrow_{m \rightarrow \infty} (Y_1, \dots, Y_k)$  in distribution.
- Spherical bound implies Gaussian bound.
- Some approximation arguments needed when sets are not closed.

# Open Problem 1 - Finite Dimensionality?

## 1. Finite dimensionality

Is the supremum  $M(H, m, V)$  a maximum? Is it obtained in a finite dimension?

### 1.a Finite dimensionality variant

Same question assuming  $f_s = f_1$  and  $m_{s,j} = m_{1,j}$  for  $1 \leq s \leq r$ ?  
(Conj. of O. Regev:  $n = \infty$  for  $r = 2, q = 2, H(a, b) = 1(a \neq b)$ ).

### Comment : Approximate Finite Dimensionality

Find explicit  $n(\epsilon, H)$  or  $n(\epsilon, H, m, V)$  such that sup in dimension  $n$  is  $\epsilon$  close to  $M(H, m, V)$ ? (Seems doable using dimension reduction ideas (see Raghavendra-Steurer-09)).

# Open Problem 2 - Other Optimal partitions?

## More Examples

Find other optimal Gaussian partitions!

## The Standard Simplex Conjecture (Isaksson-M-11)

Suppose  $X, Y \sim N(0, I_n)$  and  $\text{Cov}(X, Y) = \rho I_n$ . Let  $A_1, \dots, A_q \subseteq \mathbb{R}^n$  be a partition of  $\mathbb{R}^n$  and  $S_1, \dots, S_q \subseteq \mathbb{R}^n$  a standard simplex partition. Then,

i) If  $\rho \geq 0$  and  $A_1, \dots, A_q$  is *balanced*, then

$$\mathbb{P}((X, Y) \in A_1^2 \cup \dots \cup A_q^2) \leq \mathbb{P}((X, Y) \in S_1^2 \cup \dots \cup S_q^2) \quad (1)$$

ii) If  $\rho < 0$ :

$$\mathbb{P}((X, Y) \in A_1^2 \cup \dots \cup A_q^2) \geq \mathbb{P}((X, Y) \in S_1^2 \cup \dots \cup S_q^2) \quad (2)$$

# The Standard Simplex Partition

## definition

For  $n+1 \geq q \geq 2$ ,  $A_1, \dots, A_q$  is a *standard simplex partition* of  $\mathbb{R}^n$  if for all  $i$

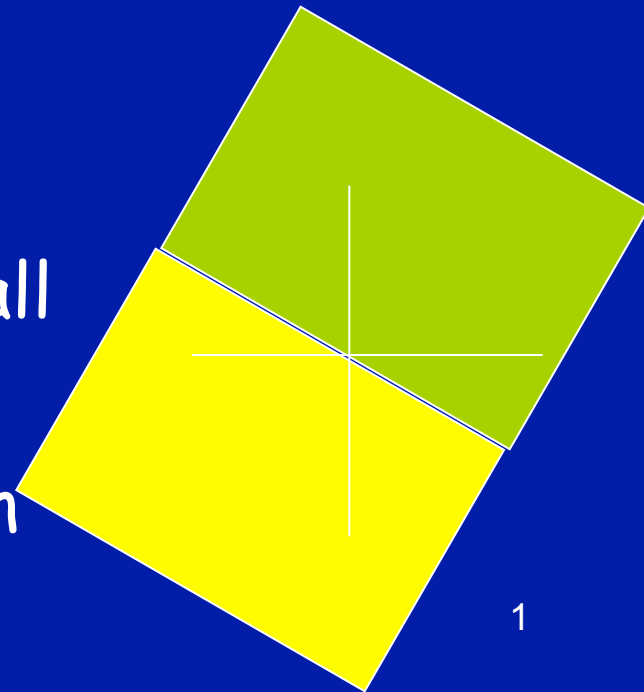
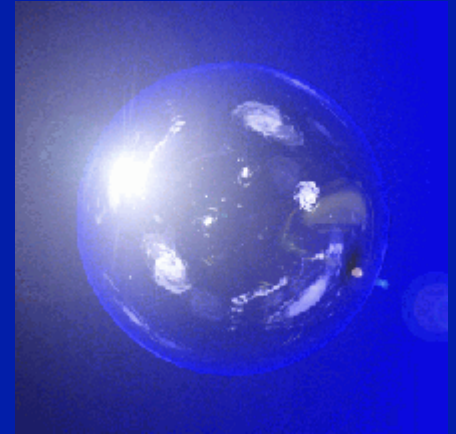
$$A_i \supseteq \{x \in \mathbb{R}^n \mid x \cdot a_i > x \cdot a_j, \forall j \neq i\} \quad (3)$$

where  $a_1, \dots, a_q \in \mathbb{R}^n$  are  $q$  vectors satisfying

$$a_i \cdot a_j = \begin{cases} 1 & \text{if } i = j \\ -\frac{1}{q-1} & \text{if } i \neq j \end{cases} \quad (4)$$

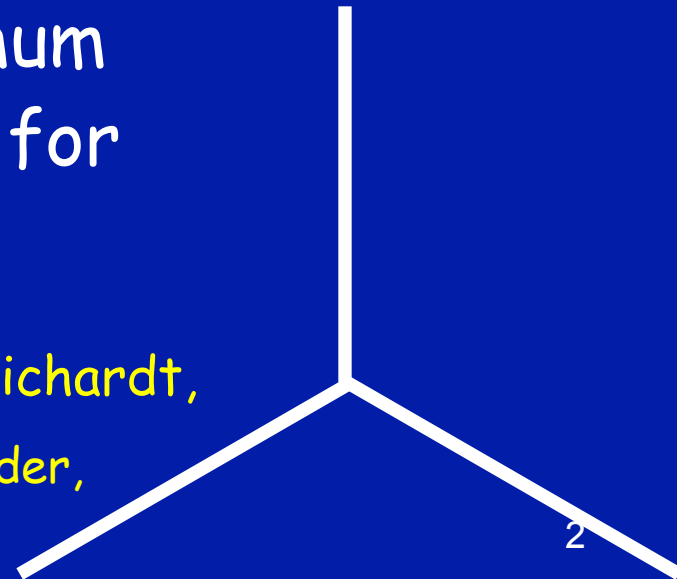
# Isoperimetric context

- I. Ancient: Among all sets with  $v_n(A) = 1$  the minimizer of  $v_{n-1}(\partial A)$  is  $A = \text{Ball}$ .
- II. Recent (Borell, Sudakov-Tsierlson 70's) Among all sets with  $\gamma_n(A) = a$  the minimizer of  $\gamma_{n-1}(\partial A)$  is  $A = \text{Half-Space}$ .
- III. More recent (Borell 85): For all  $\rho$ , among all sets with  $\gamma(A) = a$  the maximizer of  $E[A(N)A(M)]$  is given by  $A = \text{Half-Space}$ .



# Double bubbles

- Thm1 (“Double-Bubble”):
- Among all pairs of disjoint sets  $A, B$  with  $v_n(A) = a$   $v_n(B) = b$ , the minimizer of  $v_{n-1}(\partial A \cup \partial B)$  is a “Double Bubble”
- Thm2 (“Peace Sign”):
- Among all partitions  $A, B, C$  of  $\mathbb{R}^n$  with  $\gamma(A) = \gamma(B) = \gamma(C) = 1/3$ , the minimum of  $\gamma(\partial A \cup \partial B \cup \partial C)$  is obtained for the “Peace Sign”
- 1. Hutchings, Morgan, Ritore, Ros. + Reichardt, Heilmann, Lai, Spielman 2. Corneli, Corwin, Hurder, Sesum, Xu, Adams, Dvais, Lee, Vissochi



# Newer Isoperimetric Results

- Conj (Isaksson-M, Israel J. Math 2011):

For all  $0 \leq \rho \leq 1$ :

$$\operatorname{argmax} E[A(X)A(Y) + B(X)B(Y) + C(X)C(Y)]$$

= “Peace Sign”



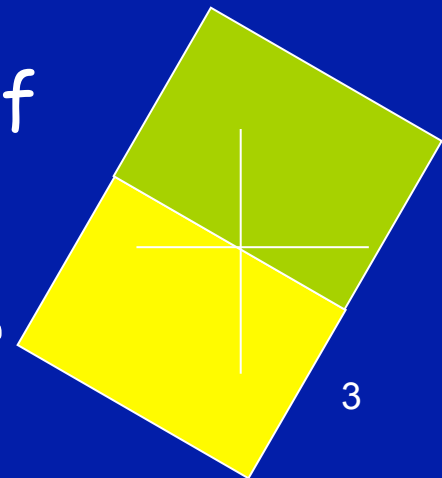
Peace sign

where max is over all partitions  $(A, B, C)$  of  $\mathbb{R}^n$  with  $\gamma_n(A) = \gamma_n(B) = \gamma_n(C) = 1/3$  is

Later we'll see applications

- Challenges:

- Can one extend the double bubble proof to the Gaussian setup?
- Develop symmetrisation techniques for partition into 3 parts.



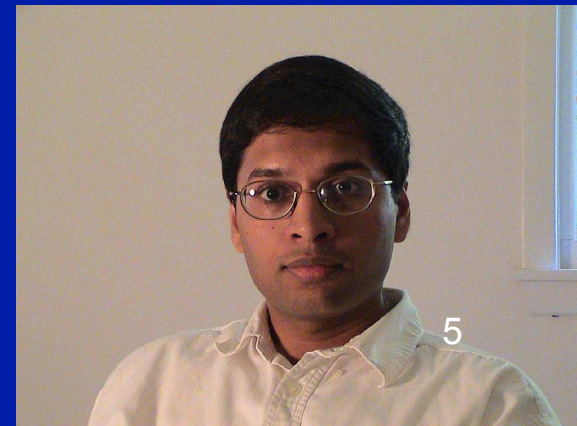
# Motivation

- Approximate Optimization
  - Unique Games and Optimization.
- Quantitative Social choice
  - Quantitative Arrow theorem.



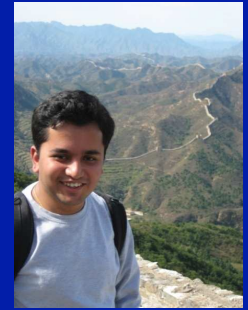
# Approximate Optimization

- Many optimization problems are NP-hard.
- Instead: Approximation algorithms
- These are algorithms that guarantee to give a solution which is at least
- $\alpha \text{ OPT}$  or  $\text{OPT} - \epsilon$ .
- S. Khot (2002) invented a new paradigm for analyzing approximation algorithms - called UGC (Unique Games Conjecture)



# Other Approximation problems

- Work of KKM04, MOO-05 gives best approximation factor for Max-Cut.
- Crucially uses Borell's optimal partition.
- A second result using Invariance of M 08;10
- Raghavendra 08: Duality between Algorithms and Hardness for Constraint Satisfaction Problems.
- $\Rightarrow$  Solution to Gaussian partition problem implies "best" approximation factor/ algorithm for the corresponding optimization problem.

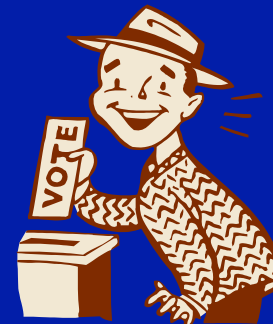


# Majority is Stablest

- Let  $(X_i, Y_i) \in \{-1, 1\}^n$  &  $E[X_i] = E[Y_i] = 0$ ;  $E[X_i Y_i] = \rho$ .
- Let  $\text{Maj}(x) = \text{sgn}(\sum x_i)$ .
- Thm (Sheffield 1899):
- $E[\text{Maj}(X) \text{Maj}(Y)] \rightarrow M(\rho) := (2 \arcsin \rho)/\pi$
- Thm (MOO; “Majority is Stablest”):
- Let  $f : \{-1, 1\}^n \rightarrow \{-1, 1\}$  with  $E[f] = 0$ .
- $I_i(f) := P[f(X_1, \dots, X_i, \dots, X_n) \neq f(X_1, \dots, -X_i, \dots, X_n)]$ ,
- $I = \max I_i(f)$
- Then:  $E[f(X) f(Y)] \leq M(\rho) + C/\log^2(1/I)$
- Proof follows Borell's result and invariance.

## Quantitative Social Choice

- Quantitative social choice studies different voting methods in a quantitative way.
- Standard assumption is of uniform voting probability.
- A "stress-test" distribution  
Bias distributions are not sensitive to errors/manipulation/paradoxes etc.
- Consider general voting rule  
 $f: \{-1,1\}^n \rightarrow \{-1,1\}$  or  $f: [q]^n \rightarrow [q]$  etc.



## Errors in Voting

- Suppose each vote is re-randomized with probability  $\epsilon$  (by voting machine):
- Majority is Stablest (MOO 05;10):
- Majority minimizes probability of error in outcome among low influence functions.
- Follows from Borll's partition result.
- Plurality is Stablest (IM) 11:
- The statement that
- Plurality minimizes probability of error in outcome among low influence functions is equivalent to
- Peace-Sign conjecture.



## Errors in Voting

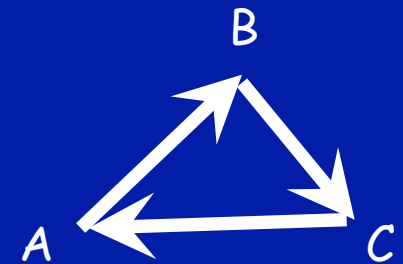
- Majority is Most Predictable (M 08; 10):
- Suppose each voter is in a poll with prob.  $p$  independently.
- Majority is most predictable from poll among all low influence functions.
- Next Example - Arrow theorem
- Fundamental theorem of modern social choice.



# Condorcet Paradox



- $n$  voters are to choose between 3 options / candidates.
- Voter  $i$  ranks the three candidates  $A, B$  &  $C$  via a permutation  $\sigma_i \in S_3$
- Let  $x^{AB}_i = +1$  if  $\sigma_i(A) > \sigma_i(B)$   
 $x^{AB}_i = -1$  if  $\sigma_i(B) > \sigma_i(A)$
- Aggregate rankings via:  $f, g, h : \{-1, 1\}^n \rightarrow \{-1, 1\}$ .
- Thus:  $A$  is preferred over  $B$  if  $f(x^{AB}) = 1$ .
- A **Condorcet Paradox** occurs if:  
 $f(x^{AB}) = g(x^{BC}) = h(x^{CA})$ .
- Defined by Marquis de Condorcet in 18' th century.





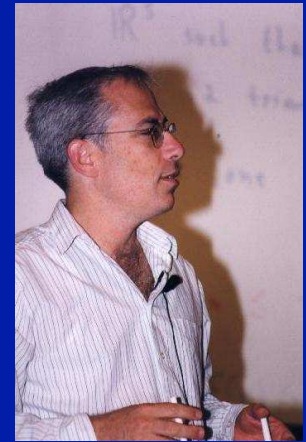
# Arrow's Impossibility Thm

- Thm (Condorcet): If  $n > 2$  and  $f$  is the majority function then there exists rankings  $\sigma_1, \dots, \sigma_n$  resulting in a Paradox
- Thm (Arrow's Impossibility): For all  $n > 1$ , unless  $f$  is the dictator function, there exist rankings  $\sigma_1, \dots, \sigma_n$  resulting in a paradox.
- Arrow received the Nobel prize (72)





# Probability of a Paradox



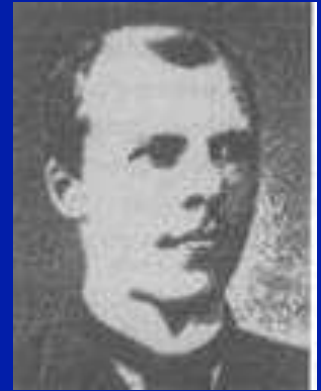
- What is the probability of a **paradox**:
- $PDX(f) = P[f(x^{AB}) = f(x^{BC}) = f(x^{CA})]$ ?
- Arrow's:  $f = \text{dictator}$  iff  $PDX(f) = 0$ .
- Thm(Kalai 02): Majority is Stablest for  $\rho=1/3 \Rightarrow$  majority minimizes probability of paradox among low influences functions (7-8%).
- Thm(Isacsson-M 11): Majority maximizes probability of a unique winner for any number of alternatives.
- (Proof uses invariance + Exchangeable Gaussian Theorem)

# Summary

- Prove the "Peace Sign Conjecture" (Isoperimetry)
- $\Rightarrow$  "Plurality is Stablest" (Low Inf Bounds)
- $\Rightarrow$  MAX-3-CUT hardness (CS) and voting.
- +  $\Rightarrow$  New isoperimetric results.



# Lindeberg & Berry Esseen



- Let  $X_i = +/-$  w.p  $\frac{1}{2}$  ,  $N_i \sim N(0,1)$  ind.
- $f(x) = \sum_{i=1}^n c_i x_i$  with  $\sum c_i^2 = 1$ .
- Thm: (Berry Esseen CLT):
- $\sup_t |P[f(X) \leq t] - P[f(N) \leq t]| \leq 3 \max |c_i|$
- Note that  $f(N) = f(N_1, \dots, N_n) \sim N(0,1)$ .
- Lindeberg idea: can replace  $X_i$  with  $N_i$  as long as all coefficients are small.
- Q: can this be done for other functions  $f$ ?  
e.g. polynomials?

# Some Examples

- Q: Is it possible to apply Lindeberg principle to other functions with small coefficients?
- Ex 1:  $f(x) = (n^3/6)^{-1/2} \sum_{i < j < k} x_i x_j x_k \rightarrow \text{Okay}$
- Limit is  $N^3 - 3N$
- Ex 2:  $f(x) = (2n)^{-1/2} (x_1 - x_2) (x_1 + \dots + x_n) \rightarrow \text{Not OK}$
- For  $X$ :  $P[f(X) = 0] \geq \frac{1}{2}$ .

# Invariance Principle

- Thm (MOO := M-O' Donnell-Oleszkiewicz; FOCS05, Ann. Math10):
- Let  $Q(x) = \sum_S c_S X_S$  be a multi-linear polynomial of degree  $d$  with  $\sum c_S^2 = 1$ .
- $I_i(Q) := \sum_{S:i \in S} c_S^2$      $I(Q) = \max_i I_i(Q)$
- Then:
- $\sup_t |P[f(X) \leq t] - P[f(N) \leq t]| \leq 3 d I^{1/8d}$
- Works if  $X$  has  $2+\varepsilon$  moments + other setups.



# The Role of Hyper-Contraction

- Pf Ideas:
- Lindeberg trick (replace one variable at a time)
- Hyper-contraction allows to bound high moments in term of lower ones.
- $X$  is  $(2, q > 2, a)$  Hyper-contractive if for all  $x$ :
- $|x + aX|_q \leq |x + X|_2$
- Key fact: A degree  $d$  polynomial of  $(2, q, a)$  variables is  $(2, q, a^d)$  hyper-contractive.
- Key fact 2: If  $|X|_q < \infty$  then it is  $(2, q, a)$  hyper-contractive for  $a = |X|_2 / (q-1)^{1/2} |X|_q$

# Related Work

- Many works generalizing Lindeberg idea:
- Chatterjee 06: Lindeberg - worst case influence.
- Rotar 79: Similar result no Berry Esseen bounds.
- New in our work: use of hyper-contraction.
- Classical results for  $U, V$  statistics.
- M (FOCS 08, Geom. and Functional Analysis 10):
- Multi-function versions.
- General “noise”.
- Bounds in terms of cross influences.



# Majority is Stablest

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- $I = \max I_i(f)$
- Then:  $E[f(X) f(Y)] \leq M(\rho) + C/\log^2(1/I)$

# Majority is Stablest - Pf Idea

- Pf Ideas: Use “non-linear invariance” +
- “noise truncation” (reduction to bdd degree  $f$ 's) equivalent to the following regarding normal vectors:
- Let  $N, M$  be two  $n$ -dim normal vectors
- where  $(N_i, M_i)$  i.i.d. &  $E[N_i] = E[M_i] = 0$ ;  $E[N_i M_i] = \rho$ .
- Then
- (\*)  $\text{Argmax} \{E[f(N) f(M)] : E[f] = 0, f \in \pm 1\}$  is  $f(x) = \text{sgn}(x_1)$ .
- (\*) was proved by C. Borell 1985.

# Majority is Stablest - Context

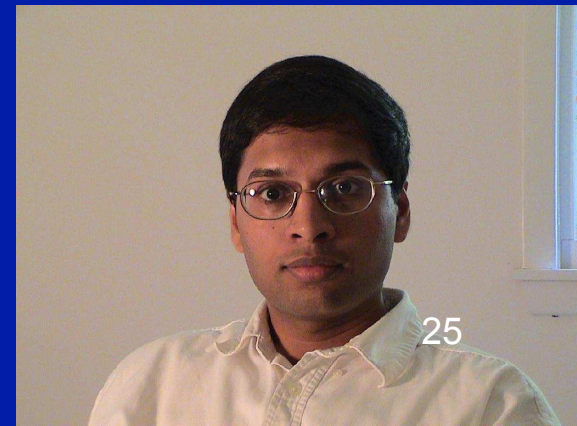
- Context:
- Implies social choice conjecture by Kalai 2002.
- Proves the conjecture of Khot-Kindler-M-O' Donnell 2005 in the context of approximate optimization.
- Strengthen results of Bourgain 2001.
- More general versions proved in M-10
- M-10 allows truncation in general “noise” structure.
- E.g: In M-10: Majority is most predictable:
- Among low influence functions majority outcome is most predictable give a random sample of inputs.<sup>23</sup>

# Motivation

- Approximate Optimization
  - Unique Games and Optimization.
- Quantitative Social choice
  - Quantitative Arrow theorem.

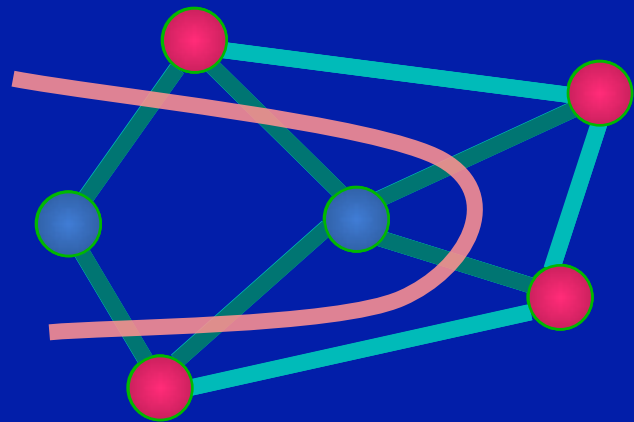
# Approximate Optimization

- Many optimization problems are NP-hard.
- Instead: Approximation algorithms
- These are algorithms that guarantee to give a solution which is at least
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- S. Khot (2002) invented a new paradigm for analyzing approximation algorithms - called UGC (Unique Games Conjecture)



# Example 1: The MAX-CUT Problem

- $G = (V, E)$
- $C = (S^c, S)$ , partition of  $V$
- $w(C) = |(S \times S^c) \cap E|$
- $w : E \rightarrow \mathbb{R}^+$
- $w(C) = \sum_{e \in E \cap S \times S^c} w(e)$



# Example: The Max-Cut Problem

- $OPT = OPT(G) = \max_C \{|C|\}$

- **MAX-CUT problem:**

- find  $C$  with  $w(C) = OPT$

- **$\alpha$ -approximation:**

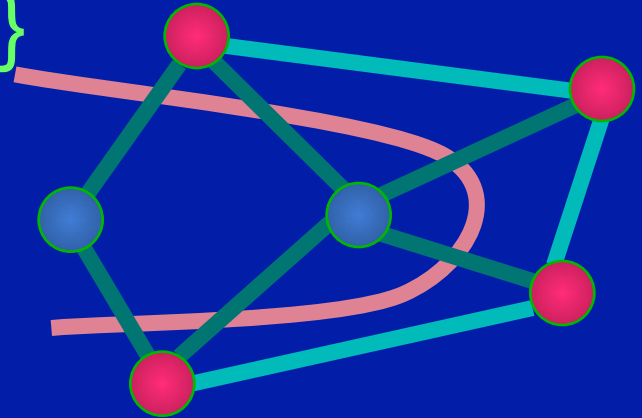
- find  $C$  with  $w(C) \geq \alpha \cdot OPT$

- Goemans-Williamson-95:

- Rounding of

- **Semi-Definite Program** gives an

- $\alpha = .878567$  approximation algorithm.



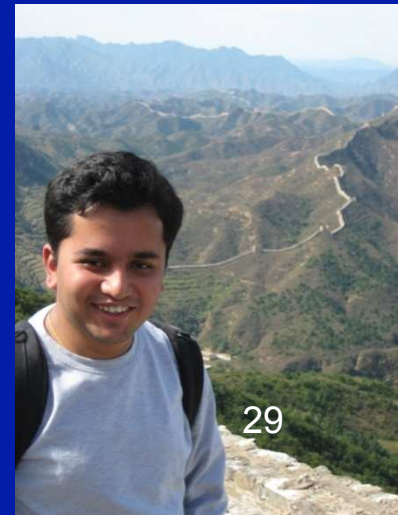
# MAX-Cut Approximation

- Thm (KKMO = Khot-Kindler-M-O' Donnell, FOCS 2004, Siam J. Computing 2007):
- Under **UGC**, the problem of finding an  $\alpha > \alpha_{GW} = 0.87\dots$  approximation for **MAX-CUT** is **NP-hard**.
- Moral: Semi-definite program does the best.
- Thm (IM-2010): Same result for **MAX-q-CUT** assuming the **Peace-Sign Conjecture**.



# Other Approximation problems

- Work of KKM04,MOO-05 show gives best approximation factor for Max-Cut.
- Crucially uses Borell's optimal partition.
- A second result using Invariance of M 08;10
- Raghavendra 08: Duality between Algorithms and Hardness for Constraint Satisfaction Problems.
- $\Rightarrow$  Any optimal solution to
- Gaussian partition problem gives "best" approximation factor/algorithm for the corresponding optimization problem.



## Quantitative Social Choice

- Quantitative social choice studies different voting methods in a quantitative way.
- Standard assumption is of uniform voting probability.
- A "stress-test" distribution  
Bias distributions are not sensitive to errors/manipulation/paradoxes etc.
- Consider general voting rule  
 $f: \{-1,1\}^n \rightarrow \{-1,1\}$  or  $f: [q]^n \rightarrow [q]$  etc.



# Errors in Voting

- Suppose each vote is re-randomized with probability  $\epsilon$  (by voting machine):
- Majority is Stablest (MOO 05;10):
- Majority minimizes probability of error in outcome among low influence functions.
- Plurality is Stablest (IM) 11:
- The statement that
- Plurality minimizes probability of error in outcome among low influence functions is equivalent to Peace-Sign conjecture.



## Errors in Voting

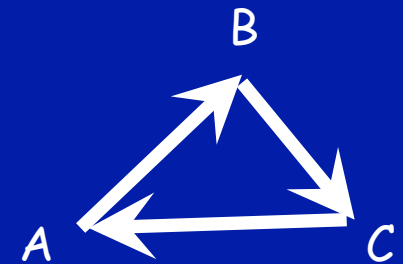
- Majority is Most Predictable (M 08; 10):
- Suppose each voter is in a poll with prob.  $p$  independently.
- Majority is most predictable from poll among all low influence functions.
- Next Example - Arrow theorem
- Fundamental theorem of modern social choice.



# Condorcet Paradox



- $n$  voters are to choose between 3 options / candidates.
- Voter  $i$  ranks the three candidates  $A, B$  &  $C$  via a permutation  $\sigma_i \in S_3$
- Let  $x^{AB}_i = +1$  if  $\sigma_i(A) > \sigma_i(B)$   
 $x^{AB}_i = -1$  if  $\sigma_i(B) > \sigma_i(A)$
- Aggregate rankings via:  $f, g, h : \{-1, 1\}^n \rightarrow \{-1, 1\}$ .
- Thus:  $A$  is preferred over  $B$  if  $f(x^{AB}) = 1$ .
- A **Condorcet Paradox** occurs if:  
 $f(x^{AB}) = g(x^{BC}) = h(x^{CA})$ .
- Defined by Marquis de Condorcet in 18' th century.



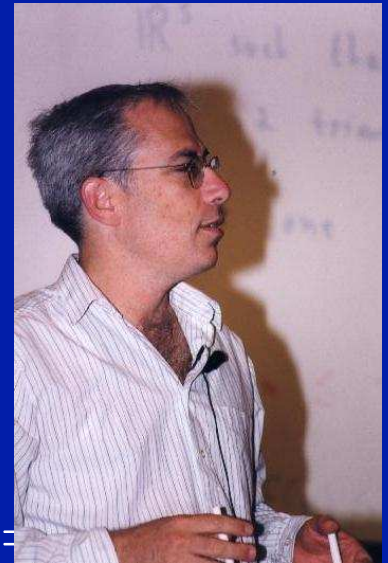
# Arrow's Impossibility Thm

- Thm (Condorcet): If  $n > 2$  and  $f$  is the majority function then there exists rankings  $\sigma_1, \dots, \sigma_n$  resulting in a Paradox
- Thm (Arrow's Impossibility): For all  $n > 1$ , unless  $f$  is the dictator function, there exist rankings  $\sigma_1, \dots, \sigma_n$  resulting in a paradox.
- Arrow received the Nobel prize (72)



# Probability of a Paradox

- What is the probability of a **paradox**:
- $PDX(f) = P[f(x^{AB}) = f(x^{BC}) = f(x^{CA})]$ ?
- Arrow's:  $f = \text{dictator}$  iff  $PDX(f) = 0$ .
- Thm(Kalai 02): Borell's optimal partition is Stablest for  $\rho=1/3 \rightarrow$  majority minimizes probability of paradox among low influences functions (7-8%).
- Thm(Isacsson-M 11): Majority maximizes probability of a unique winner for any number of alternatives.
- (Proof uses invariance + Exchangeable Gaussian Theorem)





## Probability of a Paradox

- Arrow's:  $f = \text{dictator}$  iff  $\text{PDX}(f) = 0$ .
- Kalai 02: Is it true that  $\forall \varepsilon \exists \delta$  such that
- if  $\text{PDX}(f) < \delta$
- then  $f$  is  $\varepsilon$  close to dictator?
  
- Kalai 02: Yes if there are 3 alternatives under technical condition.
  
- M-11: True for any number of alternatives.
  
- Pf uses Majority is stablest and inverse hypercontractive inequalities.



# Summary

- Prove the "Peace Sign Conjecture" (Isoperimetry)
  - $\Rightarrow$  "Plurality is Stablest" (Low Inf Bounds)
  - $\Rightarrow$  MAX-3-CUT hardness (CS) and voting.
- +  $\Rightarrow$  Results in Geometry.

