A composition lemma for the Fourier Entropy-Influence Conjecture

Ryan O'Donnell (CMU) and Li-Yang Tan (Columbia)

ICALP 12 July 2013, Riga Fourier analysis of Boolean functions

 Every Boolean function f: {−1,1}ⁿ → {−1,1} can be expressed as a polynomial p : Rⁿ → R

$$f(x) = \sum_{S \subseteq [n]} \hat{f}(S) \prod_{i \in S} x_i$$

MAJ
$$(x_1, x_2, x_3) = \frac{1}{2}x_1 + \frac{1}{2}x_2 + \frac{1}{2}x_3 - \frac{1}{2}x_1x_2x_3$$

- Introduced into TCS by Kahn-Kalai-Linial 1988.
- Indispensable tool in TCS: hardness of approximation, learning theory, circuit complexity, communication complexity,
- Analytic methods to study inherently combinatorial object.

Parseval's identity

For every $f: \{-1,1\}^n \to \{-1,1\}$,

$$\sum_{S\subseteq[n]}\hat{f}(S)^2=1.$$

MAJ
$$(x_1, x_2, x_3) = \frac{1}{2}x_1 + \frac{1}{2}x_2 + \frac{1}{2}x_3 - \frac{1}{2}x_1x_2x_3$$

Every f induces distribution D_f over all $S \subseteq 2^{[n]}$ where $\Pr_{D_f}[S] = \hat{f}(S)^2$.

"Fourier weight of *f* on *S*"

This talk: understanding two fundamental properties of D_f

1. Is D_f concentrated on few sets, or spread out among many? \approx Is f close to a sparse polynomial?

2. Does D_f place most of its weight on high or low degree or large sets S? \approx Is f close to a low-degree polynomial?

Entropy[f] $\leq C \cdot \text{Influence}[f]$ for some universal constant C?

"Fourier Entropy-Influence Conjecture" Ehud Friedgut and Gil Kalai, 1996



outline

- The FEI conjecture.
- Motivation, applications, previous work.
- This work:
 - 1. Composition lemma for FEI
 - 2. FEI true for read-once formulas
- Thoughts about FEI.

the conjecture

Let $f: \{-1,1\}^n \to \{-1,1\}$, distribution D_f over $2^{[n]}$ where $\Pr_{D_f}[S] = \hat{f}(S)^2$.

Entropy
$$[f] = H[D_f] = \sum_{S \subseteq [n]} \hat{f}(S)^2 \cdot \log_2\left(\frac{1}{\hat{f}(S)^2}\right)$$

Influence[
$$f$$
] = E_{S~D_f}[$|S|$] = $\sum_{S \subseteq [n]} \hat{f}(S)^2 \cdot |S|$ = Avg-degree[f]

 $MAJ(x_1, x_2, x_3) = \frac{1}{2}x_1 + \frac{1}{2}x_2 + \frac{1}{2}x_3 - \frac{1}{2}x_1x_2x_3$ $Entropy[MAJ] = 4 \cdot \left(\frac{1}{2}\right)^2 \log_2(2^2) = 2$ $Influence[MAJ] = \left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2 + \left(-\frac{1}{2}\right)^2 \cdot 3$

the conjecture

Let $f: \{-1,1\}^n \to \{-1,1\}$, distribution D_f over $2^{[n]}$ where $\Pr_{D_f}[S] = \hat{f}(S)^2$.

Entropy
$$[f] = H[D_f] = \sum_{S \subseteq [n]} \hat{f}(S)^2 \cdot \log_2\left(\frac{1}{\hat{f}(S)^2}\right)$$

Influence $[f] = E_{S \sim D_f}[|S|] = \sum_{S \subseteq [n]} \hat{f}(S)^2 \cdot |S|$



Fourier Entropy-Influence Conjecture:

There exists a universal constant C > 0 s.t. Entropy $[f] \le C \cdot \text{Influence}[f]$.

FEI: "If f is close to low-degree, then f is close to sparse"



motivation and applications

- Friedgut-Kalai: threshold phenomena in random graphs.
 - e.g. probability that $G \sim G(n, p)$ is connected.
 - sharp threshold: probability jumps from 0.1 to 0.9 by increasing p a little.
- Implies Mansour's conjecture on Fourier spectrum of DNFs.
 - \Rightarrow efficient algorithm for agnostically learning DNFs.
 - \Rightarrow improved PRGs for DNFs.
- Implies the Kahn-Kalai-Linial theorem.
 - Fundamental inequality in analysis of Boolean functions.
 - Inapproximbability, metric embeddings, social choice, ...

previous work

- Folklore: Entropy $[f] \le O(\log n) \cdot \text{Influence}[f]$.
- No published progress for 15 years!
- Klivans-Lee-Wan 2010: random poly(n)-term DNFs.
- O'Donnell-Wright-Zhou 2011:
 - symmetric functions
 - read-once decision trees



read-once de Morgan formulas



- AND₂, OR₂: extremely simple Fourier spectra, FEI trivially holds.
- Yet prior to this work, FEI open for read-once formulas.

Starting point of this research:

Is FEI preserved under disjoint composition?

(i.e. Can we prove a composition lemma for FEI?)

a first attempt, dream version

For all C > 0, suppose $F: \{-1,1\}^k \to \{-1,1\}$ satisfies $\operatorname{Ent}[F] \leq C \cdot \operatorname{Inf}[F]$, and $g_1, \dots, g_k: \{-1,1\}^\ell \to \{-1,1\}$ satisfy $\operatorname{Ent}[g_i] \leq C \cdot \operatorname{Inf}[g_i]$. Then $f = F(g_1(x^1), \dots, g_k(x^k))$ satisfies $\operatorname{Ent}[f] \leq C \cdot \operatorname{Inf}[f]$.



- Would immediately imply FEI for read-once formulas
- Unfortunately, easily seen to be false

(e.g.
$$F = OR_2, g_1, g_2 = AND_2$$
)

Solution: reformulate FEI carefully so that it "bootstraps itself"

this work

1. Strengthen FEI to "FEI+"

 $\operatorname{Ent}[F] \leq C \cdot (\operatorname{Inf}[f] - \operatorname{Var}[f])$

2. Generalize FEI+ to " μ -biased FEI+"

Ent^{μ}[F] $\leq C \cdot (Inf^{\mu}[f] - Var^{\mu}[f])$ for all product distributions μ over $\{-1,1\}^n$

3. Prove composition lemma for μ -biased FEI+

composition theorem for FEI

Let $\mu = (\mu_1, ..., \mu_n)$ be a product distribution over $\{-1, 1\}^n$. The μ -biased Fourier transform of $f : \{-1, 1\}^n \to \{-1, 1\}$ is:

$$f(x) = \sum_{S \subseteq [n]} \tilde{f}(S) \prod_{i \in S} \frac{x_i - \mu_i}{1 - \mu_i^2}$$

- Simply the "usual" Fourier transform when $\mu = (0, ..., 0)$.
- Ent^{μ}[f] and Inf^{μ}[f] defined analogously w.r.t. $\tilde{f}(S)^{2}$'s.

 $\begin{aligned} \text{Main Theorem [O'Donnell-T.].} \\ \text{Suppose } g_1, \dots, g_k \text{satisfy } \text{Ent}[g_i] &\leq C \cdot (\text{Inf}[g_i] - \text{Var}[g_i]), \\ \text{and } F \text{ satisfies } \text{Ent}^{\mu}[F] &\leq C \cdot (\text{Inf}^{\mu}[F] - \text{Var}^{\mu}[F]) \text{ where } \mu = (\text{E}[g_1], \dots, \text{E}[g_k]) \\ \text{Then } f &= F(g_1(x^1), \dots, g_k(x^k)) \text{ satisfies } \text{Ent}[f] &\leq C \cdot (\text{Inf}[f] - \text{Var}[f]). \end{aligned}$

discussion

$$\begin{split} \text{Main Theorem [O'Donnell-T.].}\\ \text{Suppose } g_1, \dots, g_k \text{satisfy } \text{Ent}[g_i] \leq C \cdot (\text{Inf}[g_i] - \text{Var}[g_i]),\\ \text{and } F \text{ satisfies } \text{Ent}^{\mu}[F] \leq C \cdot (\text{Inf}^{\mu}[F] - \text{Var}^{\mu}[F]) \text{ where } \mu = (\text{E}[g_1], \dots, \text{E}[g_k])\\ \text{Then } f = F(g_1(x^1), \dots, g_k(x^k)) \text{ satisfies } \text{Ent}[f] \leq C \cdot (\text{Inf}[f] - \text{Var}[f]). \end{split}$$

- μ-biased generalization natural on hindsight:
 - $F(g_1(x^1), ..., g_k(x^k))$ with *uniform* $x^1, ..., x^k$ induces *biased* product distribution $\mu = (E[g_1], ..., E[g_k])$ on F.
- Main conceptual contribution: reformulation and strengthening of FEI
 - Composition lemma: evidence that this is the "correct" formulation?
- Difficulty was in finding right statement to prove.
 - Proof = careful Fourier-analytic computations.



read-once formulas revisited

- Dream version of composition \Rightarrow FEI by structural induction.
- Need to prove $\operatorname{Ent}^{\mu}[\operatorname{AND}_2] \leq C \cdot (\operatorname{Inf}^{\mu}[\operatorname{AND}_2] \operatorname{Var}^{\mu}[\operatorname{AND}_2])$ for some constant *C* independent of μ . Likewise for OR_2 .
- Surprisingly tricky, even for 2-variable functions!
- But after much Fourier analysis...

Theorem [O'Donnell-T.]. Every $F: \{-1,1\}^k \rightarrow \{-1,1\}$ satisfies $\operatorname{Ent}^{\mu}[F] \leq 2^k \cdot (\operatorname{Inf}^{\mu}[F] - \operatorname{Var}[F])$ for all product distributions $\mu = (\mu_1, \dots, \mu_k)$.

read-once formulas revisited

Theorem [O'Donnell-T.].

Every $F: \{-1,1\}^k \to \{-1,1\}$ satisfies $\operatorname{Ent}^{\mu}[F] \le 2^k \cdot (\operatorname{Inf}^{\mu}[F] - \operatorname{Var}[F])$ for all product distributions $\mu = (\mu_1, \dots, \mu_k)$.

Combining with composition lemma, we get:

Corollary [O'Donnell-T.].

FEI holds for the class of read-once de Morgan formulas.

Corollary [O'Donnell-T.].

FEI holds for *any* class read-once formulas over *arbitrary* basis.



thank you!