

Postdoc Discovers One Weird Fourier Trick  
for Combinatorial Data  
Graph theorists hate him!

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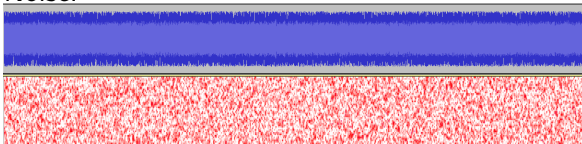
A Friday Morning in Montreal

# Usual Fourier Transform

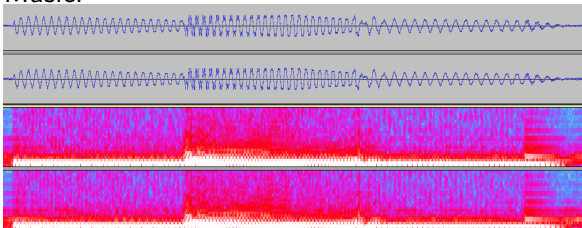
- Time Domain: Function  $f : S^1 \rightarrow \mathbb{C}$ .
- Frequency Domain: Fourier transform  $\hat{f} = (\dots, \hat{f}_{-1}, \hat{f}_0, \hat{f}_1, \hat{f}_2, \dots)$ .
- Extremely useful: Frequency domain often has simpler structure, and some operations become very easy. (Convolution, etc.)
  
- We call  $f$  **band-limited** if all but a few of the coefficients  $\hat{f}_i$  are zero.

# Band Limited Functions

- Noise:



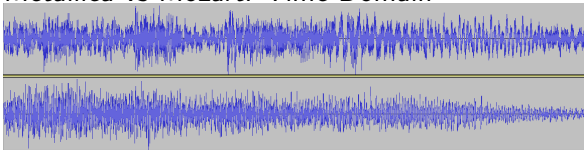
- Music:



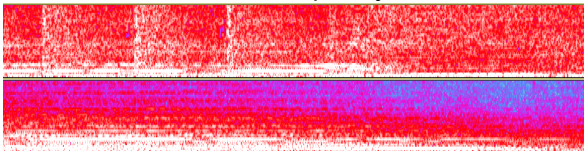
# Usage in Machine Learning

It is often easier to find structural differences (ie, learn) in frequency space.

- Metallica vs Mozart: Time Domain



- Metallica vs Mozart: Frequency Domain



## Fourier Transforms over $S_n$

Take  $f : S_n \rightarrow \mathbb{C}$ .

Choose a representation  $\rho$  of  $S_n$ ; in particular,  $\rho(\sigma)$  is a matrix for any  $\sigma \in S_n$ .

### Definition

The Fourier transform of  $f$  at  $\rho$  is the matrix:

$$\hat{f}_\rho := \sum_{\sigma \in S_n} f(\sigma) \rho(\sigma).$$

For the FT at an irreducible representation  $\rho_\lambda$ , we write  $\hat{f}_\lambda$ .

## Properties of $S_n$ Fourier Transform

- *Fourier Inversion Theorem*: For a collection  $\{\rho_\lambda\}$  of irreducible representations of  $S_n$ , the collection of  $\hat{f}_\lambda$  give a complete description of  $f$ .
- *Mean value* is given by trivial representation. Constant functions have  $\hat{c}_\lambda = 0$  in all but trivial component.
- *Plancharel Formula* exists.
- *Convolution* is easy in 'frequency space:'

$$\widehat{f * g} = \hat{f} \hat{g}.$$

- *Translation*: Set  $f^\pi(\sigma) := f(\pi^{-1}\sigma)$ . Then:

$$\widehat{f^\pi} = \rho(\pi)\hat{f}.$$

# Noise

Fourier transform of a randomly generated function on  $S_4$ .

'Time'

```

>>> f
[0.434977836537475*[1, 2, 3, 4],
 0.392063492238919*[1, 2, 4, 3],
 0.521516704615953*[1, 3, 2, 4],
 0.579389780448483*[1, 3, 4, 2],
 0.523673497481391*[1, 4, 2, 3],
 0.437116226899831*[1, 4, 3, 2],
 0.940504932065627*[2, 1, 3, 4],
 0.112353444528742*[2, 1, 4, 3],
 0.323783686524932*[2, 3, 1, 4],
 0.587326505347836*[2, 3, 4, 1],
 0.650670380618791*[2, 4, 1, 3],
 0.955910936983525*[2, 4, 3, 1],
 0.601537158504575*[3, 1, 2, 4],
 0.794394823511594*[3, 1, 4, 2],
 0.679884674700317*[3, 2, 1, 4],
 0.59256006726996*[3, 2, 4, 1],
 0.446587863295809*[3, 4, 1, 2],
 0.663383056294419*[3, 4, 2, 1],
 0.973295975527333*[4, 1, 2, 3],
 0.417614417812606*[4, 1, 3, 2],
 0.193123698781817*[4, 2, 1, 3],
 0.0491074958654644*[4, 2, 3, 1],
 0.701972353428726*[4, 3, 1, 2],
 0.182927737939954*[4, 3, 2, 1]]
    
```

'Frequency'

```

>>> for lam in irr.keys(): print lam, '\n', matrix(irr[lam]), '\n'
[1, 1, 1, 1]
[-2.25844652968]

[4]
[9.38378872464]

[3, 1]
[-0.635195612906  0.594839310665 -0.372979286523]
[ 0.487581803321 -0.392255077964  0.36462945528]
[-0.695137662289 -1.29950187318 -1.16837072065]

[2, 2]
[ -0.902808786609 -0.191227218508]
[ 0.446283890917  0.00128951491858]

[2, 1, 1]
[ 1.0138981529  0.523357218317  0.505581181152]
[-0.744064342263 -0.516668991817  0.265599994452]
[ 0.949840006734 -2.21664192545  1.1634017955]
    
```

Table 1: Fourier transform of a noisy function.

# Music!

Consider the length function on  $S_n$ . Set:

$$f := \sum l(\sigma)\sigma$$

'Time' (n=4)

```

[0, 1]
[1, 2, 4, 3],
[1, 3, 2, 4],
2*[1, 3, 4, 2],
2*[1, 4, 2, 3],
3*[1, 4, 3, 2],
[2, 1, 3, 4],
2*[2, 1, 4, 3],
2*[2, 3, 1, 4],
3*[2, 3, 4, 1],
3*[2, 4, 1, 3],
4*[2, 4, 3, 1],
2*[3, 1, 2, 4],
3*[3, 1, 4, 2],
3*[3, 2, 1, 4],
4*[3, 2, 4, 1],
4*[3, 4, 1, 2],
5*[3, 4, 2, 1],
3*[4, 1, 2, 3],
4*[4, 1, 3, 2],
4*[4, 2, 1, 3],
5*[4, 2, 3, 1],
5*[4, 3, 1, 2],
6*[4, 3, 2, 1]]

```

'Frequency' (n=6)

```

[5, 1]
[ -24.0  -41.57  -58.79  -75.89  -92.95]
[ -41.57  -72.0  -101.82  -131.45  -161.0]
[ -58.79  -101.82  -144.0  -185.9  -227.68]
[ -75.89  -131.45  -185.9  -240.0  -293.94]
[ -92.95  -161.0  -227.68  -293.94  -360.0]

[6]
[5400.0]

[4, 1, 1]
[ -12.0  -8.49  -14.7  -6.57  -11.38  -16.1  -5.37  -9.3  -13.15  -16.97]
[ -8.49  -6.0  -10.39  -4.65  -8.05  -11.38  -3.79  -6.57  -9.3  -12.0]
[ -14.7  -10.39  -18.0  -8.05  -13.94  -19.72  -6.57  -11.38  -16.1  -20.78]
[ -6.57  -4.65  -8.05  -3.6  -6.24  -8.82  -2.94  -5.09  -7.2  -9.3]
[ -11.38  -8.05  -13.94  -6.24  -10.8  -15.27  -5.09  -8.82  -12.47  -16.1]
[ -16.1  -11.38  -19.72  -8.82  -15.27  -21.6  -7.2  -12.47  -17.64  -22.77]
[ -5.37  -3.79  -6.57  -2.94  -5.09  -7.2  -2.4  -4.16  -5.88  -7.59]
[ -9.3  -6.57  -11.38  -5.09  -8.82  -12.47  -4.16  -7.2  -10.18  -13.15]
[ -13.15  -9.3  -16.1  -7.2  -12.47  -17.64  -5.88  -10.18  -14.4  -18.59]
[ -16.97  -12.0  -20.78  -9.3  -16.1  -22.77  -7.59  -13.15  -18.59  -24.0]

```

Table 2: Fourier transform of a musical function.

All other  $\hat{f}_\lambda = 0!$



## Fast Fourier Transform on $S_n$

- Early 1990's: Clausen develops FFT over  $S_n$ .
- Uses embedding of  $S_{n-1}$  in  $S_n$ ,
- Young's Seminormal/Orthogonal representation, and
- Branching of partitions in Young's lattice.

$$\begin{aligned}\hat{f}_\lambda &= \sum_{\sigma \in S_n} f(\sigma) \rho_\lambda(\sigma) \\ &= \sum_{k=1}^n \sum_{\tau \in S_{n-1}} f(g_{k,n}\tau) \rho_\lambda(g_{k,n}\tau) \\ &= \sum_{k=1}^n \rho_\lambda(g_{k,n}) \sum_{\tau \in S_{n-1}} f(g_{k,n}\tau) \rho_\lambda(\tau)\end{aligned}$$

## Fast Fourier Transform on $S_n$ II

- Then FFT over  $S_n$  can be written as a sum of FFT's over  $S_{n-1}$ .
- Furthermore, restriction to  $S_{n-1}$  is a 'twisted' block diagonal matrix, with blocks given by down-set of  $\lambda$ :

$$\rho_\lambda(g_{k,n}) \sum_{\tau \in S_{n-1}} f(g_{k,n}\tau) \rho_\lambda(\tau) = \rho_\lambda(g_{k,n}) \sum_{\tau \in S_{n-1}} \bigoplus_{\mu} f(g_{k,n}\tau) \rho_\mu(\tau)$$

- Efficient Algorithm: Roughly speaking, simultaneously sort all permutations, progressively building matrices for  $\hat{f}$  at level  $S_{k+1}$  from matrices at level  $S_k$ .
- Uses  $O(n!)$  memory, and approximately  $O(n!n^3)$  time. (Clausen '93)

## Band Restriction and the FFT

- Recall that constant functions are zero in all but trivial component.
- Then if a function  $h$  is constant on (say)  $S_{n-2}$ , its Fourier transform on restriction to  $S_{n-2}$  is zero away from the trivial component.
- Start from this trivial component, induct up twice to get the full set of non-zero components of  $\widehat{h}$ .
- Set  $h_{i,j}(\sigma) = 1$  if  $\sigma$  has an inversion at  $(i,j)$ , and  $h_{i,j}(\sigma) = 0$  otherwise.
- Then  $h_{n-1,n}$  is constant on  $S_{n-2}$ , so band restricted.
- But all of the  $h_{i,j}$  are *translations* of  $h_{n-1,n}$ . Then:

$$\widehat{h_{i,j}} = \rho(\pi) \widehat{h_{n-1,n}}.$$

Thus,  $h_{i,j}$  is band-restricted as well.

## Theorem for Length Function

### Theorem (D?)

*The length function is band-restricted. In particular, the only non-zero components are those associated to the partitions  $(n)$ ,  $(n - 1, 1)$ , and  $(n - 2, 1, 1)$ .*

*The length function's Fourier transform can be computed in  $O(n^5)$  time, and stored with  $O(n^2)$  memory.*

Note: Conceivably, could have non-zero coefficients in  $\lambda = (n - 2, 2)$ , but this ends up also being zero.

Similar theorems are easily written for a wide variety of interesting combinatorial statistics, including maj, number of peaks, number of descents,  $\text{noninv}(k)$  for fixed  $k$ , and more.

## Encoding Graphs in $\mathbb{Z}S_n$

Consider a labeled graph  $G$  with adjacency matrix  $A$ . Set :

$$f_G(\sigma) = A_{\sigma(n-1), \sigma(n)}.$$

- Then  $f_G$  completely encodes the adjacency matrix of  $G$ , and is constant on  $S_{n-2}$ ; thus, severely band-restricted.
- Can compute the Fourier transform of  $f_G$  in  $O(n^3)$  time (Kondar, 2008).
- Relabeling  $G$  with  $\pi$  induces a translation of  $f_G$  by  $\pi$ . Orthogonal representation gives *power invariants*:

$$\hat{f}^t \hat{f}.$$

These are graph invariants, due to the translation property of the FT.

- Similar games yield many other invariants.

## What are these invariants?

For graphs on  $n$  vertices, consider the variables  $X = \{x_{i,j}\}$  with  $1 \leq i \neq j \leq n$  with action of the symmetric group:

$$\sigma \cdot x_{i,j} = x_{\sigma(i),\sigma(j)}.$$

- Form polynomials  $p(X)$ . . .
- Then we can evaluate at a graph  $p(G)$  by plugging in entries from the adjacency matrix.
- The symmetric group action is graph relabeling.
- Symmetrize a polynomial by Reynold's operator

$$R(p) = \sum_{\sigma} \sigma \cdot p(X).$$

## Algebra of graph invariants

- The symmetric functions in the variables  $X = \{x_{i,j}\}$  calculate invariants of unlabeled graphs.
- Introduce extra relation  $x_{i,j}^2 = x_{i,j}$  to get a finite dimensional algebra  $B_n^*$ .
- Dimension of  $B_n^*$  is number of unlabeled graphs on  $n$  vertices, graded by number of edges.
- Can encode basically every hard problem in graph theory as polynomials in  $B_n^*$ .
- Example: Set  $m_G = R(\prod x_{i,j})$  for  $(i,j) \in E(G)$ .  
Then  $m_G(H)$  counts embeddings of  $G$  into  $H$ .  
Take  $G = C_n$  to count Hamiltonian cycles. NP-complete!

## Fourier transform?

- Fourier transform gives a way to efficiently *evaluate* certain collections of invariants.
- For two functions  $f, g \in \mathbb{C}[S_n]$  (not symmetric), take **invariant product**:

$$f \odot g(\sigma) = \sum_{\tau \in S_n} f(\tau\sigma)g(\tau).$$

- Then  $\widehat{f \odot g} = \hat{f}^t \hat{g}$ , translation invariants.
- Can form  $f, g$  from any matrix associated to graph  $G$ : Powers of adjacency matrix, all-pairs-shortest-lengths, etc.
- These  $\hat{f}^t \hat{g}$  are evaluations of symmetric polynomials in  $B_n^*$ .



# Upshot

- The Fourier transform allows us to mix and match cheap invariants using simple matrix operations.
- The invariant product is algebraically different from addition, multiplication in  $B_n^*$ : Get interesting (or at least non-trivial) invariants.
- (Kondar, Borgwaldt) This is actually useful for machine learning problems involving weighted graphs. 'Skew spectrum' is a collection of 49 invariants derived in this way; outperforms established feature sets for chemical data in three out of four tests.

# Questions

- Numerous obvious directions for generalization.
- Symmetric functions on species?
- Integer eigenvalue mysteries. . .
- The algebras  $B_n^*$  and relatives are grossly understudied.  
I want:
  - Free generators for  $B_\infty$  indexed by connected graphs on  $k$  edges,
  - Hall inner product,
  - Polynomial-time evaluation of algebraic generators for  $B_n^*$ ,
  - A pony.

## Questions