Machine learning *L*-functions

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Slides available at edgarcosta.org

Joint work with Joanna Biere, Giorgi Butbaia, Alyson Deines, Kyu-Hwan Lee, David Lowry-Duda, Tom Oliver, Tamara Veenstra, and Yidi Qi.

Riemann zeta function: the prototypical L-function

$$\zeta(s = x + iy) = 1 + \frac{1}{2^{s}} + \frac{1}{3^{s}} + \frac{1}{4^{s}} + \frac{1}{5^{s}} + \dots = \sum_{n=1}^{+\infty} \frac{1}{n^{s}}$$
$$= \left(1 - \frac{1}{2^{s}}\right)^{-1} \left(1 - \frac{1}{3^{s}}\right)^{-1} \dots = \prod_{p \text{ is prime}} \frac{1}{1 - p^{-s}}$$

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Used by Chebyshev to study the distribution of primes.

The formula above works for x > 1, e.g., $\zeta(2) = \sum_{n \ge 1} \frac{1}{n^2} = \pi^2/6$.

Riemann was the first to consider it as a complex function and showed it has meromorphic continuation to \mathbb{C} .

Riemann zeta function functional equation

$$\zeta(s = x + iy) = \sum_{n=1}^{+\infty} \frac{1}{n^s} = \prod_{p \text{ is prime}} \frac{1}{1 - p^{-s}}, \qquad \Re(s) > 1$$

Functional equation relates $s \leftrightarrow 1 - s$

$$\zeta(s) = \Gamma_{\zeta}(s)\zeta(1-s)$$

Riemann showed
$$\zeta(s) = 0 \Leftrightarrow \begin{cases} s = -2n \ n \in \mathbb{N} \\ 0 < \Re(s) < 1 \end{cases}$$

Riemann hypothesis

 $\zeta(s) = 0 \text{ and } 0 < \Re(s) < 1 \Longrightarrow \Re(s) = 1/2$

One of the Millennium Prize Problems. The roots $\zeta(s)$ describe the distribution of the primes.



Riemann zeta function is an L-function

L-functions have certain properties

• Dirichlet series

$$L(s) = \sum_{n \ge 1} a_n n^{-s} \text{ where } a_{nm} = a_n a_m \text{ if } gcd(n,m) = 1$$

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• Functional equation

$$\Lambda(s) := N^{s/2} \Gamma_L(s) \cdot L(s) = \varepsilon \overline{\Lambda}((1+w) - s),$$

where:

- $\Gamma_L(s)$ are defined in terms of Γ -function.
- $\varepsilon \in \{z \in \mathbb{C} : |z|=1\}$ is the root number (for our examples today $\varepsilon = \pm 1$)
- N is the conductor of L(s),
- $w \in \mathbb{N}$ is the (motivic) weight of L(s).

L-functions can arise from many sources, and we have a database about them: www.lmfdb.org: The L-functions and Modular Forms Database

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These can be seen as good hash functions for several number theory objects. They contain a lot of arithmetic information about their sources.

• Class number formula for a number field *K*:

$$\lim_{s\to 1} (s-1)L(K,s) = \frac{2^{r_1} \cdot (2\pi)^{r_2} \cdot \operatorname{Reg}_K \cdot h_K}{w_K \cdot \sqrt{|D_K|}}$$

• Birch and Swinnerton-Dyer conjecture for an elliptic curve E:

 $\frac{L(E,s) \text{ vanishes to order } r := \operatorname{rank} E \text{ and}}{r!} = \frac{\# \operatorname{Sha}(E) \cdot \Omega_E \cdot \operatorname{Reg}_E \cdot \prod_p c_p}{(\# E_{\operatorname{tor}})^2}$

Can we harvest this arithmetic information about their sources from an approximation?

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It is sufficient a_n for $n \leq O(\sqrt{N})$, for a fixed family of *L*-functions.

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Can one do with less?

Several groups have investigated this question with partial success!

In our first experiment, we set out to investigate this question agnostic of the source, with a focus on the order of vanishing, for rational *L*-functions, i.e., $a_n \in \mathbb{Q}$.

We looked at about 250k rational *L*-functions of small arithmetic complexity



We did some principal component analysis

PCA colored by order_of_vanishing



PC1

We did some principal component analysis

3D PCA colored by order_of_vanishing

color



Looked at averaged a_p

Primes vs Average Ap values for L-functions type = all



🧐 Looked at averaged a_p , restricted to primitive *L*-functions

Primes vs Average Ap values for L-functions type = all, primitive



Primes

\mathfrak{V} Looked at averaged a_p , excluding the largest source

Primes vs Average Ap values for L-functions type = not ECNF



\mathfrak{S} Looked at averaged a_p , excluding the largest source and primitive

Primes vs Average Ap values for L-functions type = not ECNF, primitive



Primes

Training order of vanishing via a_p 's



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Saliency Map for Feature Importance (Ranked)
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🧐 Training order of vanishing via PCA



🧐 Training order of vanishing via PCA



Indeed, training just with the first principle component retains much accuracy.

- Rational *L*-functions as a dataset seem to be agnostic to their source, when normalized accordingly.
- Techniques employed for specific classes of *L*-function should generalize.
 - · Linear discriminant analysis gives a good predictors for the order of vanishing.
 - First principle component strongly contributes to training accuracy.
- The data set is quite skewed, so all this should be taken with a grain of salt.

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Can we put this theory to the test?

How do these tools perform for non-rational L-functions?

Maass forms are very similar to classical modular forms.

	Classical modular forr	m Maass form
Domain	$\{z\in\mathbb{C}:\Im(z)>0\}$	
Symmetry group	$\subset GL_2(\mathbb{Z})$	$\subset GL_2(\mathbb{R})$
eigenfunction for Δ		$\checkmark \Delta f = \lambda f$
Fourier expansion	$\sum_{n\geq 1}a_ne^{2\pi inz}$	$\sum_{n\geq 1} a_n \phi_{n,s,\lambda}(z)$
a _n	algebraic	transcendental in general
L(f,s)	$\sum_{n\geq 1}a_nn^{-s}$	
Difficulty to compute <i>L</i>	<u> (3)</u>	-

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www.lmfdb.org recently added about 35k of these to its database. Unfortunately, for about half of them, the data is incomplete 😒.

Maass forms: the missing data, the Fricke sign

$$f(z) = w_N f(-1/Nz), \quad w_N = \pm 1 = \prod_{p|N} w_p \text{ where } w_p \in \{\pm 1\}$$

and N is the Maass form's level (or conductor).

Furthermore, $a_p = -w_p/\sqrt{p}$, thus if w_p is unknown, then a_p is also unknown.

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Knowing w_N and the symmetry type of $f \in \{\pm 1\}$ determines the root number ε in

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This is impractical; instead, we would like to guess w_N (or w_p).

Can we predict it some other way?

\bigoplus Averaged a_p separated by w_N = Fricke sign

p vs Average Ap values for Maass Forms



Linear Discriminant Analysis is a good candidate for a predictor.

\bigoplus Averaged $(-1)^{s}a_{p}$ separated by w_{N} = Fricke sign and symmetry type

p vs Average Ap values for Maass Forms type - Symmetry Plots Combined



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\overline{s} Averaged $-a_p$ for odd forms, separated by (rigorous/LDA predicted) w_N

p vs Average Ap values for Predicted Maass and Rigorously Calculated Forms type



Neural networks approach: Earlier a_p and the eigenvalue λ play a bigger role



We also observed that simpler neural networks performed better.