

High Dimensional Learning rather than Computing in Quantum Chemistry

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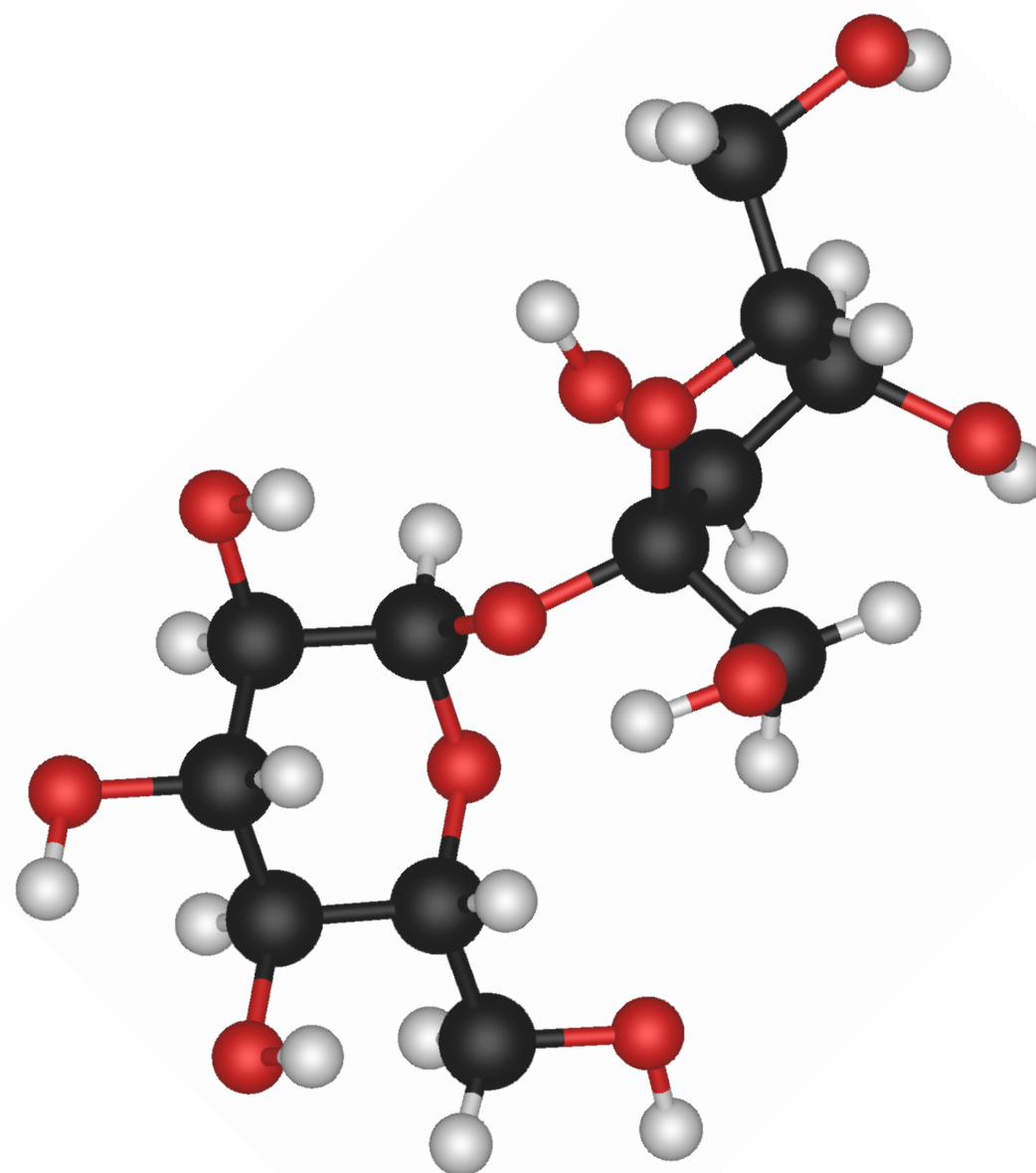
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Joint Mathematics Meetings 2015

Motivation

- Chemists want to build “Google of molecules”
- Applications in pharmaceutical industry, materials science, among others
- Need to compute potential energy of each molecule
- Billions of molecules
- Complex, time consuming computation (hours per molecule)



Sparse Linear Regression

- High dimensional $x \in \mathbb{R}^d$
- Approximate a functional $f(x)$ given n sample values $\{(x_i, f(x_i))\}_i$
- Quantum Chemistry: Energy $f(x)$ of a state $x = \{(p_k, q_k)\}_k$

- Representation of $x : \Phi(x) = \{\phi_j(x)\}_j$



- Regression $\tilde{f}(x)$ of $f(x)$ linear in $\Phi(x)$:

$$\tilde{f}(x) = \sum_j \alpha_j \phi_j(x)$$

- Few samples $\{(x_i, f(x_i))\}_i$ so want a low dimensional approximation of f to avoid curse of dimensionality
- Find regression functions $\{\phi_j\}_j$ with similar properties as f to allow us to compute a sparse regression

Energy Properties

- State: $x = \{(p_k, q_k)\}_k =$ positions and number of protons
- Energy: $f(x)$

1. Invariant to actions of the isometry group:

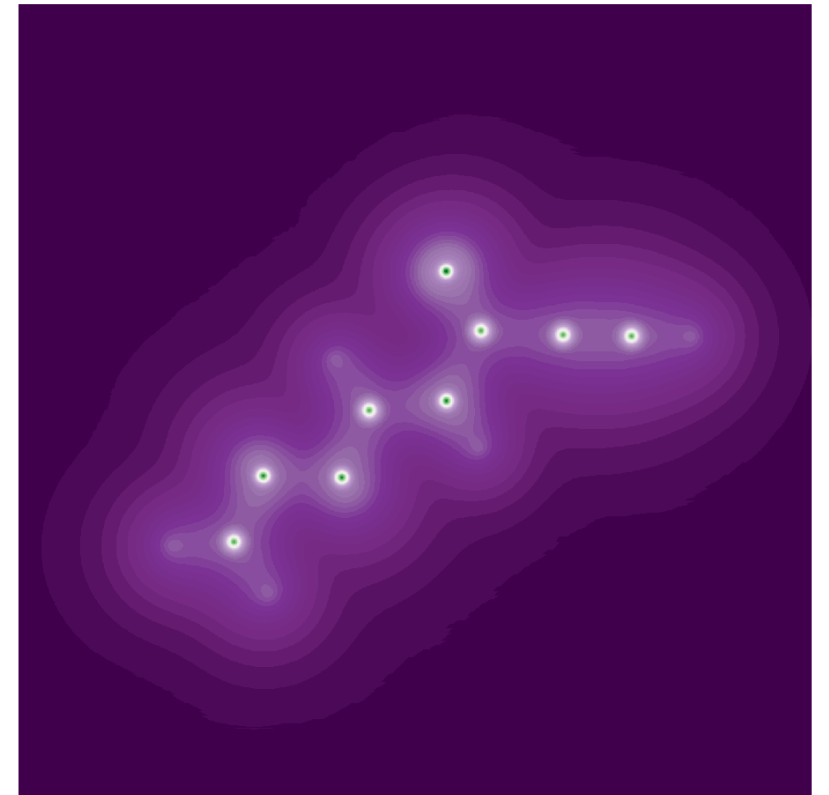
$$\mathbf{E}(3) = \mathbb{R}^3 \rtimes \mathbf{O}(3)$$

2. Multiscale structure (covalent bonds, van der Waals forces)
3. Stable to deformations of the state x

- Want a representation Φ that can take advantage of these three properties

Density Functional Theory

- State: $x = \{(p_k, q_k)\}_k$
- Energy: $f(x)$
- Electronic density: $x \mapsto \rho_x(u)$
- Hohenberg and Kohn 1964:



$$\rho_x = \arg \min_{\rho} E(\rho) \text{ and } f(x) = E(\rho_x)$$

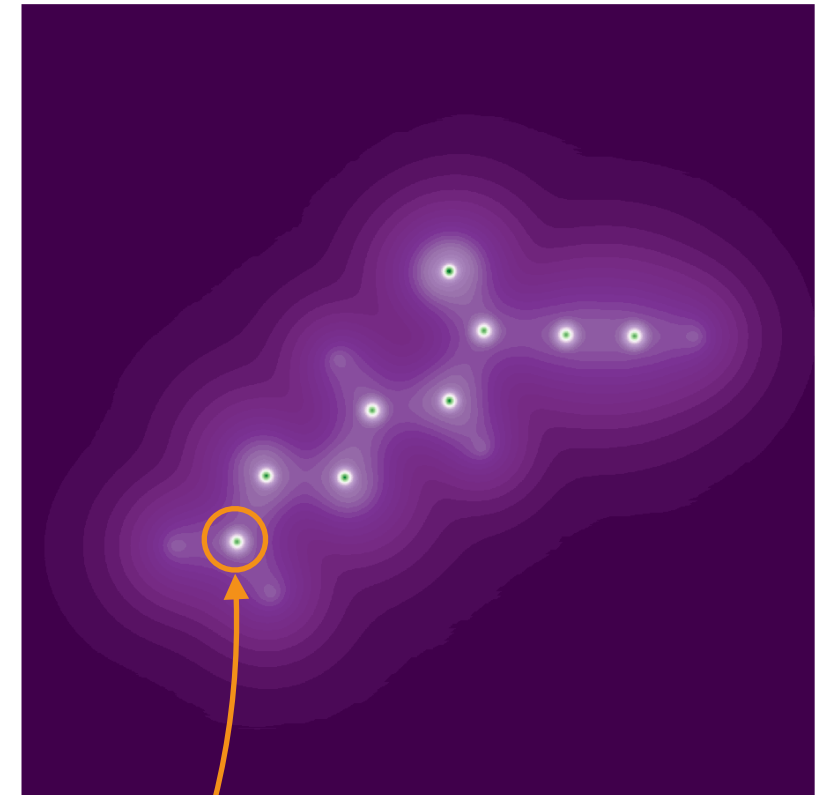
$$E(\rho) = \underbrace{T(\rho)}_{\text{Kinetic energy}} + \underbrace{\int_{\mathbb{R}^3} \rho(u) V_e(u) du}_{\text{External energy (electron-nuclei attraction)}} + \underbrace{\frac{1}{2} \int_{\mathbb{R}^3} \int_{\mathbb{R}^3} \frac{\rho(u)\rho(v)}{|u-v|} du dv}_{\text{Coulomb energy (electron-electron repulsion)}} + \underbrace{E_{\text{xc}}(\rho)}_{\text{Exchange correlation energy}}$$

Density Functional Theoretic Learning rather than Computing

- Construct a representation $\Phi(\rho) = \{\phi_j(\rho)\}_j$ and compute a linear regression:

$$\tilde{E}(\rho) = \sum_j \alpha_j \phi_j(\rho)$$

- To avoid computing ρ_x , we take ρ to be a crude approximation of ρ_x
- Local behavior near the nucleus of atom a is the same as the electronic density of that atom



$\rho_x(u)$

Density Functional Theoretic Learning rather than Computing

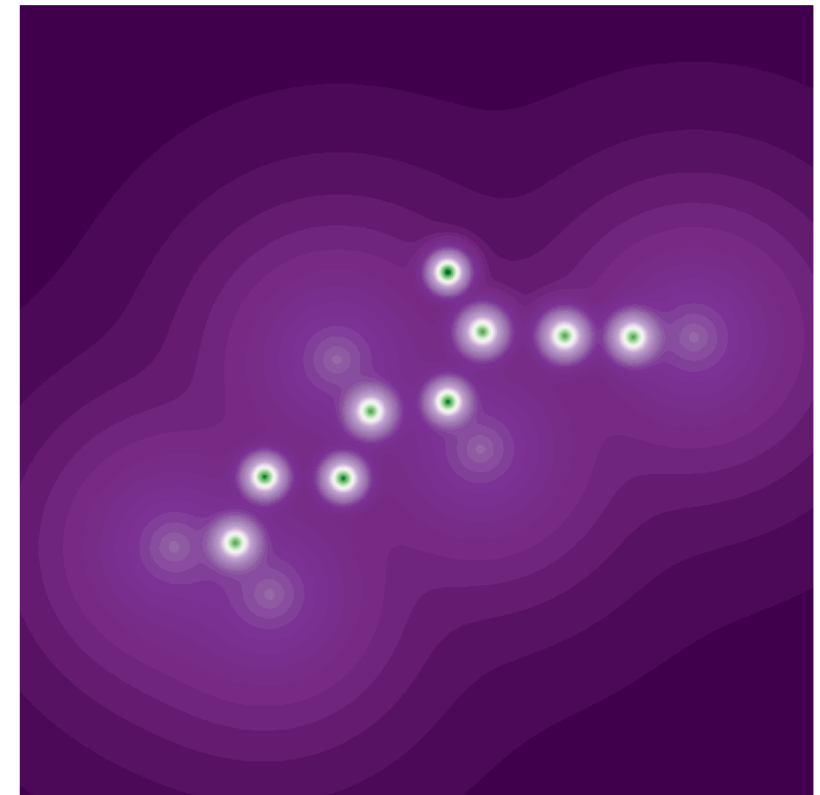
- Construct a representation $\Phi(\rho) = \{\phi_j(\rho)\}_j$ and compute a linear regression:

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- To avoid computing ρ_x , we take ρ to be a crude approximation of ρ_x
- Atomic density approximation:

$$\rho(u) = \sum_k \rho_{a(k)}(u - p_k)$$

ρ_a = density of atom a centered at zero



$\rho(u)$

Fourier and Wavelet Dictionaries

- Majority of the energy is proportional to the sum of the charges:

$$\phi_0(\rho) = \int_{\mathbb{R}^3} \rho(u) du = \sum_k q_k$$

- Fourier energy regression:

$$\tilde{E}(\rho) = \alpha_0 \phi_0(\rho) + \sum_{p=1,2} \sum_{\gamma} \alpha_{\gamma,p} \phi_{\gamma,p}^p(\rho), \quad \phi_{\gamma,p}^p(\rho) = \int_{|\omega|=\gamma} |\hat{\rho}(\omega)|^p d\omega$$

- Isometry invariant
 - Not adapted to the multiscale structure of the energy
 - Not stable to deformations
 - Too simplistic of a model (bias error dominates)
- Wavelet energy regression:
- $$\tilde{E}(\rho) = \alpha_0 \phi_0(\rho) + \sum_{p=1,2} \sum_j \alpha_{j,p} \phi_{j,p}^p(\rho), \quad \phi_{j,p}^p(\rho) = \int_{\mathbb{R}^3} \int_{O(3)} |\rho * \psi_{j,r}(u)|^p dr du$$
- Isometry invariant
 - Takes advantage of the the multiscale structure of the energy
 - Stable to deformations
 - Dictionary is too small

Scattering Dictionary

Layer 0

ρ

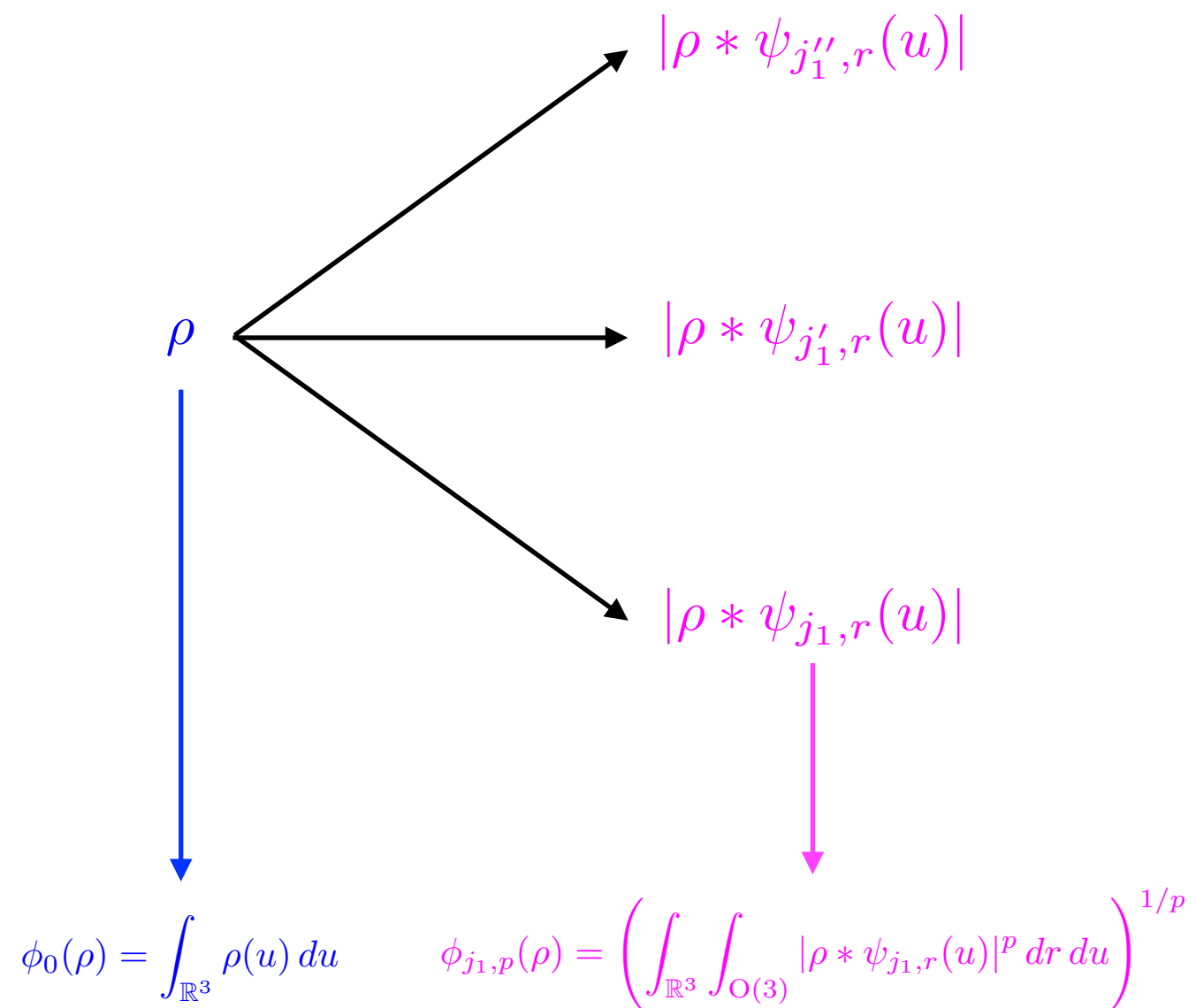


$$\phi_0(\rho) = \int_{\mathbb{R}^3} \rho(u) du$$

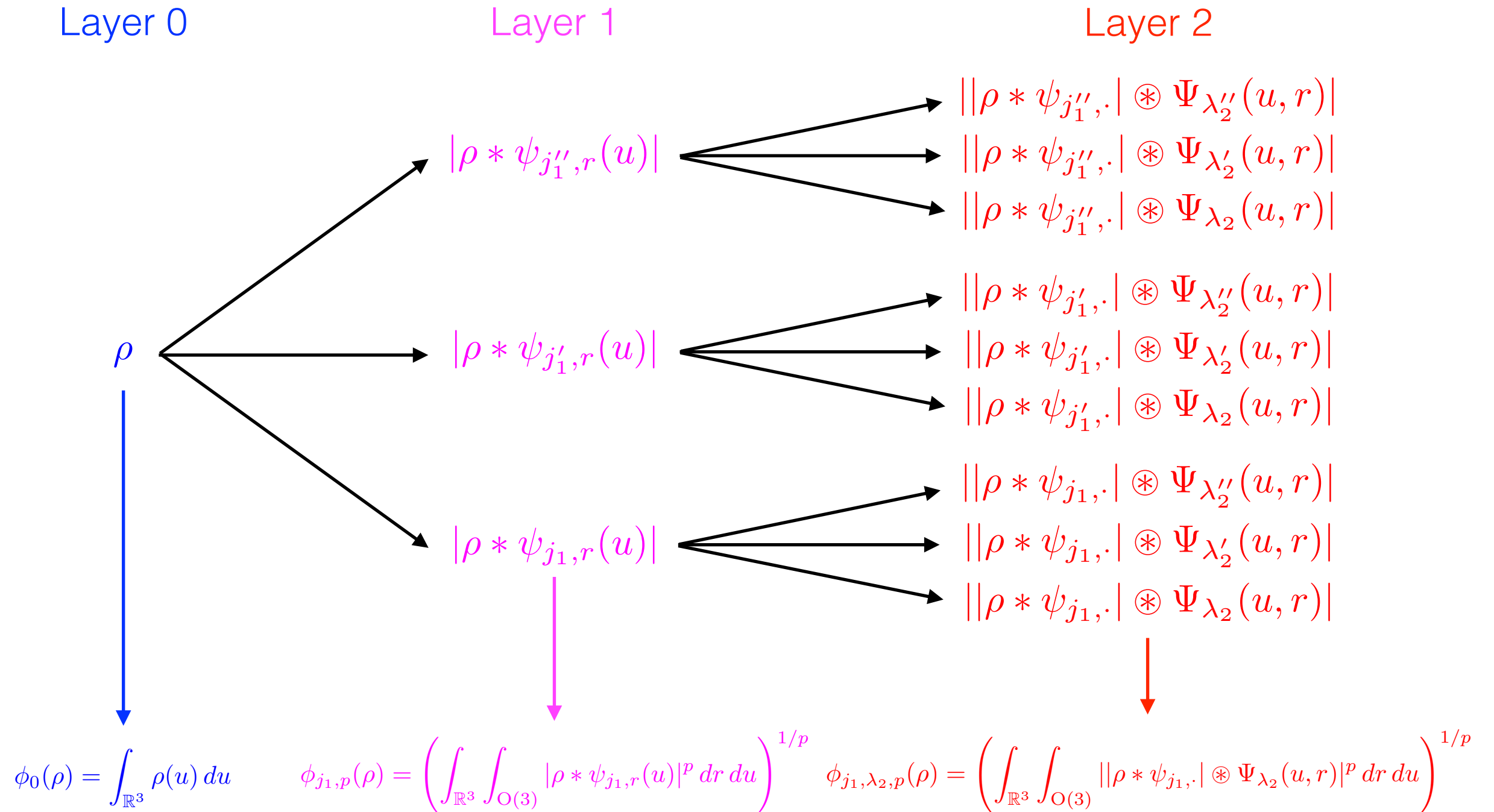
Scattering Dictionary

Layer 0

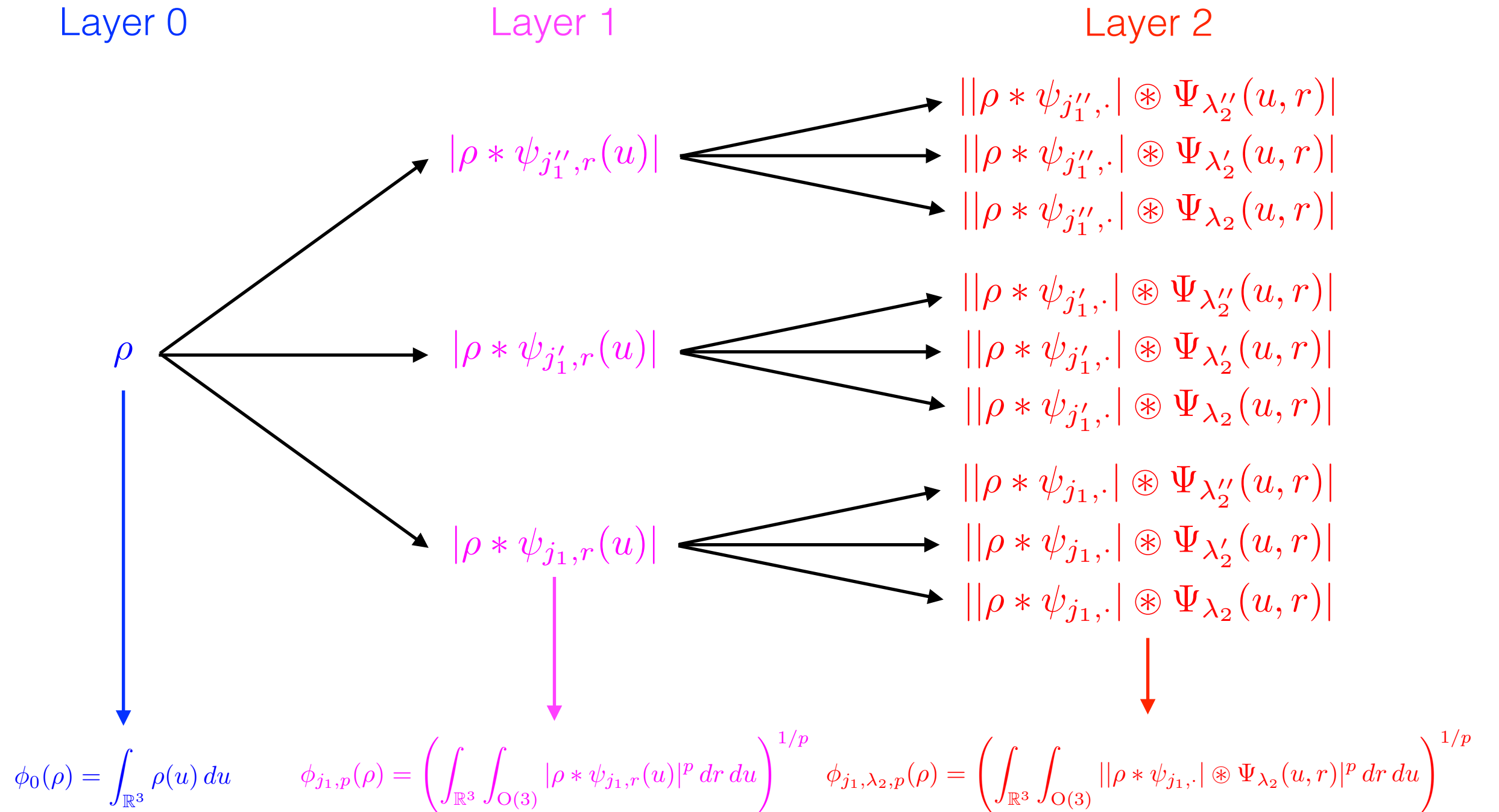
Layer 1



Scattering Dictionary



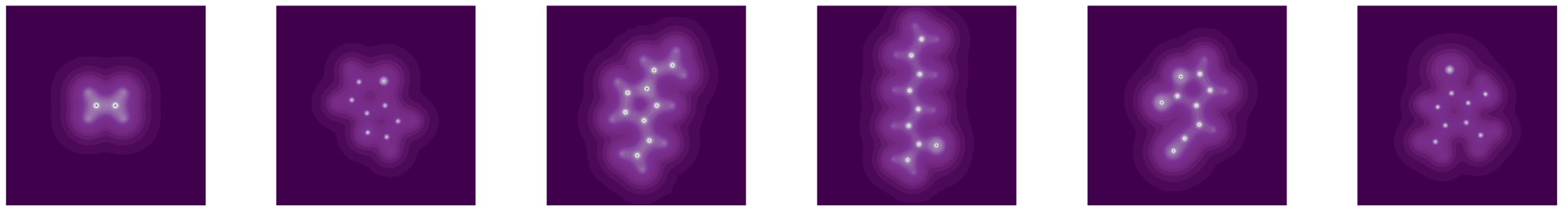
Scattering Dictionary



$$\Phi_S(\rho) = \{\phi_0(\rho), \phi_{j_1, 1}(\rho), \phi_{j_1, 2}^2(\rho), \phi_{j_1, \lambda_2, 1}(\rho), \phi_{j_1, \lambda_2, 2}^2(\rho)\}_{j_1, \lambda_2}$$

Quantum Chemistry Regression

- Two data bases $\{x_i, f(x_i)\}_i$ of planar, organic molecules with up to 20 atoms



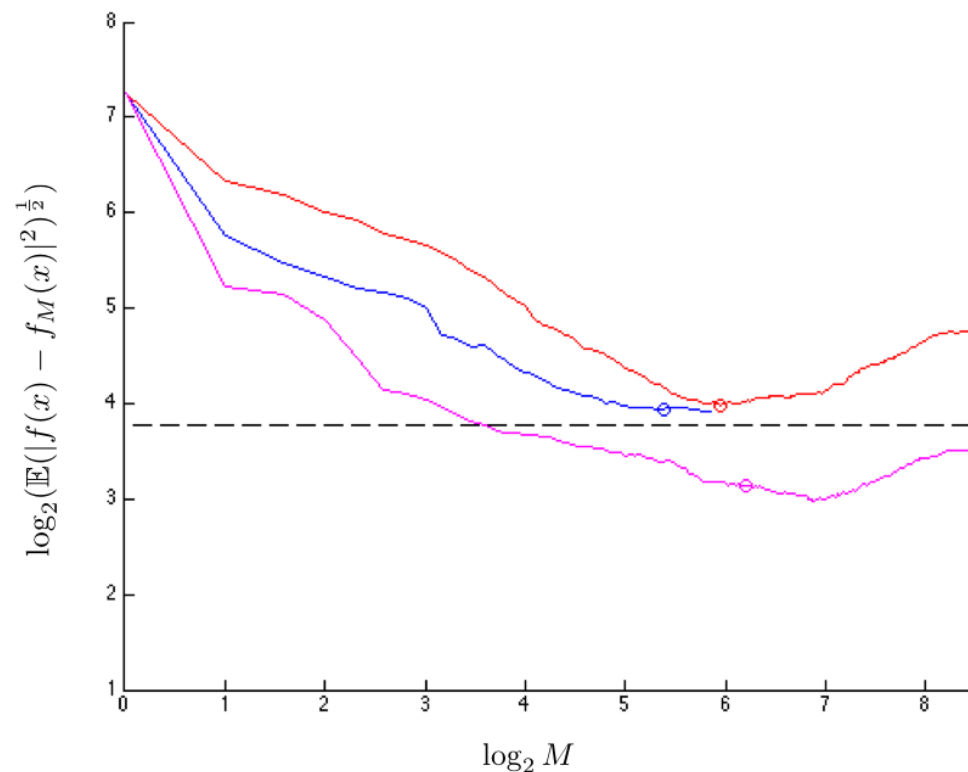
- Regression over Fourier, Wavelet, and Scattering dictionaries
- M-term sparse regression via greedy Orthogonal Least Squares computed on a training set:

$$\tilde{E}_M(\rho) = \sum_{k=1}^M \alpha_{j_k} \phi_{j_k}(\rho)$$

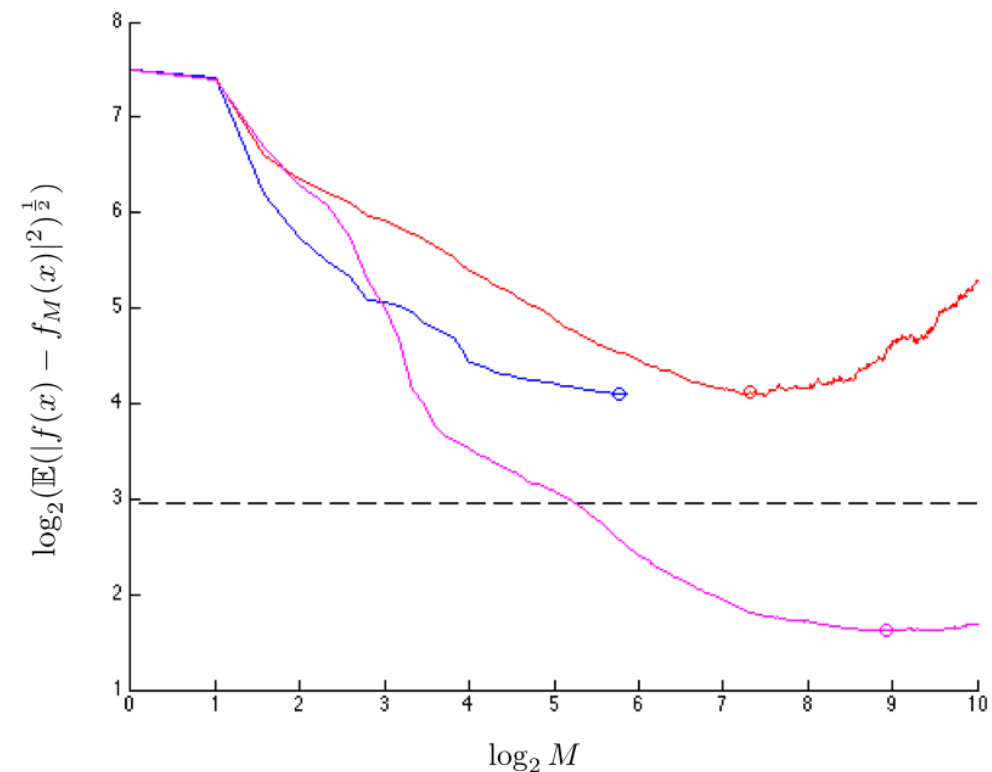
M-term Regression Error

Key: Fourier, Wavelets, Scattering, Coulomb (dashed line)

400 molecules



4000 molecules



Conclusion

- The scattering transform defines a representation that captures the fundamental properties of the quantum molecular energy, and which is sufficiently rich to achieve highly accurate energy estimates.
- One can learn physics through data and compute fast.
- Can we learn other physical functionals?

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