Machine learning and chemistry

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the Kulik group at MIT, `hjkgrp.mit.edu/`

under the supervision of Professor Heather J. Kulik

for the most recent version and demos: `github.com/jpjanet/ML-chem-workshop`
this revision: `795e5c5440fb08de2cf673d2742e989915a0e4e0` on branch `master`

compiled 03/04/2019

Rise of the (chemical) machines

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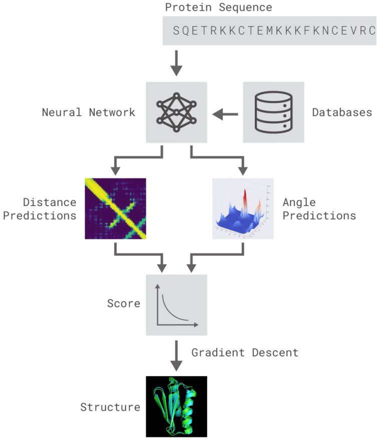

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"*It is not that machines are going to replace chemists. It's that the chemists who use machines will replace those that do not*"
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This is probably a bit strong, but all scientists generate data as a product. ML provides new, powerful ways to exploit their that information.

Types of machine learning

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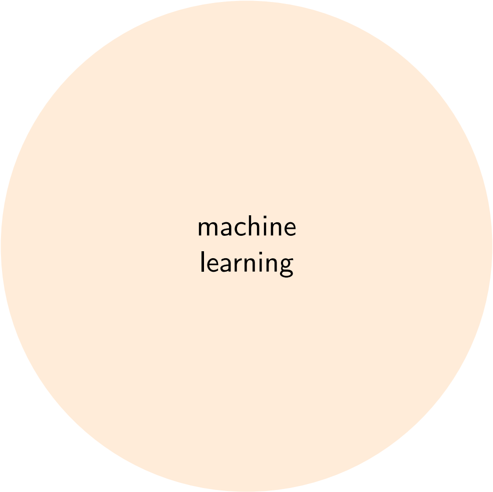

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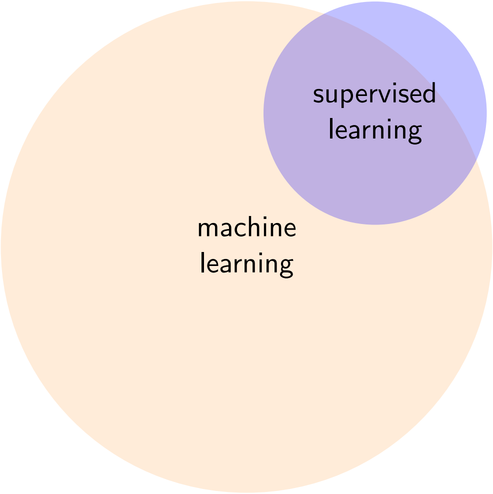

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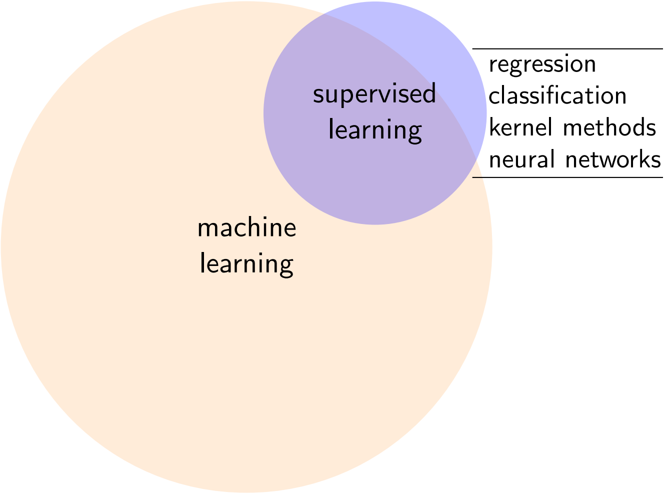

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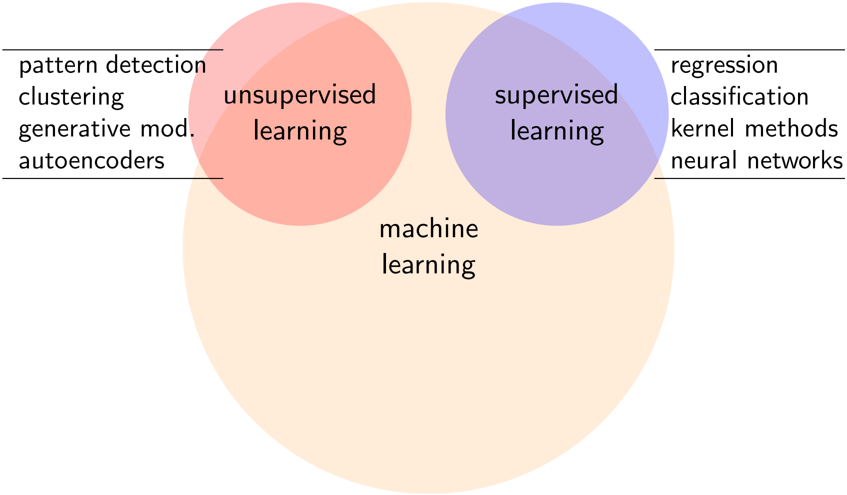

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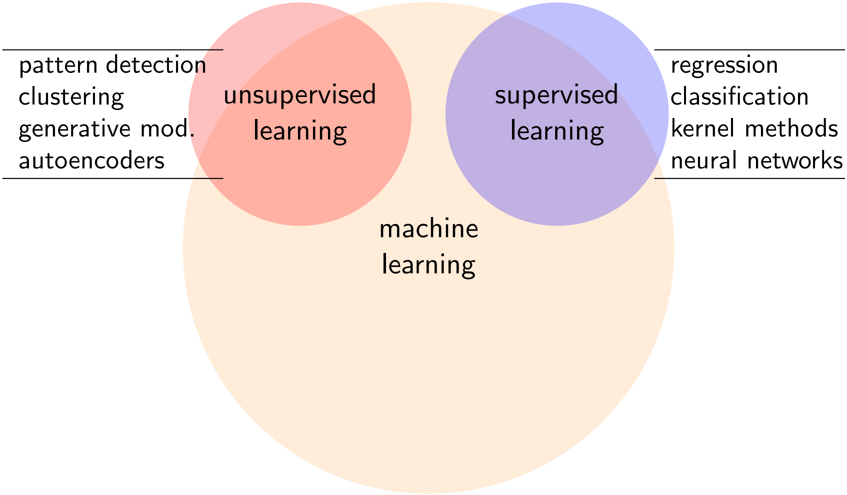

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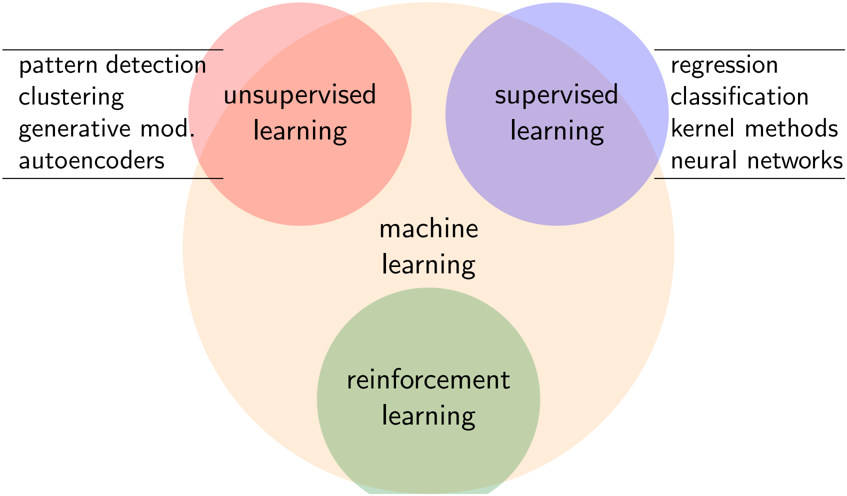

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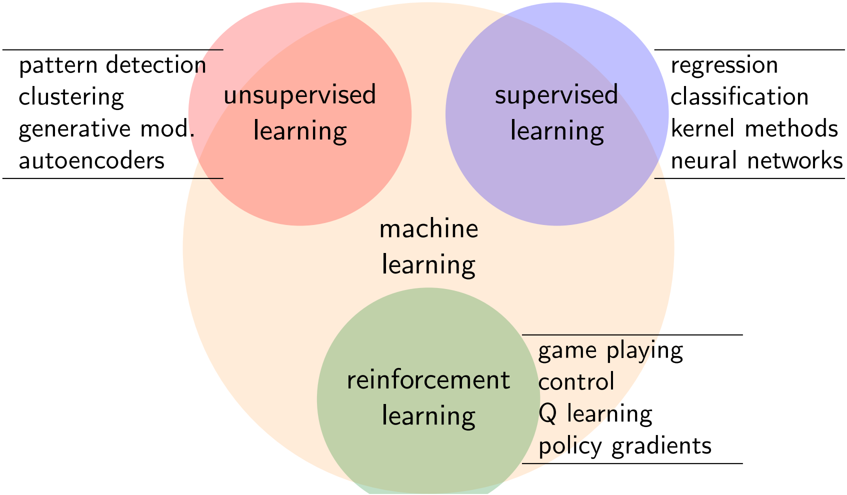

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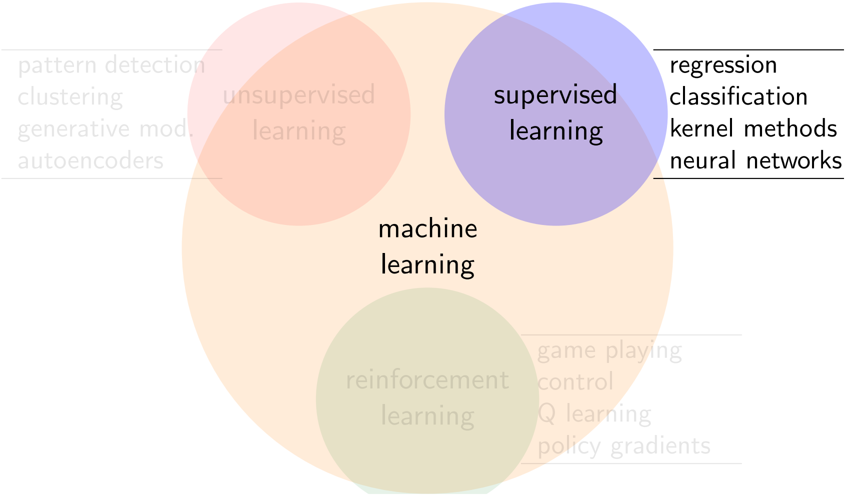
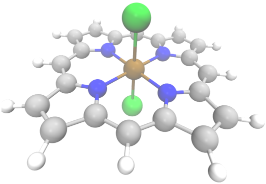


Why ML in chemistry?



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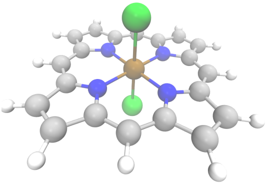

property

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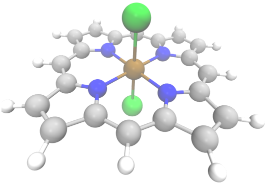

experiment

days, weeks

property

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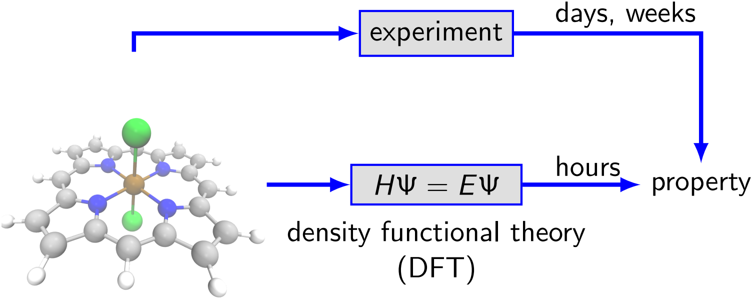

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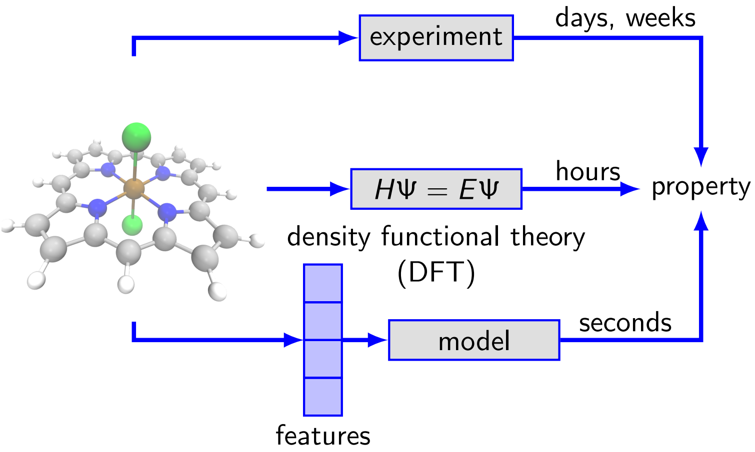

Structure of this talk

We will cover the following topics:

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Please ask questions throughout!

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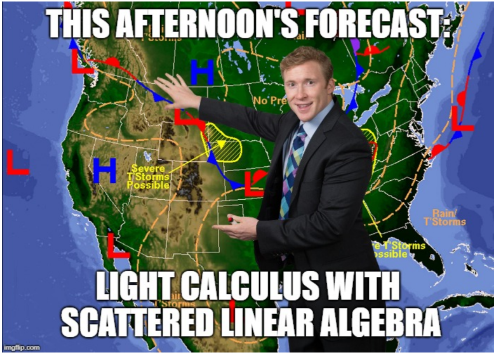

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Some useful notation:

X	training data, as rows
x^*	one new molecule/systems
$y, \hat{y}$	property(energy?), predicted value
$\mathcal{L} = \|y - \hat{y}\|_2^2$	loss function
W, w	model parameters
$\hat{y} = f(x, W)$	our model

The goal of statistical learning

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observation

property

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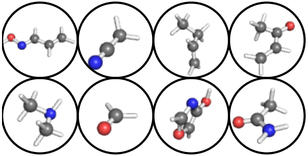
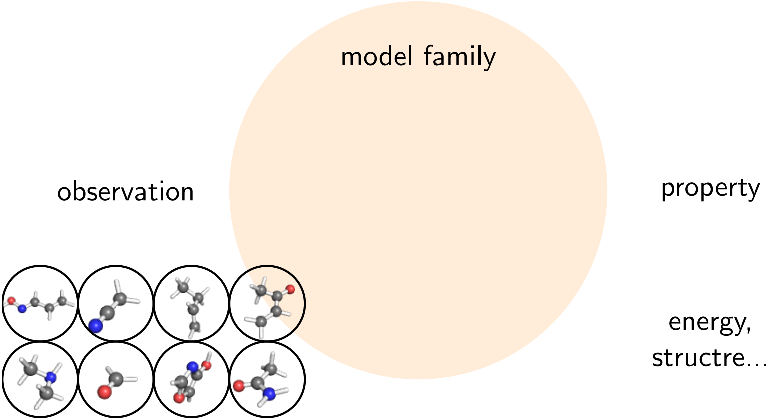


energy,
structre...

The goal of statistical learning



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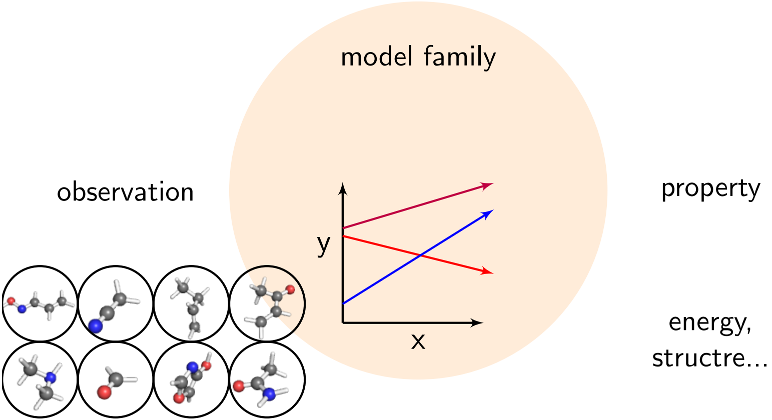

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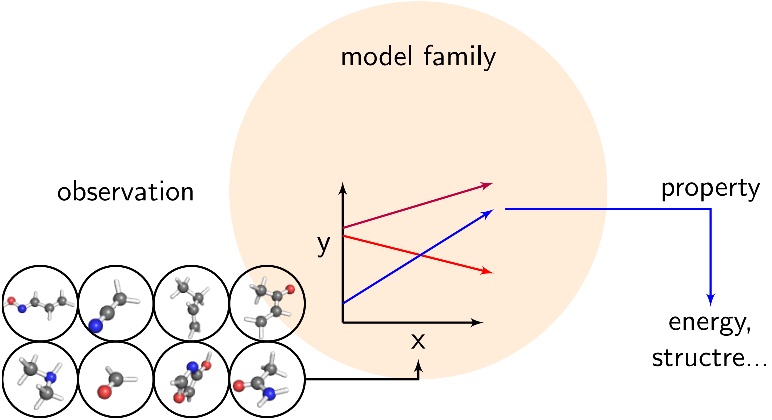

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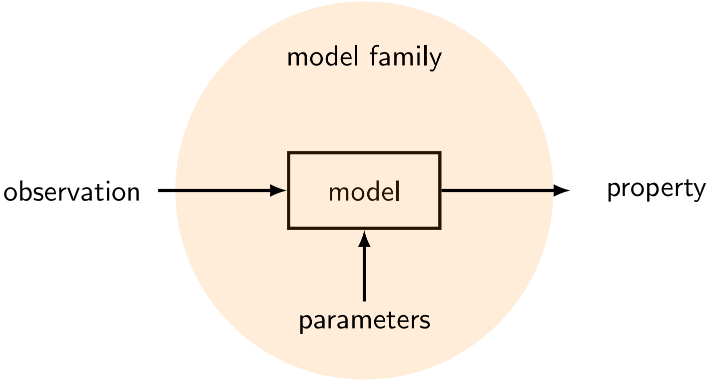

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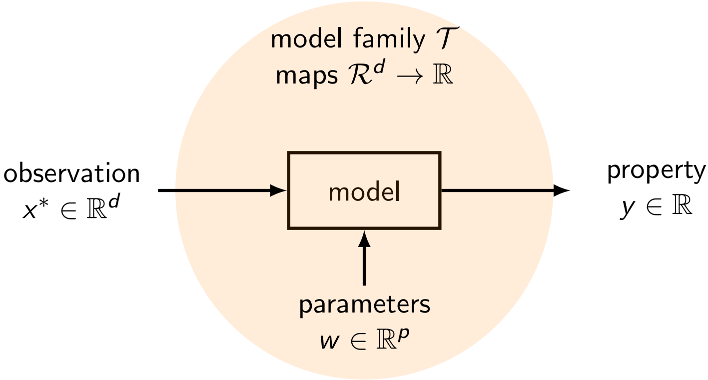
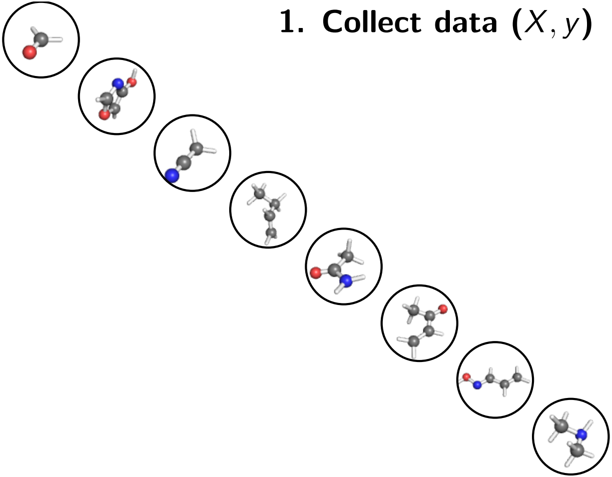
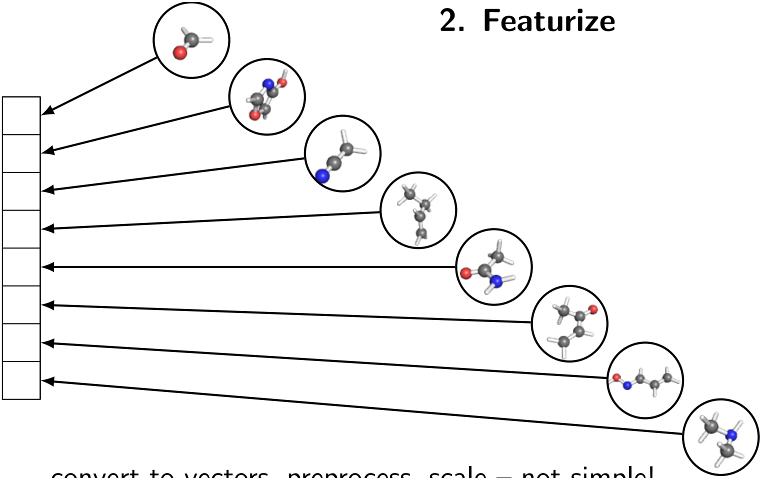


Overview of supervised learning



1. Collect data (X, y)

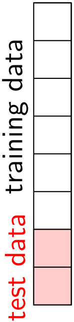
Overview of supervised learning



convert to vectors, preprocess, scale – not simple!

Overview of supervised learning

3. Partition data



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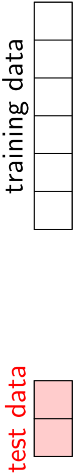

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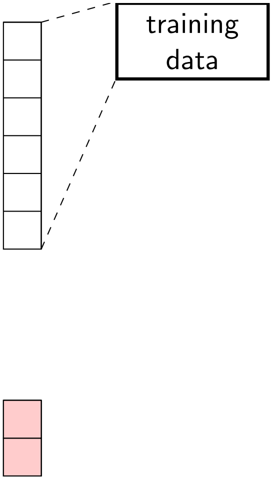

4. Learning phase

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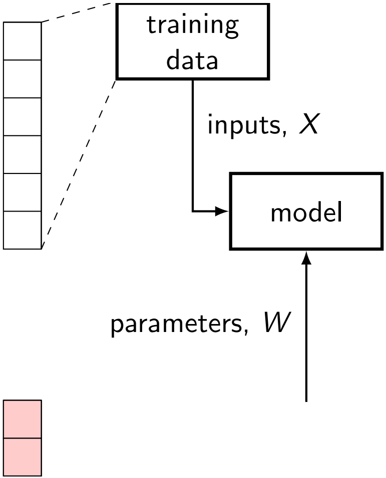

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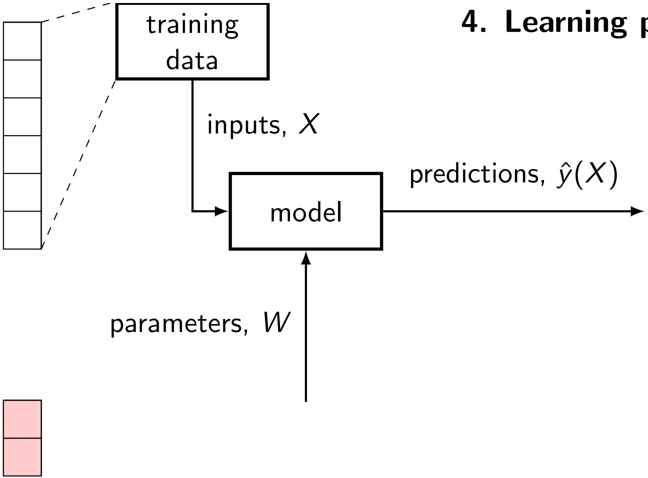

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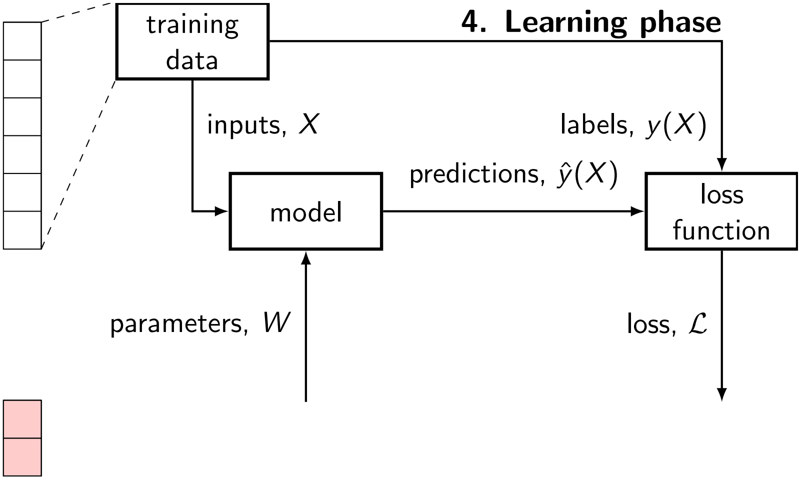

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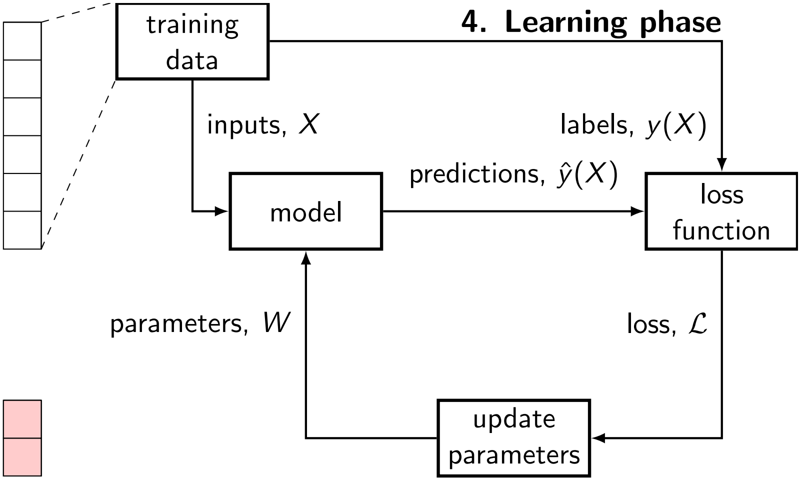

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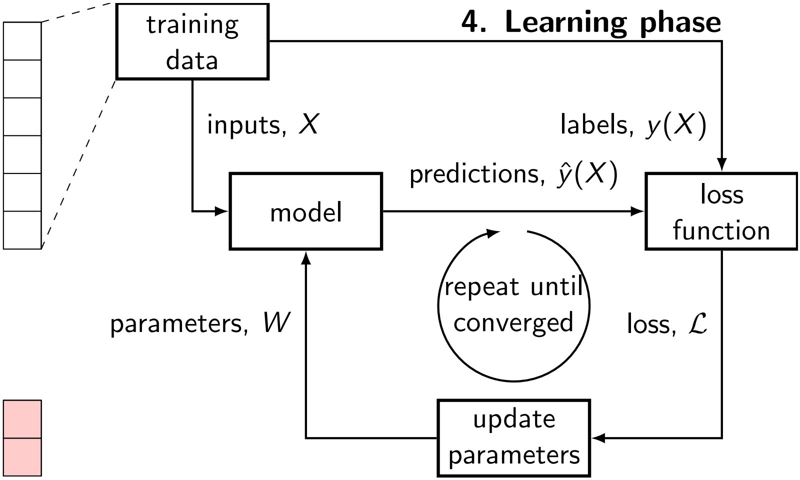

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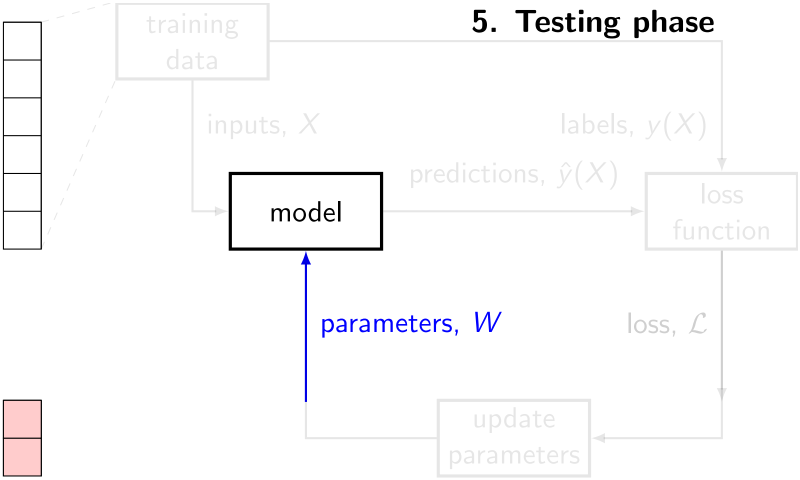

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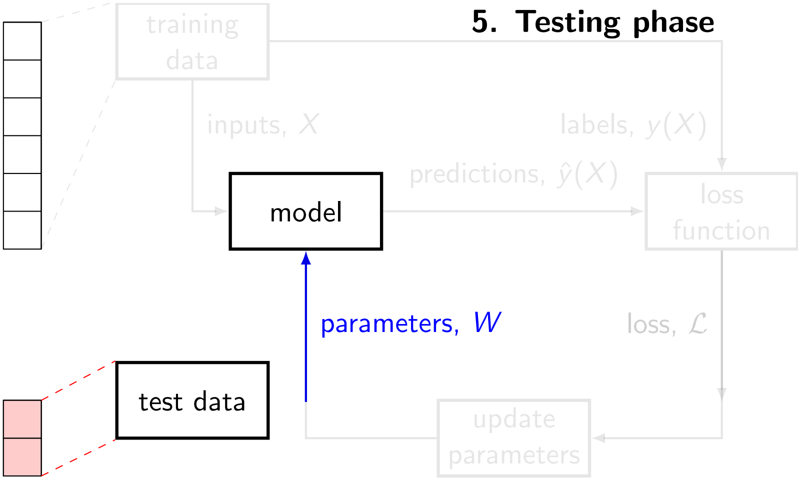

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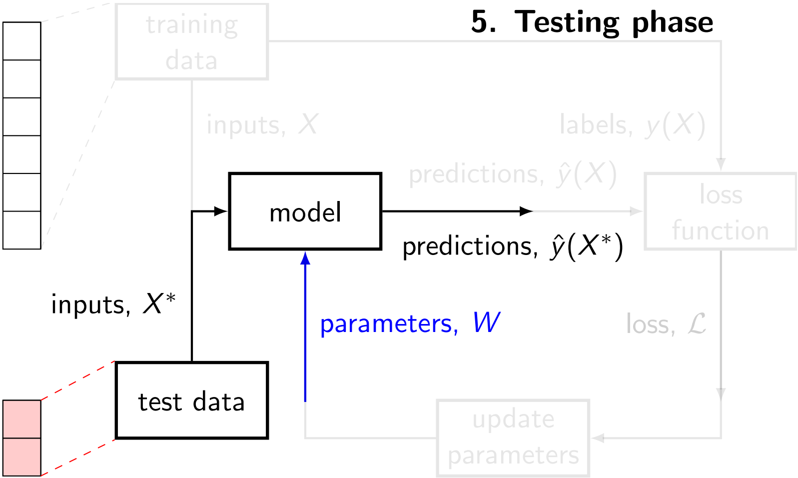

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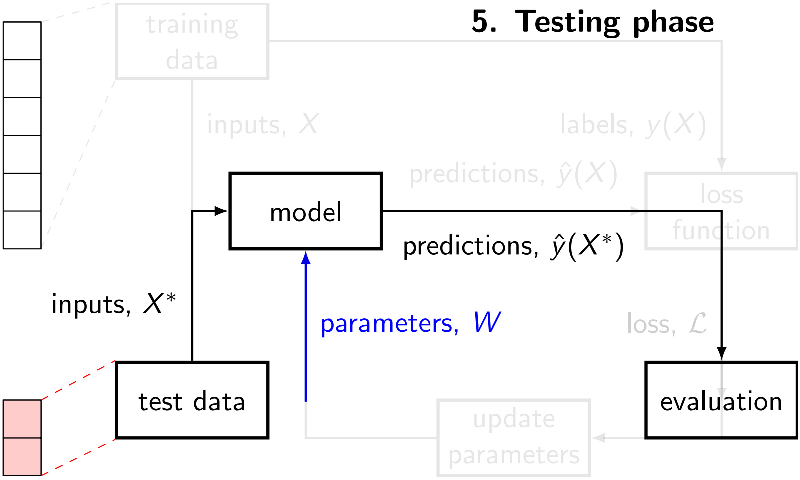

Risk and generalization - I

Our training data defines the *empirical risk*

$$\mathcal{E}_{emp}(f) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}(y_i, f(x_i)) = \frac{1}{n}\sum_{i=1}^{n} (y_i - f(x_i))^2$$

we choose the model to minimize $\mathcal{E}_{emp}(f)$ over all the models in $\mathcal{T}$

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with minimum

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Risk and generalization - II

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Two critical ideas that are worth noting. Under mild assumptions one can show that:

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We want $\mathcal{T}$ to be large/complicated enough to have low approximation error, **but no more complicated**.

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With limited data, we are often better off searching for a model in a simpler family models of that ‘learn’ more robustly and quickly as opposed to very complicated models with lots of parameters.

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2. estimation error is inversely related to model complexity, i.e. more complicated spaces of models require more data to generalize.

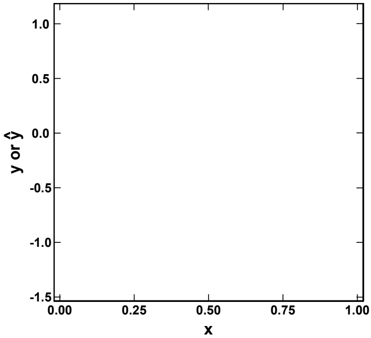
Conversely, a simple model will stop improving with more data past a certain point – where the approximation error dominates.

Risk and generalization - IV

Let us use **polynomials** to estimate:

$$y(x) = \sin(2\pi x)$$

Note that $f^* \notin \mathcal{T}$!



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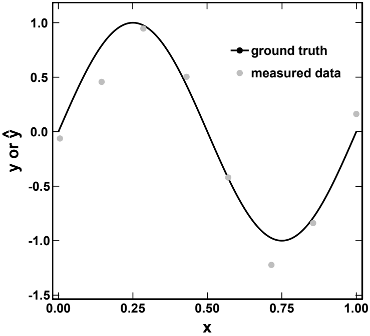
Assume 8 measurements with noise $\mathcal{N}(0, 0.2)$



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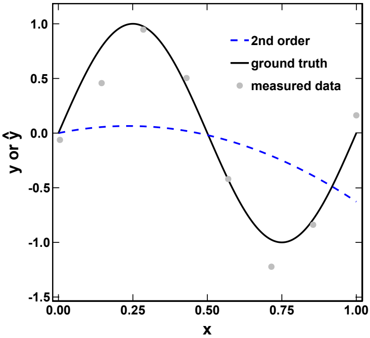

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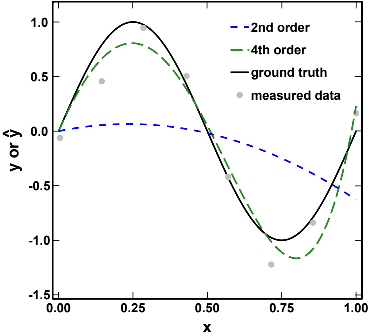
Start with degree 2...What happens when we increase the order?



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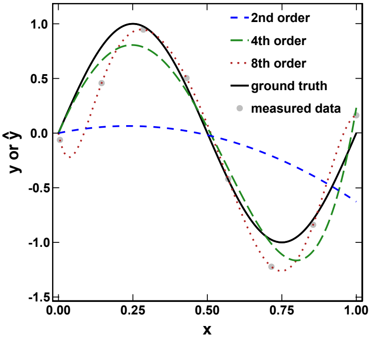

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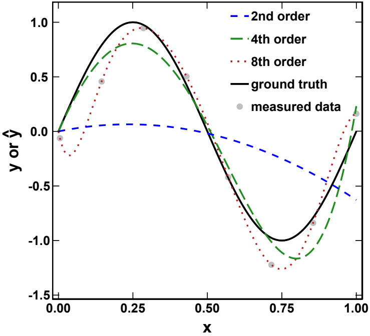
What do the risk terms look like?



Risk and generalization - IV

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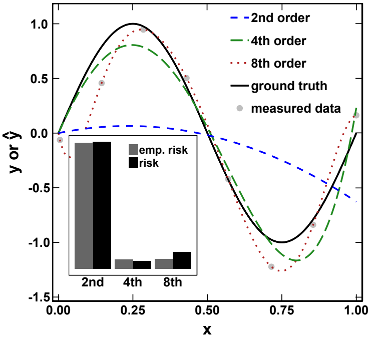
What do the risk terms look like?

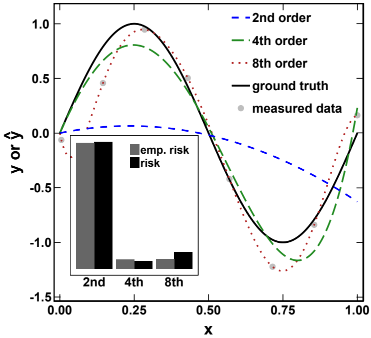


Risk and generalization - IV

Let us use **polynomials** to estimate:

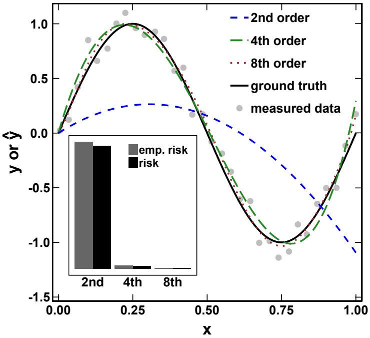
$$y(x) = \sin(2\pi x)$$

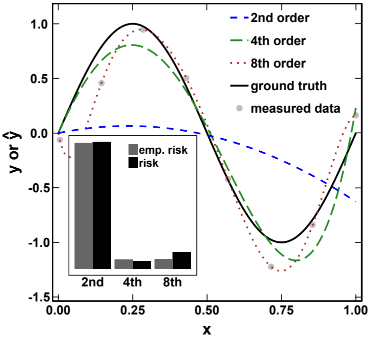
Note that $f^* \notin \mathcal{T}$!



What happens if we add more data?

Risk and generalization - IV





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Controlling Complexity

Adapting model complexity to fit the problem is necessary. However, it is not obvious how to do this is a constrolled way. Hence, we need a way prevent over-fitting that is applicable to many different types of model – **regularization**.

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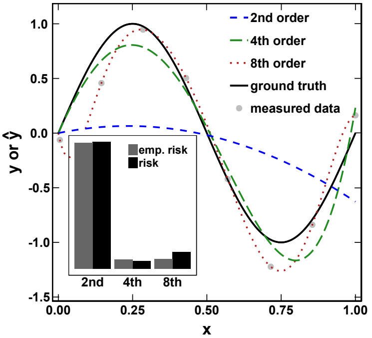
We choose to penalize terms with large weights, i.e. complicated functions.

- This makes empirical errors worse.
- This *can* improve generalization/excess risk.

Controlling Complexity

Let's return to our previous example:



Remember: larger λ = simpler, flatter model.

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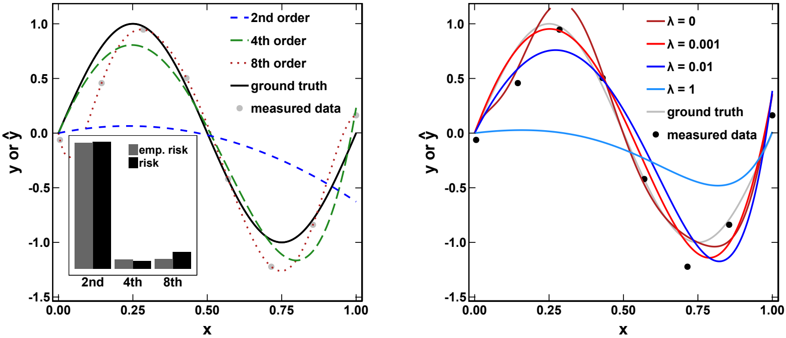

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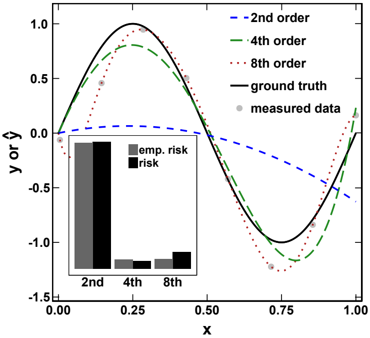

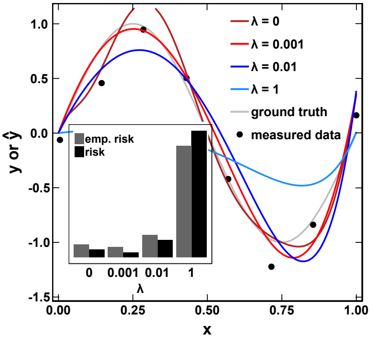

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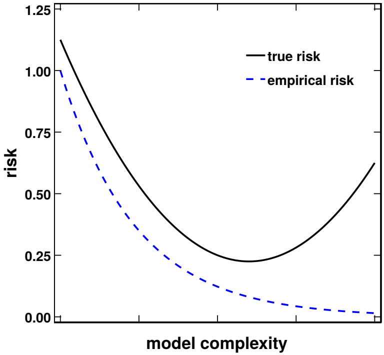

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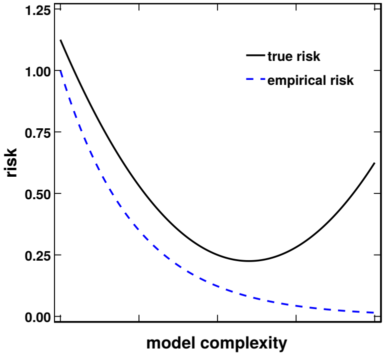
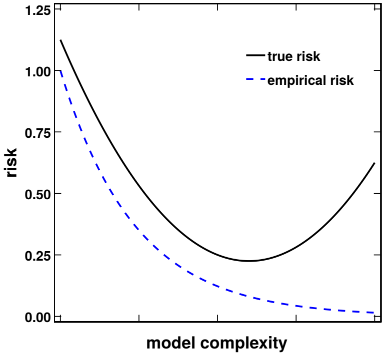


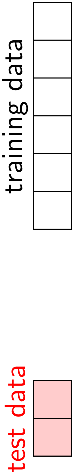
None of this helps us understand a how complicated our model should be.

Controlling Complexity



None of this helps us understand a how complicated our model should be. Unfortunately, **errors on our training data cannot tell us the answer**

(Cross)-validation



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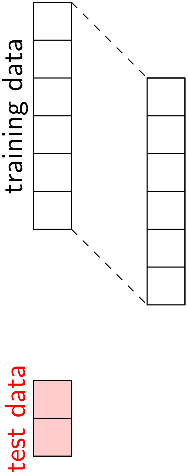

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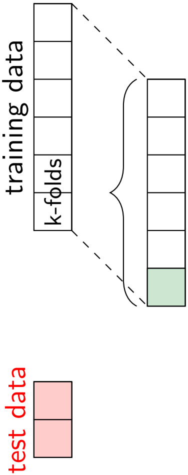

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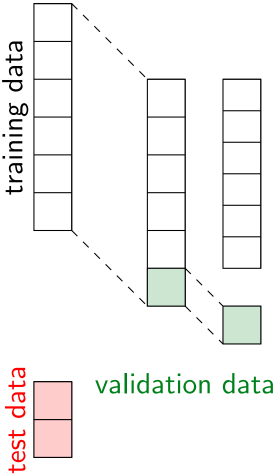

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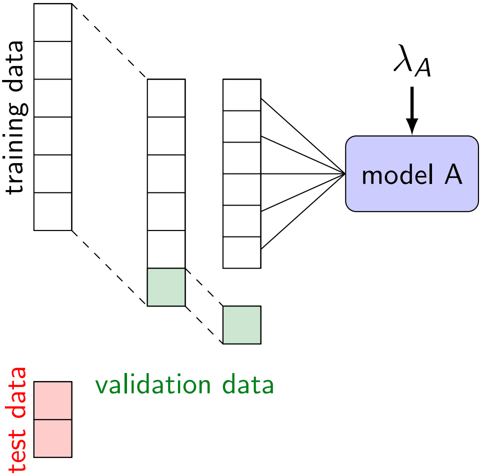

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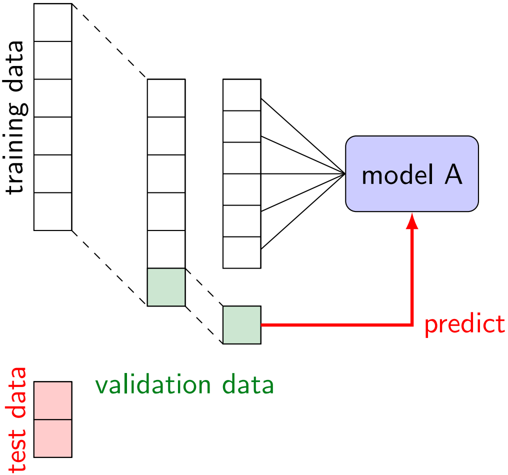

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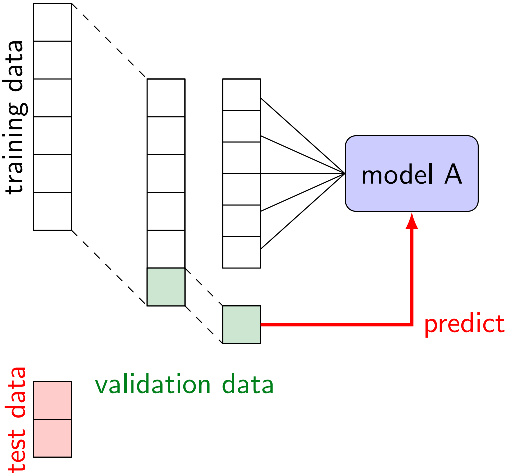

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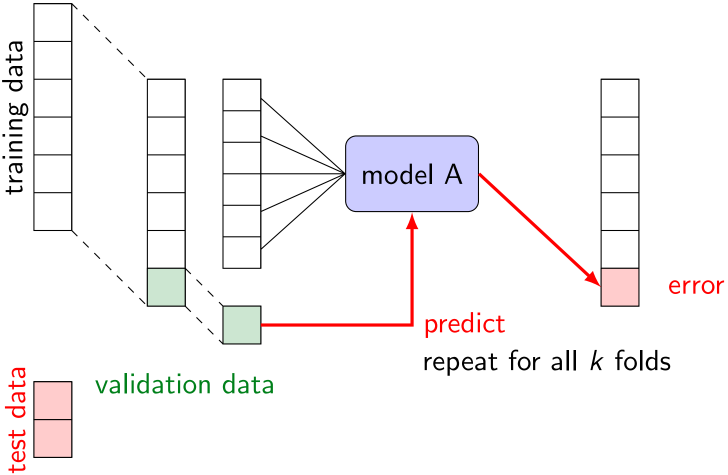

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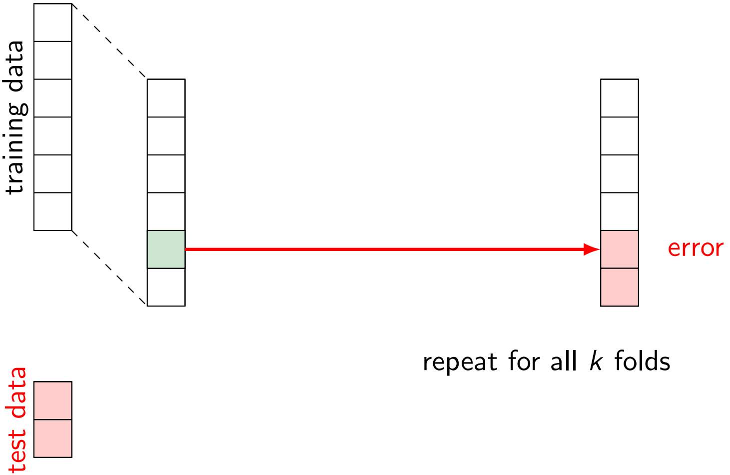

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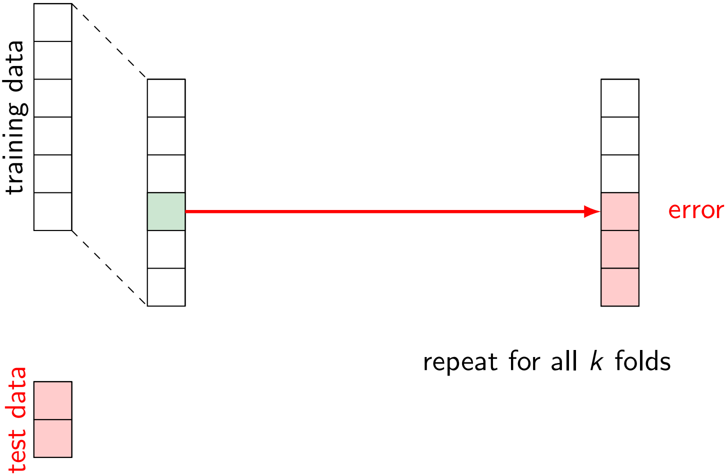

repeat for all k folds

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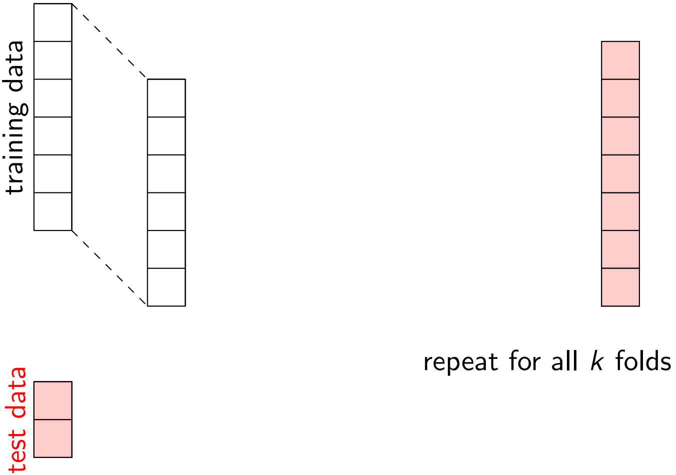

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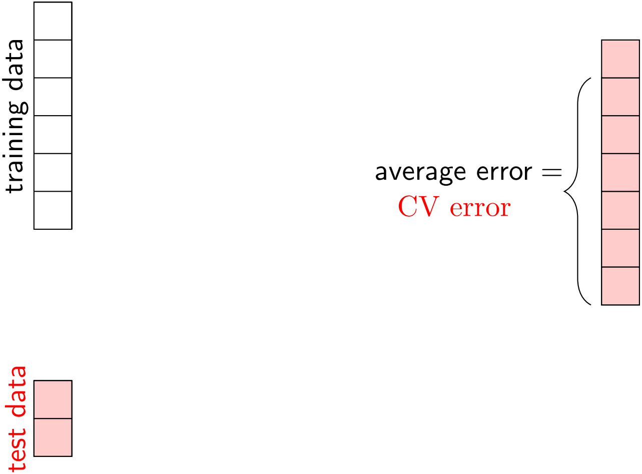

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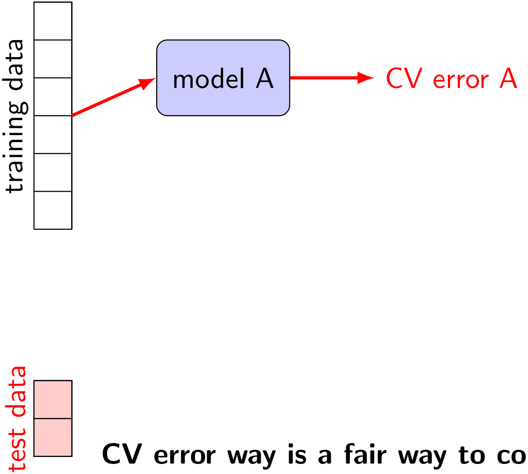
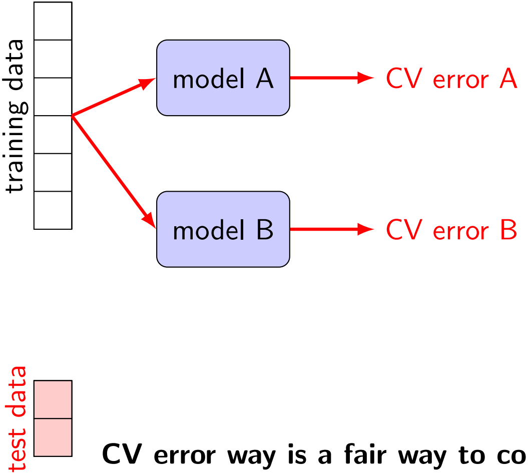


CV error way is a fair way to compare models

(Cross)-validation



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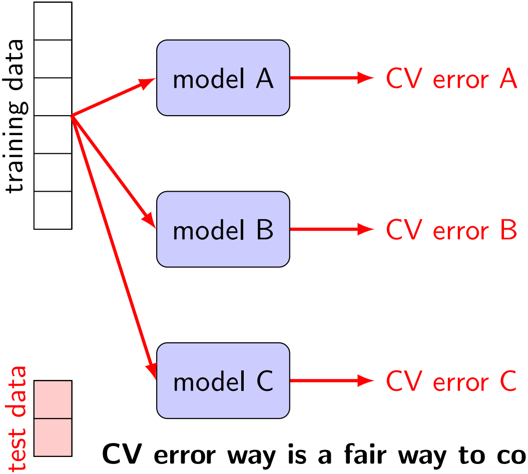

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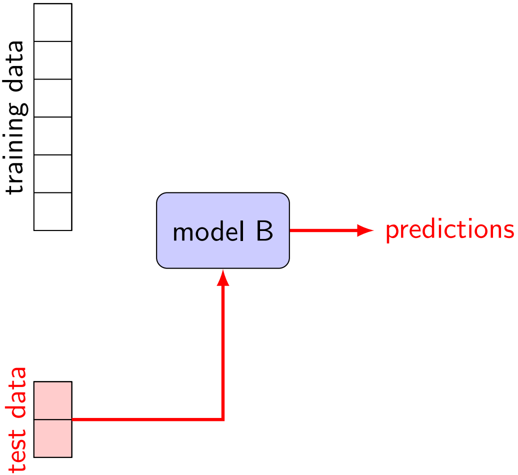

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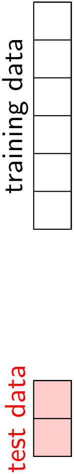

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Deep neural networks (might) need better theories.

Multiple linear regression

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Linear models give $\hat{y}$ as linear function of the data matrix of X:

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We can write this in a matrix form as well:

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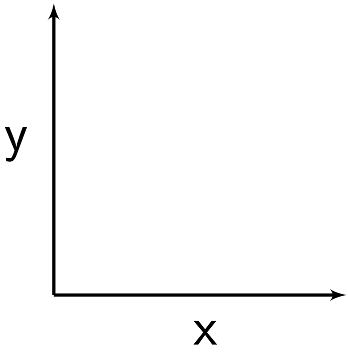
Notice how we handle the constant terms

Multiple linear regression II

Let's solve our regularized least-squares problem:

$$
\begin{aligned}
w &= \arg\min_{w \in \mathbb{R}^p} \frac{1}{n} \left\| y_{data} - Xw \right\|_2^2 + + \lambda \left\| w \right\|_2^2 \\
&= \frac{1}{n} \left(y_{data} - Xw \right)^T \left(y_{data} - Xw \right) + \lambda w^T w \\
\frac{\partial \mathcal{L}}{\partial w} &= -\frac{2}{n} X^T \left(y_{data} - Xw \right) + 2\lambda w = 0 \\
\implies (\lambda I + X^T X) w &= X^T y_{data} \\
w &= \left(\lambda I + X^T X \right)^{-1} X^T y_{data}
\end{aligned}
$$

Simple example in 1D



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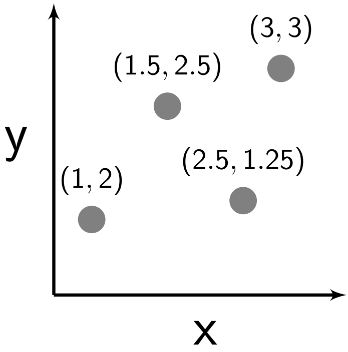

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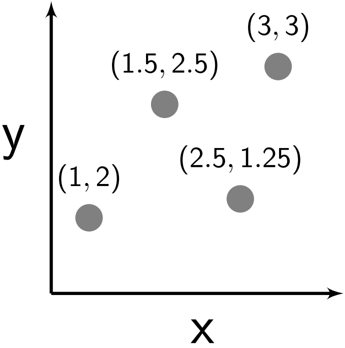

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 1.5 \\ 1 & 2.5 \\ 1 & 3.0 \end{bmatrix}, \; y_{data} = \begin{bmatrix} 2 \\ 2.5 \\ 1.25 \\ 3 \end{bmatrix}$$

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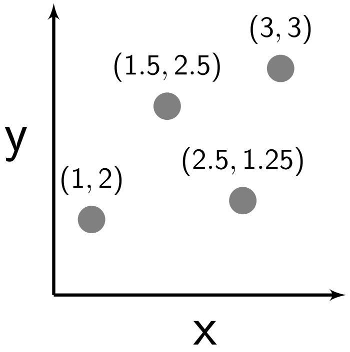

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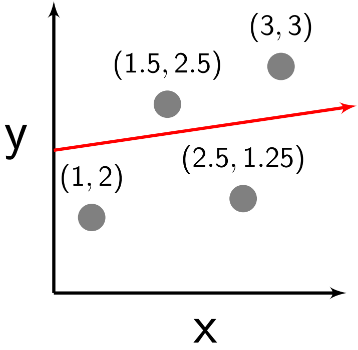

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$$= \begin{bmatrix} 1.9 \\ 0.15 \end{bmatrix} (\lambda = 0.0)$$

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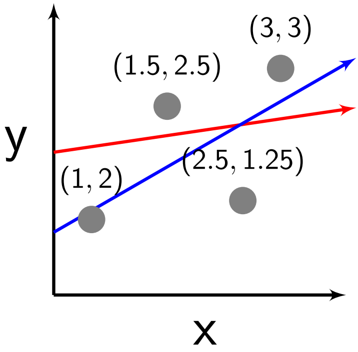

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$$= \begin{bmatrix} 0.82 \\ 0.58 \end{bmatrix} \; (\lambda = 1.0)$$

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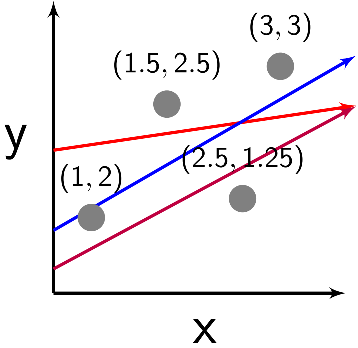

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$$= \begin{bmatrix} 0.32 \\ 0.54 \end{bmatrix} (\lambda = 10)$$

The linear kernel

We can rewrite our result to express $w = X^T a$ for $a \in \mathbb{R}^n$ (shift of basis).

$$\hat{y}_{MLR}(x^*) = x^* w = \sum_{j=1}^{d} x_j^* w_j$$

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$$= \sum_{i=1}^{n} x^* x_i^T a_i = \sum_{i=1}^{n} k\left(x^*, x_i\right) a_i$$

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The term $k\left(x^*, x_i\right) = x^* x_i^T = \langle x^*, x_i \rangle$is the **linear kernel**.

The linear kernel II

The matrix $K_{i,j} = \langle x_i, x_j \rangle$ is called the (linear) **kernel matrix**.
We can write the solution of the regression problem in this form – it is **exactly equivalent**:

$$\hat{y}(X) = Ka$$
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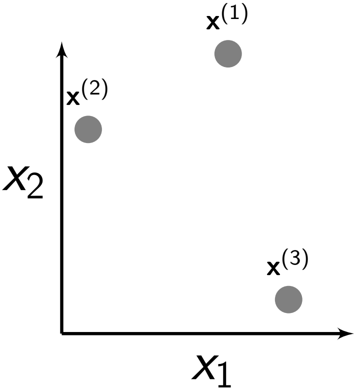
The prediction at any new point is proportional to the inner product of each training point and the new point:

$$\hat{y}_{MLR}(x^*) = \sum_{i=1}^{n} k\left(x^*, x_i\right) a_i = \sum_{i=1}^{n} k\left\langle x^*, x_i\right\rangle a_i$$

Linear kernel geometric picture

$$y(x^*) = w_1 x_1^* + w_2 x_2^*$$



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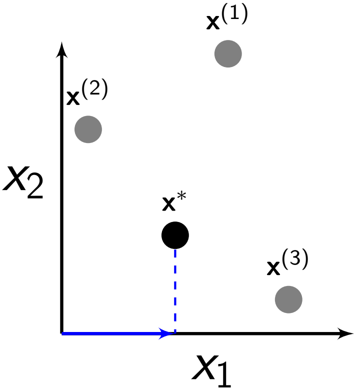

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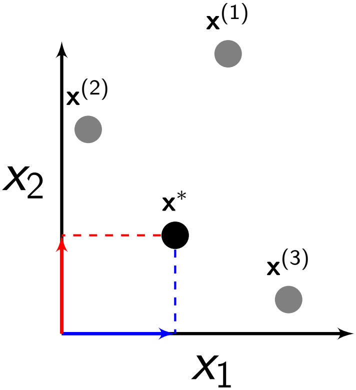

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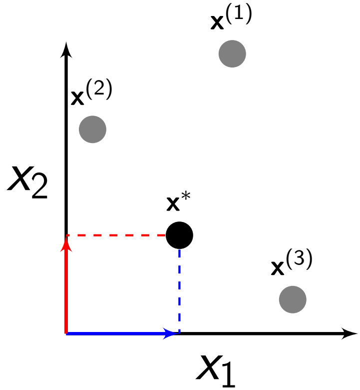

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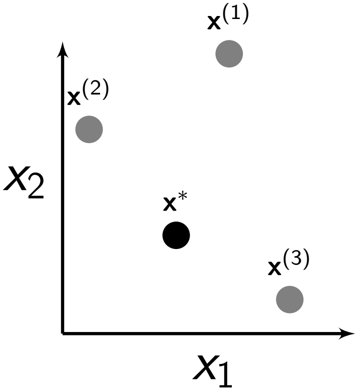

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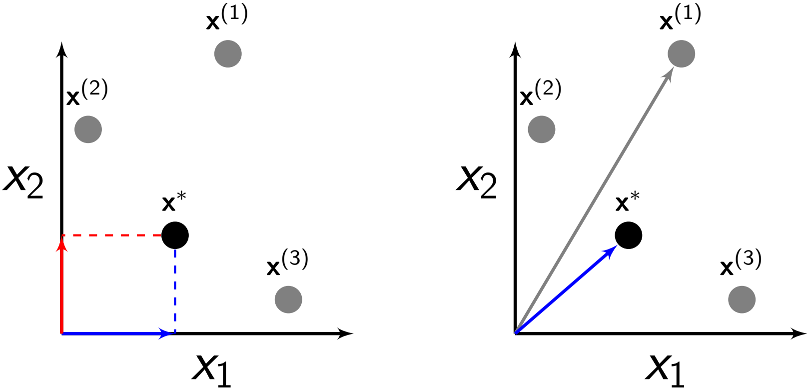

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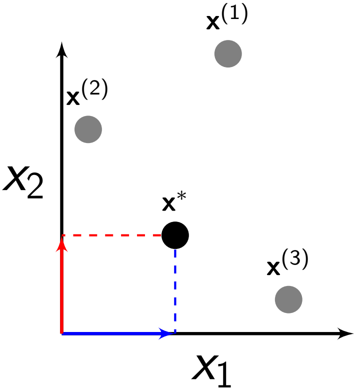

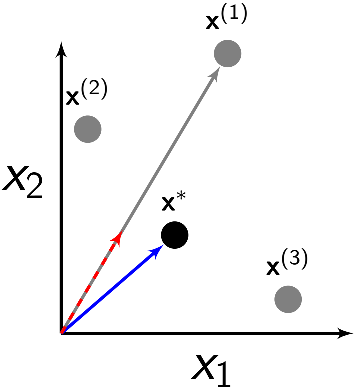

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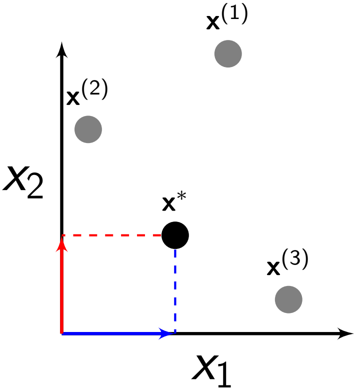

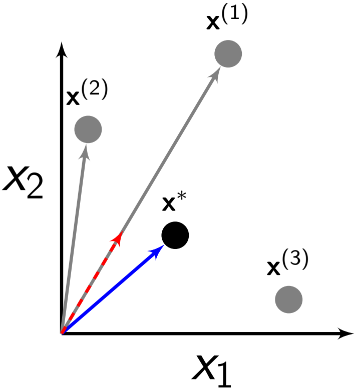

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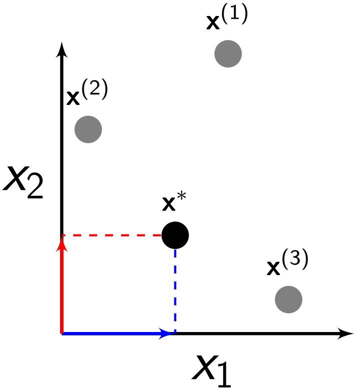

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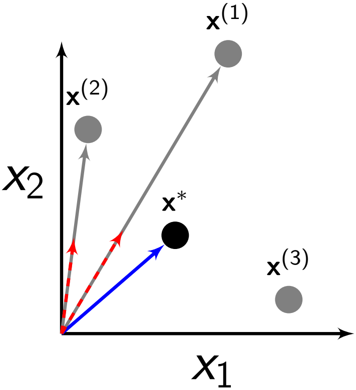

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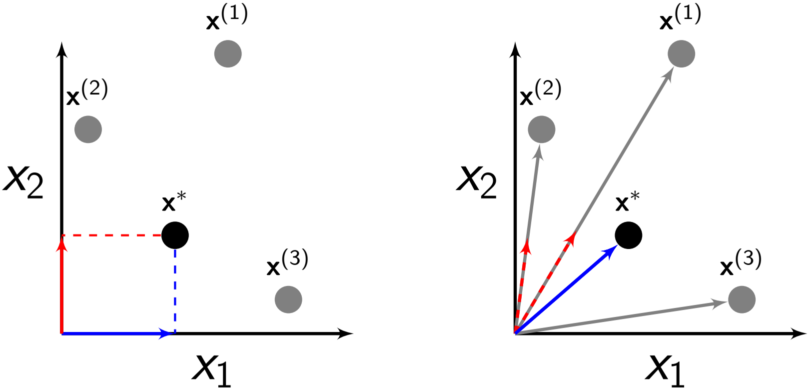

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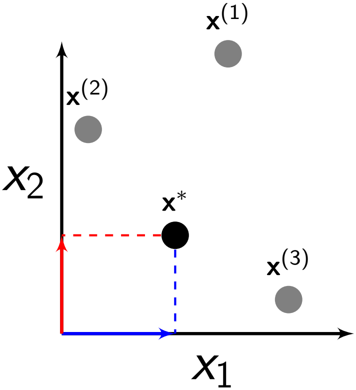

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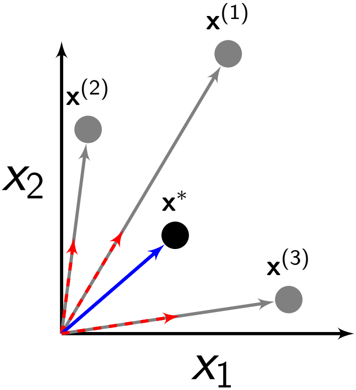

Nonlinear regression

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Notice that this is *linear* in w for a 'lifted' feature space, $\varphi(X)$:

$$\begin{aligned} y_{QUAD}(x) &= \varphi(X)w \\ &= \begin{bmatrix} 1 & \sqrt{2}x_1^{(1)} & \sqrt{2}x_2^{(1)} & \sqrt{2}x_1^{(1)}x_2^{(1)} & (x_1^{(1)})^2 & (x_2^{(1)})^2 \\ \vdots & & \vdots & & & \\ 1 & \sqrt{2}x_1^{(n)} & \sqrt{2}x_2^{(n)} & \sqrt{2}x_1^{(1)}x_2^{(n)} & (x_1^{(n)})^2 & (x_2^{(n)})^2 \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_6 \end{bmatrix} \end{aligned}$$

except the dimension has increased from $\mathbb{R}^{n\times 2} \rightarrow \mathbb{R}^{n\times 6}$

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by direct analogy to the previous slides, there is also a kernel form:

$$\hat{y}(x^*) = \sum_{i=1}^{n} k(x^*, x_i)\, a_i$$
$$k(x^*, x_i) = \langle \varphi(x_i), \varphi(x_j) \rangle$$
$$= \begin{bmatrix} 1 & \sqrt{2}x_1^{(i)} & \dots & (x_1^{(i)})^2 & (x_2^{(i)})^2 \end{bmatrix} \begin{bmatrix} 1 \\ \sqrt{2}x_1^{(j)} \\ \vdots \\ (x_1^{(j)})^2 \\ (x_2^{(j)})^2 \end{bmatrix}$$

The "kernel trick"

Notice that all that is required is vector products, i.e.

$$K_{i,j} = \langle \varphi(x_i), \varphi(x_j) \rangle$$

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$$K_{i,j} = \left((x^{(i)})^T x^{(j)} + 1 \right)^2 = (x_1^{(i)})^2 (x_1^{(j)})^2 + 2 x_1^{(i)} x_1^{(j)} x_2^{(i)} x_2^{(j)} + \dots$$

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which can be computed entirely using vectors in $\mathbb{R}^2$, so we never have to allocate the (factorially large) feature space.

Detailed example of nonlinear regression

jupyter notebook: `github.com/jpjanet/ML-chem-workshop/blob/master/notebooks/workshop_compare_models.ipynb`

General kernels

Both kernel methods are the same except:

	linear	quadratic
K_{ij}	$(x^{(i)})^T x^{(j)}$	$\left((x^{(i)})^T x^{(j)} + 1\right)^2$

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From the perspective of similarity, we can imagine arbitrary functions to be our kernel, without ever needing to know what the underlying feature map φ is.

The Gaussian kernel and KRR

The most widely used kernel is the Gaussian kernel:o

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Depends on σ to control non-locality.

Similarity and Gaussian KRR

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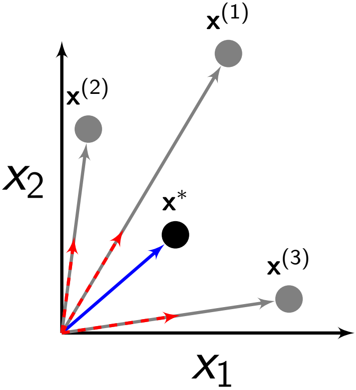

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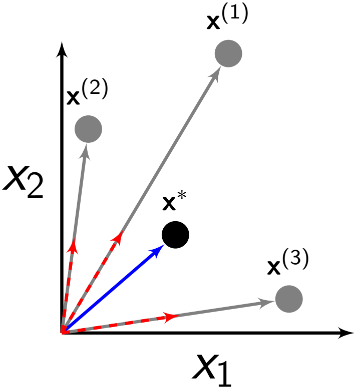

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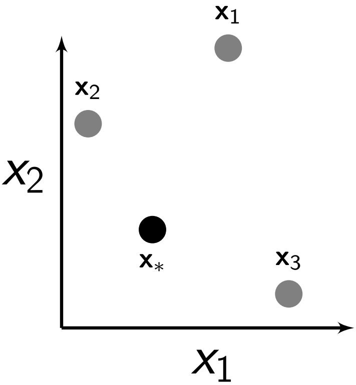

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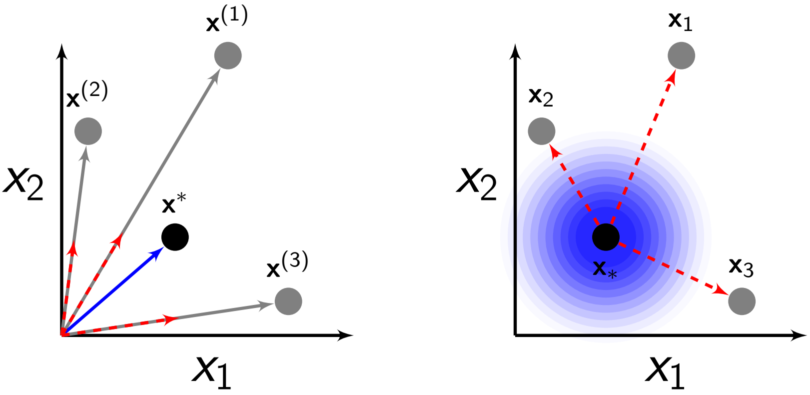

linear kernel **Gaussian kernel**

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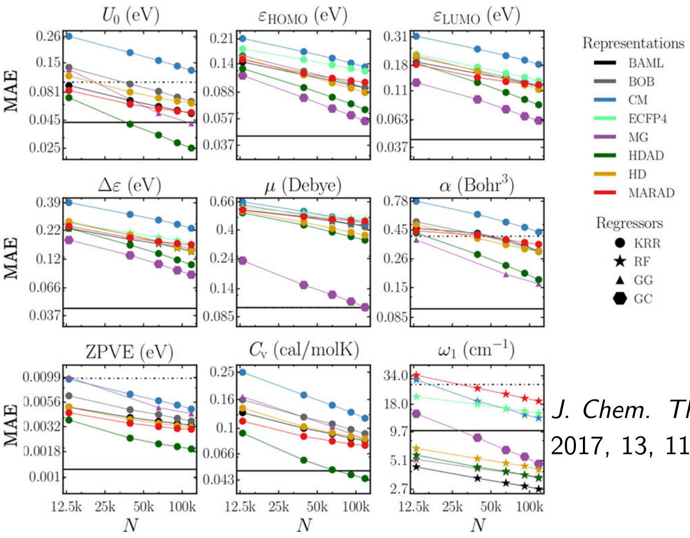
4. check using cross-validation to choose σ and λ

KRR is widely used in chemistry



J. Chem. Theory Comput. 2017, 13, 11, 5255–5264

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KRR example

jupyter notebook: `github.com/jpjanet/ML-chem-workshop/blob/master/notebooks/KRR.ipynb`

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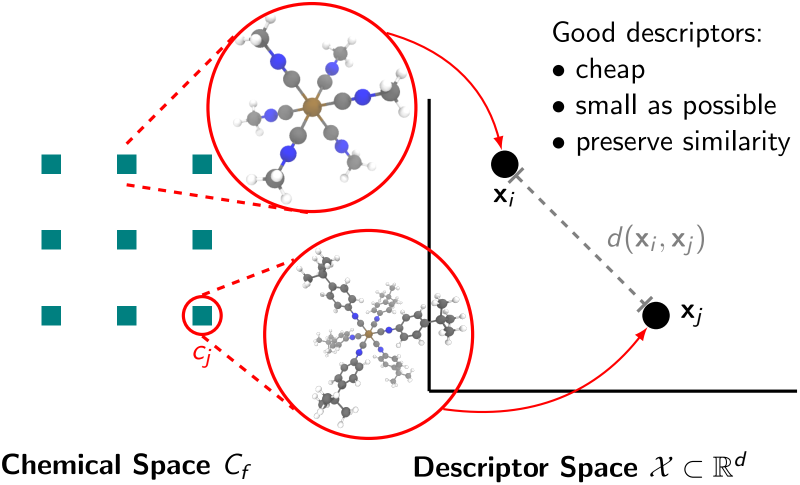

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- cheap
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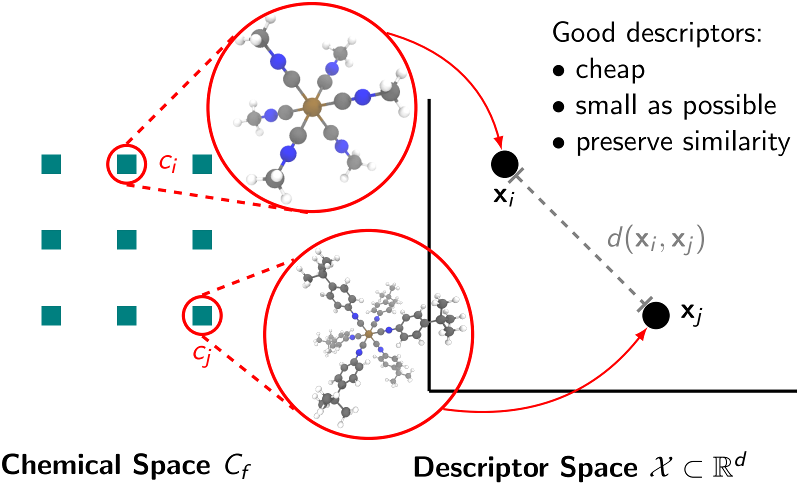

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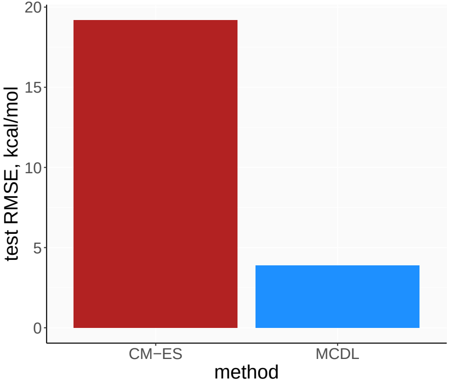

Janet, J.P., and Kulik, H.J. *Chem. Sci.*, 2017, 8, 5137-5152.

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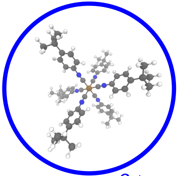
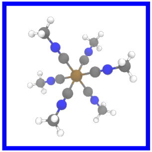


$Fe[pisc]_6^{3+}$



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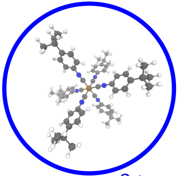

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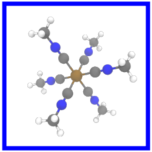
$\Delta E_{\text{H-L}} = 37.7$ kcal/mol



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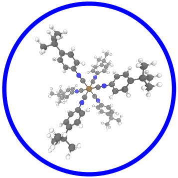

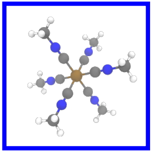

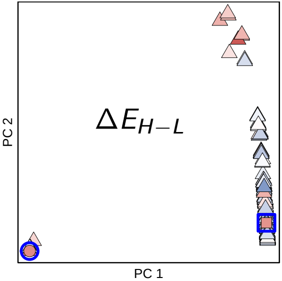

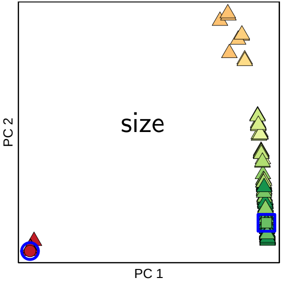

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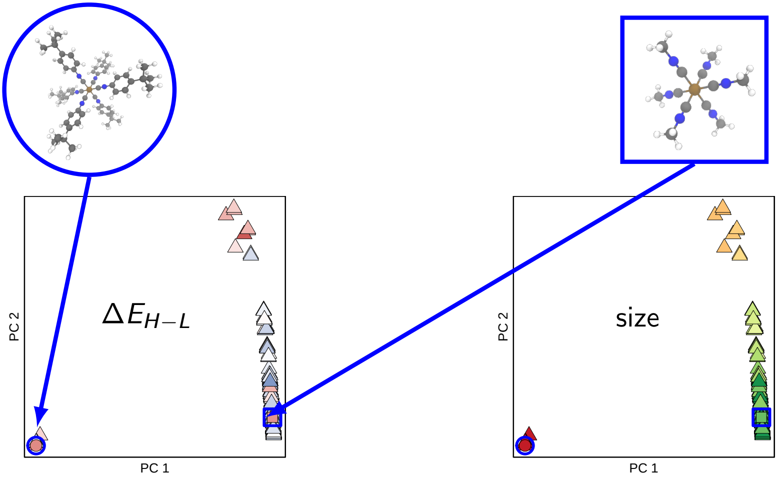

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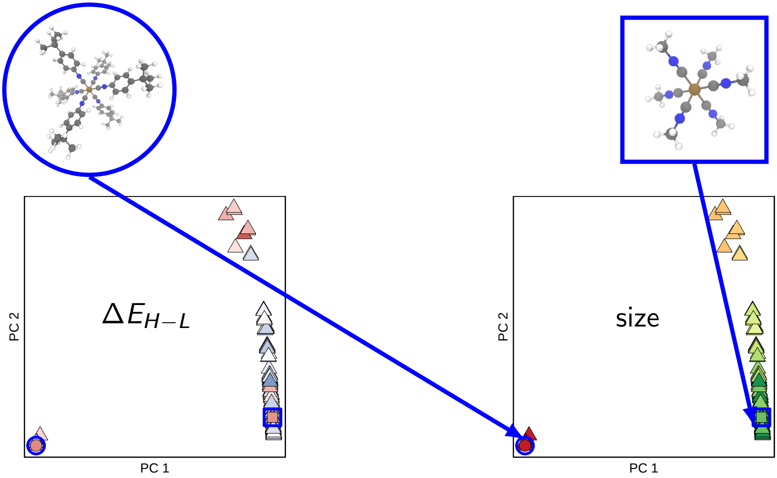

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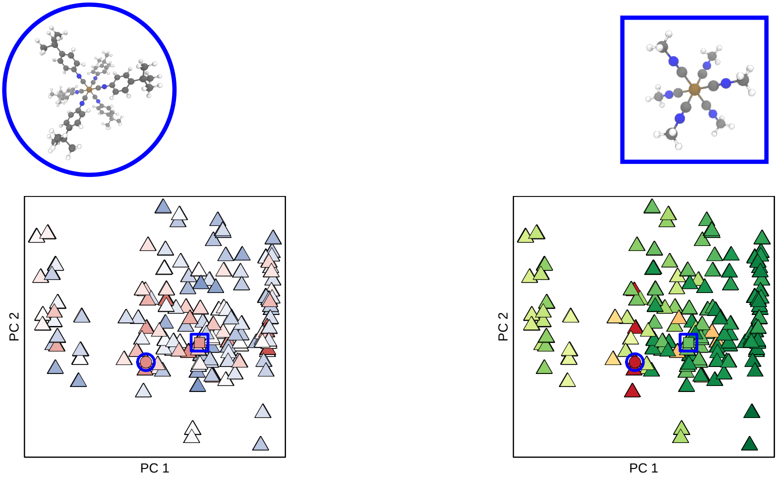

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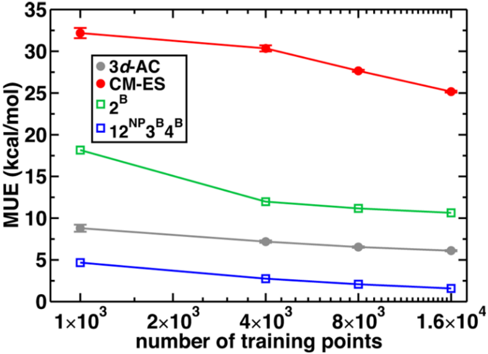

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3D structure

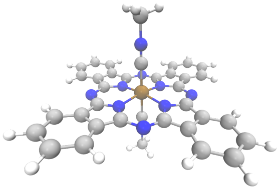
– fine-grained structural information in 3D

– mimic input to a quantum chemistry code

–expensive to compute, rich information

Ad-hoc properties

Sometimes, simple lists of atomic propties are sufficient, especially if informed by domain knowledge:



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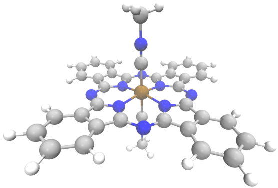
identity

Fe(II)

oxidation state



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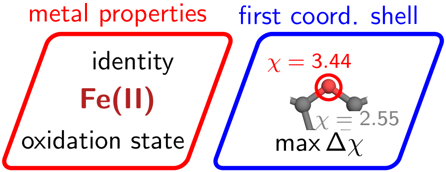

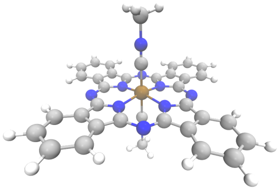

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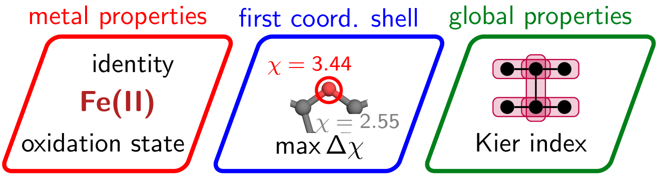

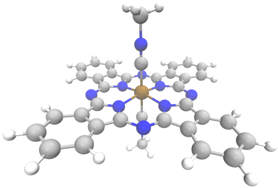

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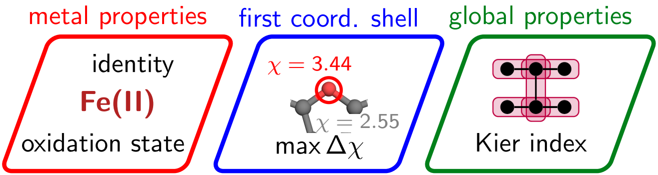

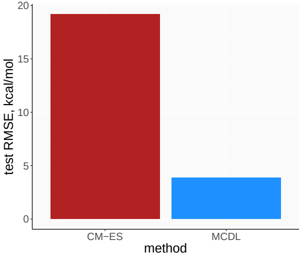

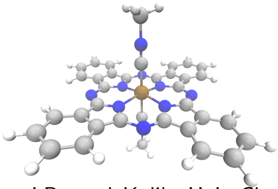

Janet, J.P., and Kulik, H.J. *Chem. Sci.*, 2017, 8, 5137-5152.

Fingerprints and the low-information limit

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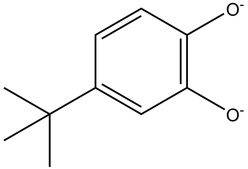

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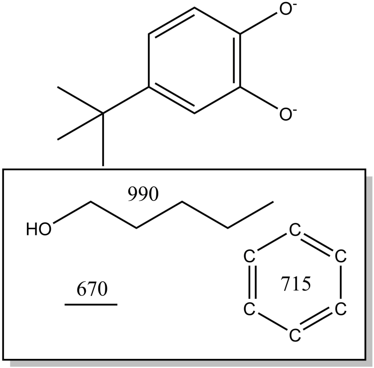

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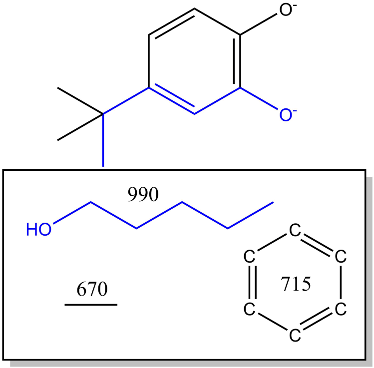
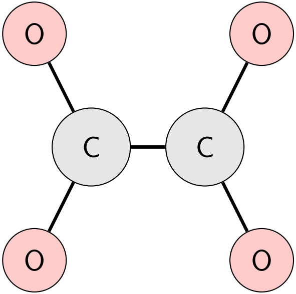


Molecular graphs

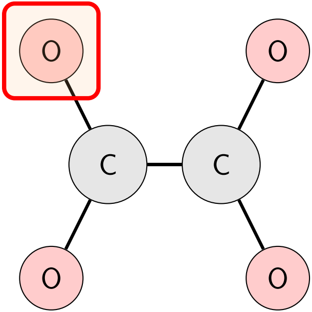
Based on autocorrelations[1]



[1] Broto, P., Moreau, G. and Vandycke, C. *Eur. J. Med. Chem.*, 19(1):71-78, 1984.

Molecular graphs

Based on autocorrelations and modified for TMCs[4]



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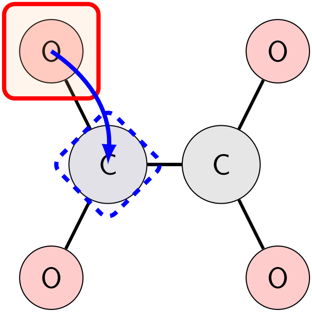

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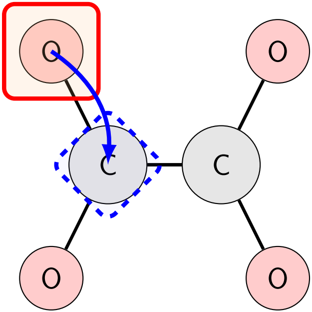

$$d_1 : \sum_{O,C} Z_O Z_C = 48$$

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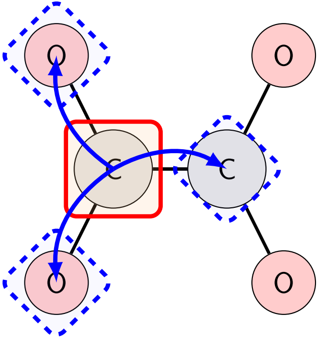

d_1 : $48 + \sum_{C,O} Z_O Z_C = 144 + 48$

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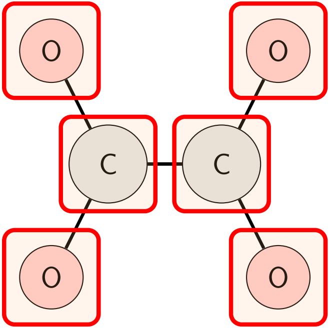

$d_1 : \sum_i \sum_j Z_i Z_j \delta(d_{i,j}, 1)$

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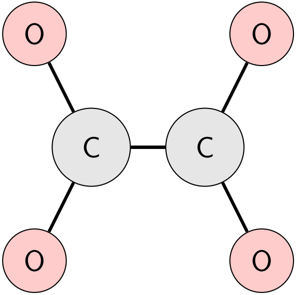
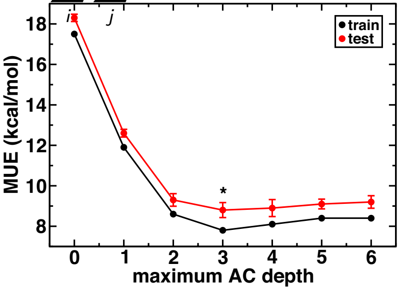


$$d_x : \sum_i \sum_j Z_i Z_j \delta(d_{ij}, x)$$



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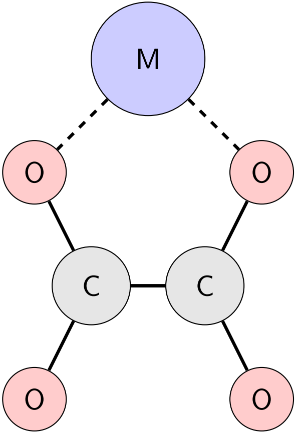

How to adapt to TM complexes?

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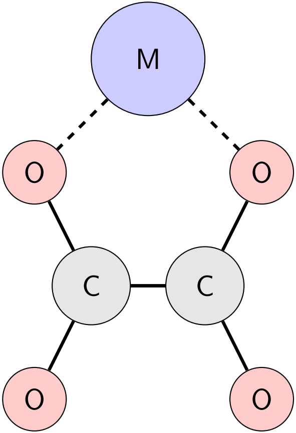

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restrict the scope to focus on
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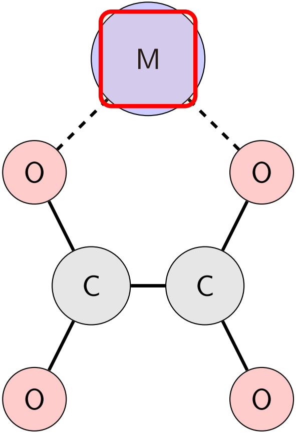

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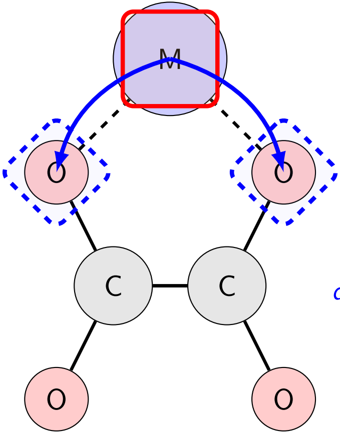

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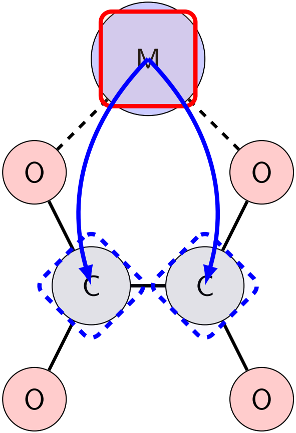

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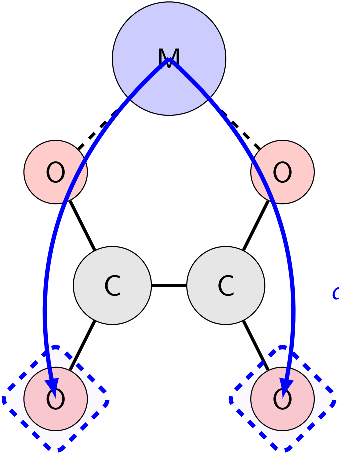

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$$d_3 : \sum_{M,O} Z_M Z_O$$

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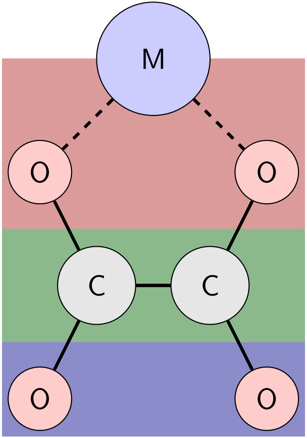

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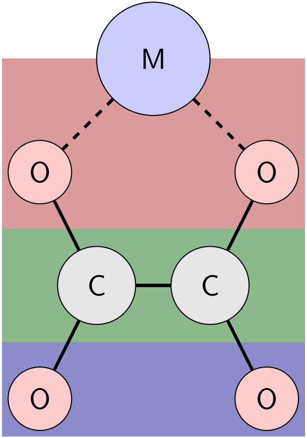

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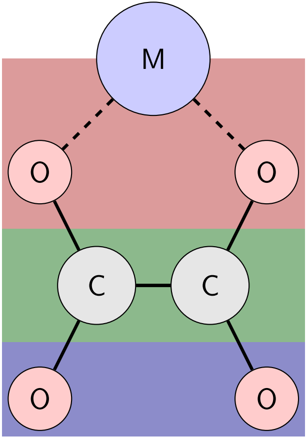

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properties: T, χ, Z, I, S

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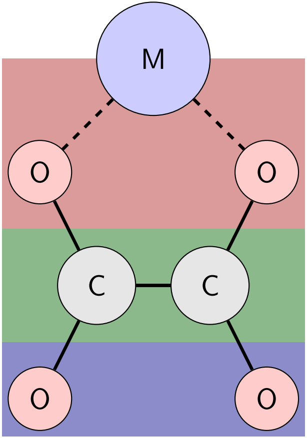

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$\boxed{\sim 160 \text{ features in total}}$

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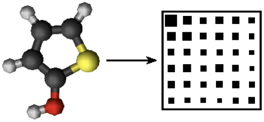
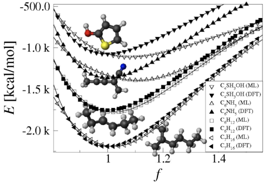
Coulomb matrices

One family of 3D desciptors attempt to copy information used in quantum chemistry codes, e.g. Coulomb Matricies:

Montavon, G. *et al.*. Learning Invariant Representations of Molecules for Atomization Energy Prediction, NIPS 25, 2012

$$M_{I,J} = \begin{cases} 0.5 Z_I^{2.4} & \text{for } I = J \\ \frac{Z_I Z_J}{|R_I - R_J|} & \text{for } I \neq J \end{cases}$$





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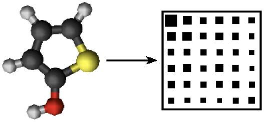
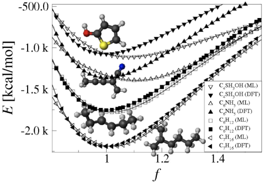


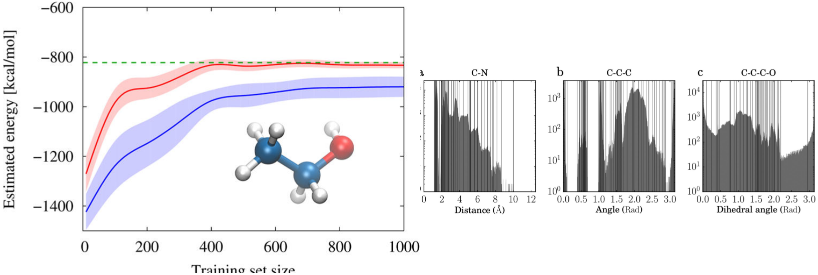


rotational and translational invariance

HDAD and beyond-CM

Subsequent work adds descriptors derived from geometric parameters, i.e. bonds, angles, and dihedral angles:

Faber, F. *et al.*. Prediction Errors of Molecular Machine Learning Models Lower than Hybrid DFT Error, *J. Chem. Theory Comput.* 2017, 13, 11, 5255-5264



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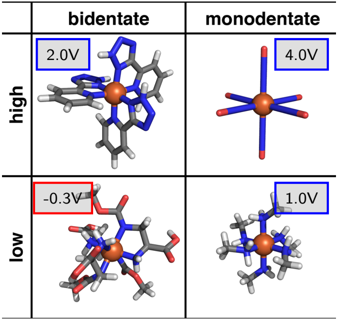

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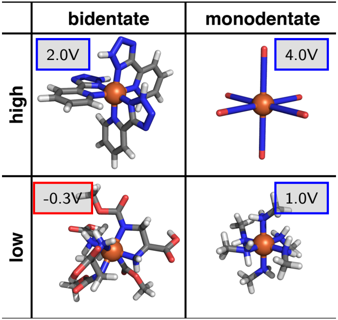

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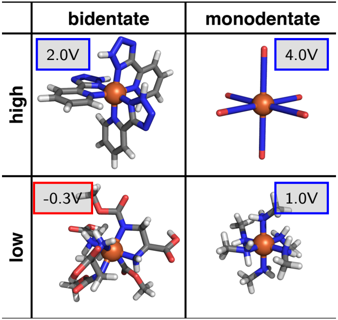

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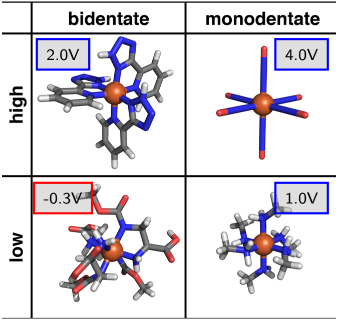

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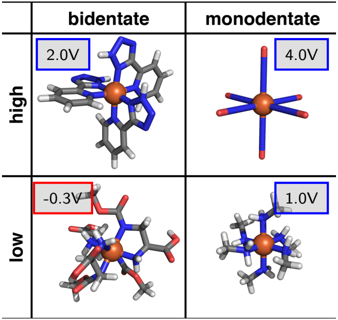

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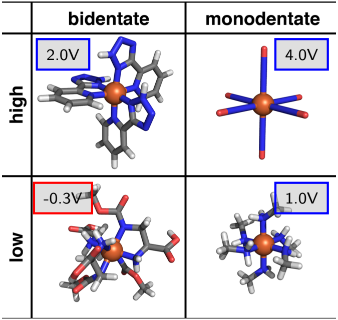

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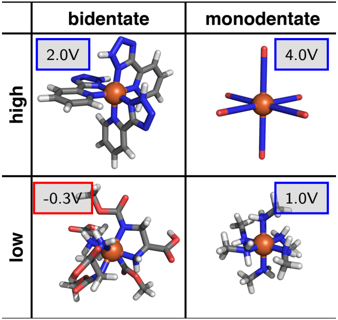

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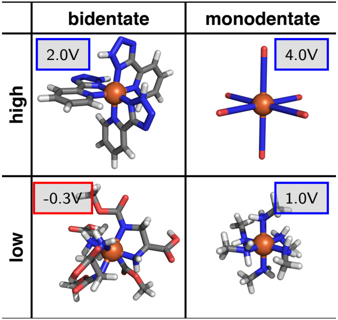

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$$\eta_{i,0} = p_i p_i$$

$$\eta_{i,k} = \sum_{i \neq j} p_i p_j \delta(d_{i,j} - d_k), \quad k \neq 0$$

$$\mathrm{AC}_k = \sum_i \eta_{i,k}$$

4 properties, $k \in [0, 5]$ $\implies$ 28 variables.

How to choose?

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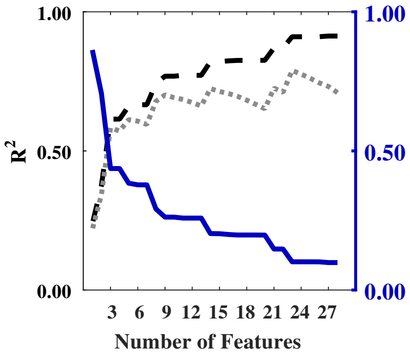

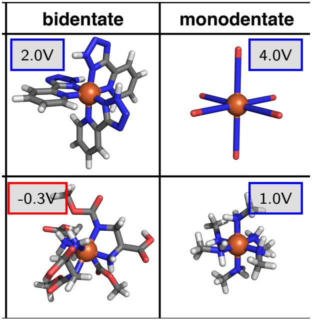

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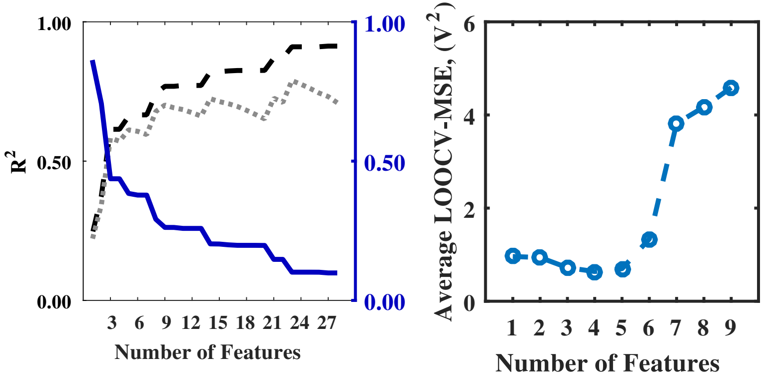

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How to pick important features?

Using unnecessary features can degrade model performance, so we want to able to pick the subset of variables that is best correlated with our objective, formally:

$$w = \arg\min_{w\in} \left(\|y_{data} - Xw\|_2^2 + \lambda \|w\|_0^0 \right)$$

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We don't know the optimal number upfront, and this is a combinatorial problem – possible for ≤ 30 dimensions or so, but rapidly becomes unfeasible.

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Instead, we can do recursive feature addition/removal. Starting from all (or no) features, we test each feature and remove the one that improves performance most (**crucial to use CV error here**):

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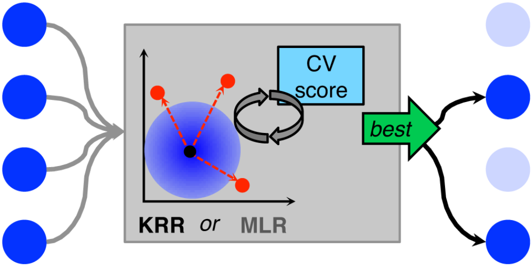

LASSO regression

LASSO regression gives us a one-shot option for linear models:

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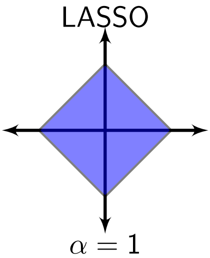

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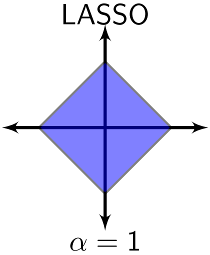

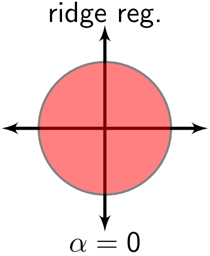

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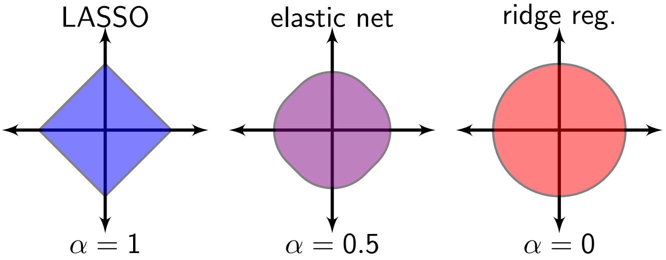

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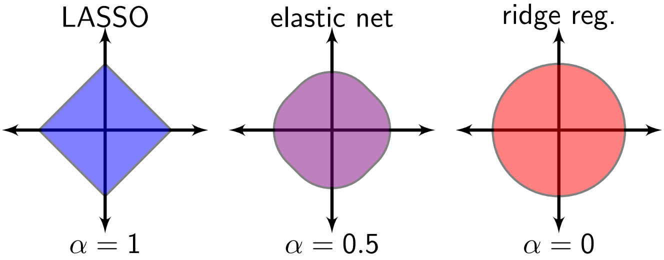

Using even a small $\alpha > 0$ ensures the minimization is stable.

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Why not use even lower norms such as $\|w\|_{0.5}^{0.5}$? Convexity!

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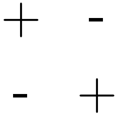

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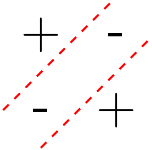

Decision boundary

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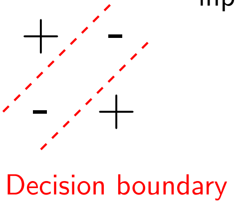

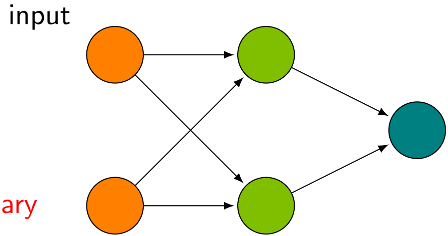

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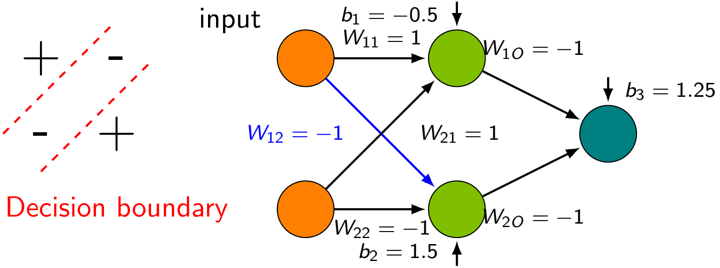
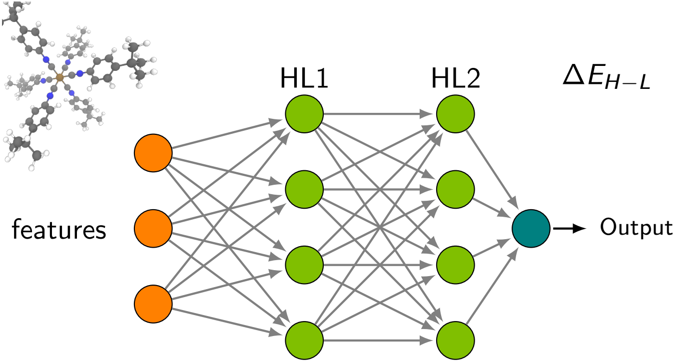


What do they look like?



Backpropagation (chain rule!)

Back-propagation updates neural network weights $\rightarrow$ example

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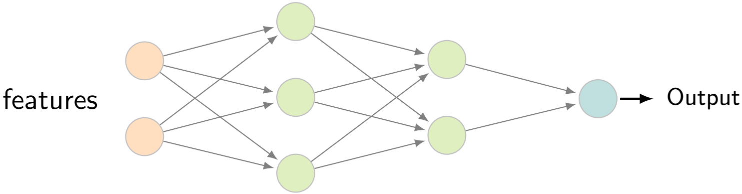

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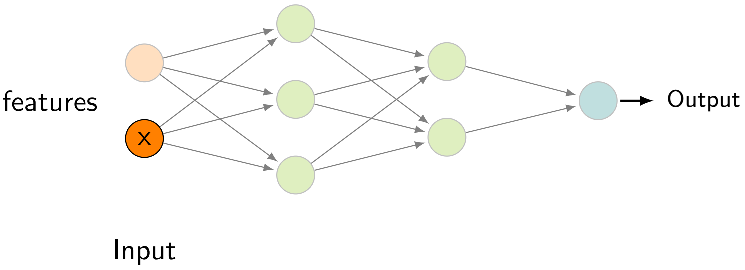

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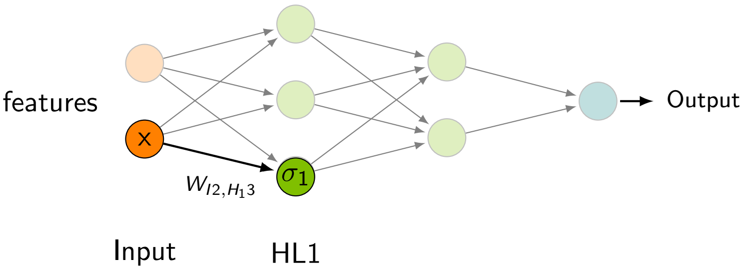

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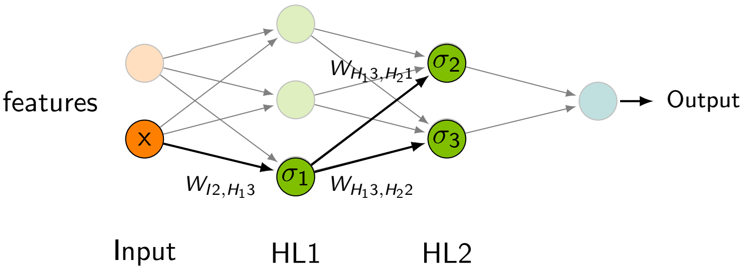

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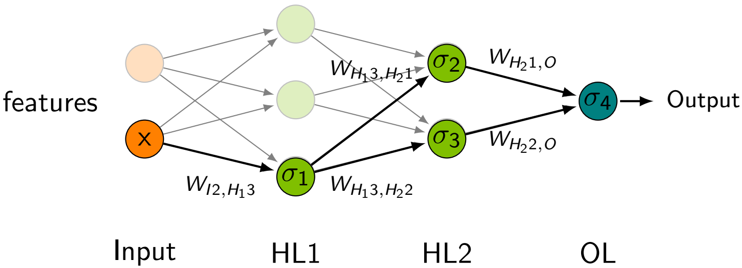

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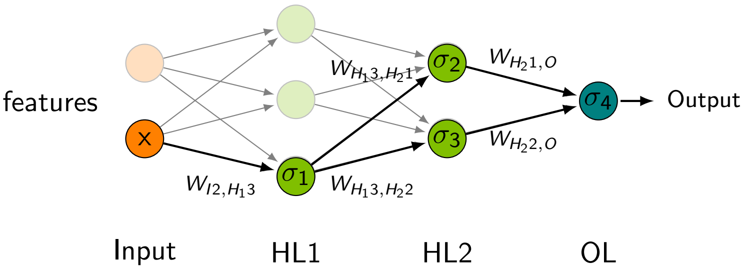

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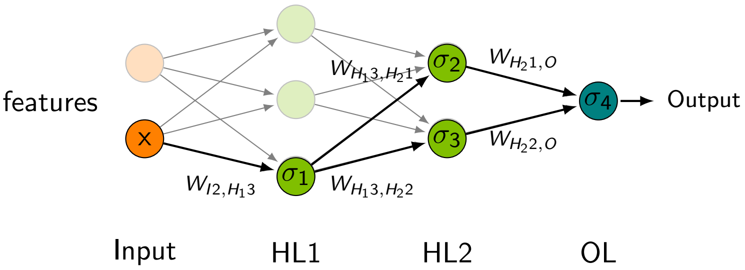

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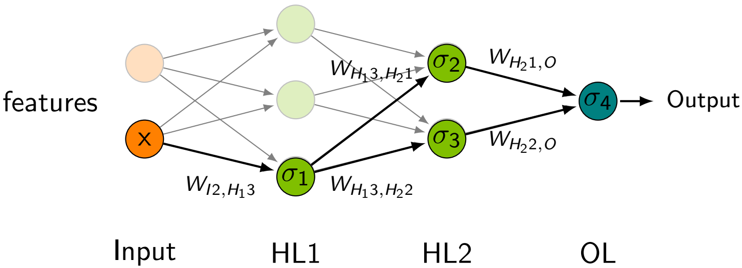

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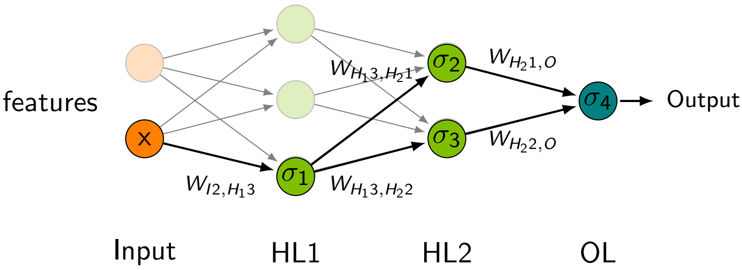
$$\left(\frac{\partial \mathcal{L}}{\partial W_{I2,H_13}}\right) = \left(\frac{\partial \mathcal{L}}{\partial \sigma_4}\right)$$



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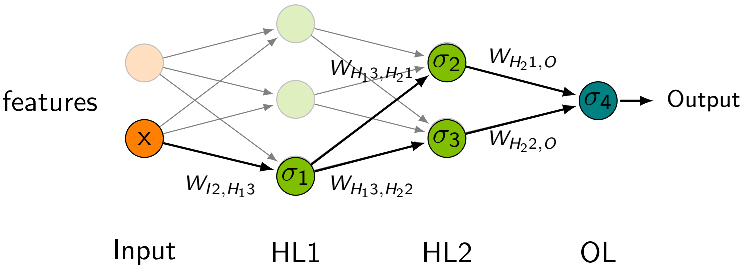
$$\left(\frac{\partial \mathcal{L}}{\partial W_{I2,H_1 3}}\right) = \left(\frac{\partial \mathcal{L}}{\partial \sigma_4}\right)\left(\frac{\partial \sigma_4}{\partial z_4}\right)$$



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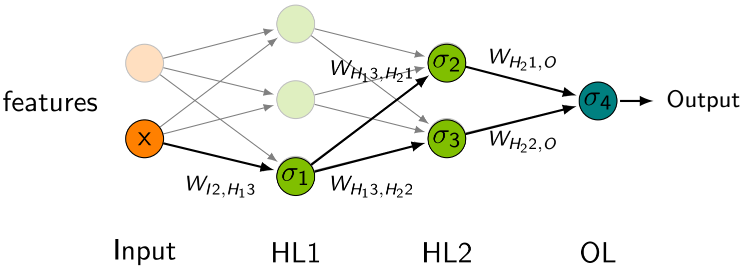

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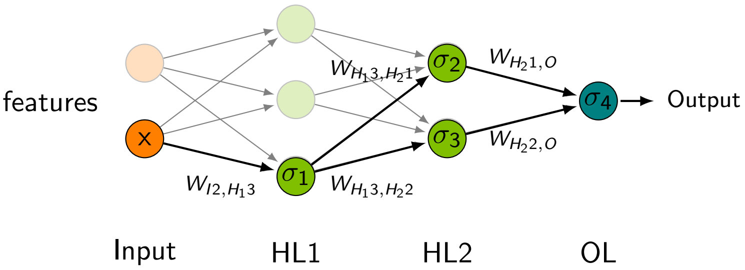
$$\left(\frac{\partial \sigma_1}{\partial z_1}\right)\left(\frac{\partial z_1}{\partial W_{I2,H_13}}\right) + \left(\frac{\partial z_4}{\partial W_{H_22,O}}\right)\left(\frac{\partial W_{H_22,O}}{\partial \sigma_3}\right)\left(\frac{\partial \sigma_3}{\partial z_3}\right)\left(\frac{\partial z_3}{\partial W_{H_13,H_22}}\right)\left(\frac{\partial W_{H_13,H_22}}{\partial \sigma_1}\right)\left(\frac{\partial \sigma_1}{\partial z_1}\right)\left(\frac{\partial z_1}{\partial W_{I2,H_13}}\right)\Bigg]$$



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$$SGD \rightarrow \left(\frac{\partial Loss}{\partial W}\right) \rightarrow \text{one/few examples} \rightarrow \text{MUCH noisier!} \rightarrow \text{less stuck}$$

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Recurrent→ Layers that "store" information about previous times, thus commonly used in speech or handwriting recognition

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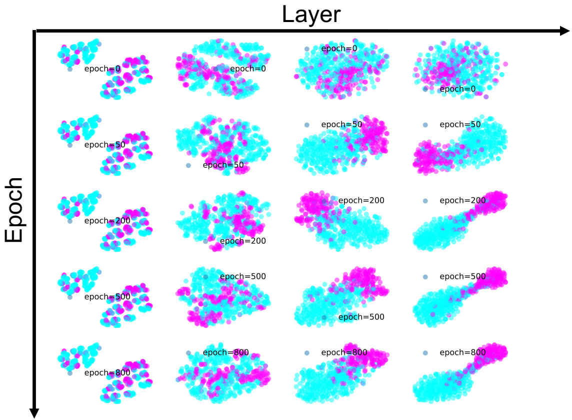

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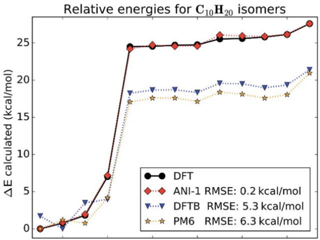
3. We can understand neural networks as automatic feature selection/transformation, followed by linear regression

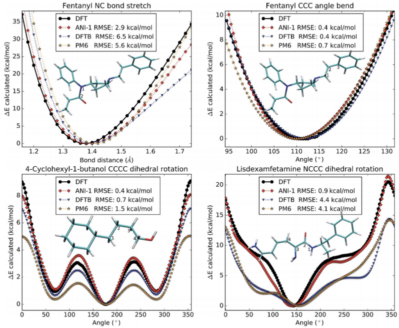
ANN example

jupyter notebook: `github.com/jpjanet/ML-chem-workshop/blob/master/notebooks/ANN.ipynb`

Neural network potentials

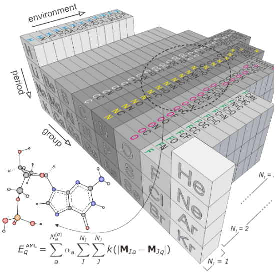
Smith, J. S., Isayev, O., and Roitberg, A. E. ANI-1: an extensible neural network potential with DFT accuracy at force field computational cost. *Chem. Sci.*, **2017**, *8*, 3192-3203.

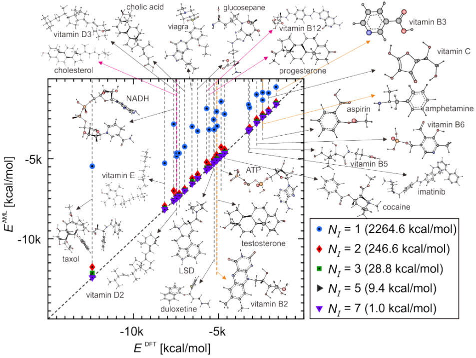




Property predictions

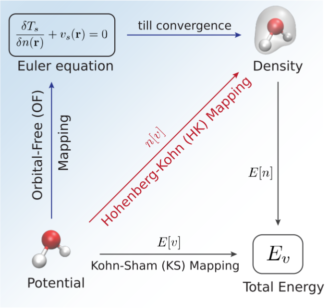
Huang, B. & von Lilienfeld, O.A. *arXiv* 1707.04146, "The 'DNA'of chemistry: Scalable quantum machine learning with amons", 2017.

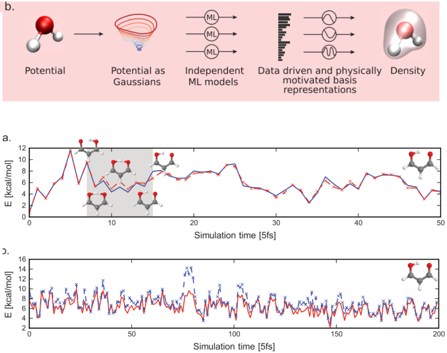




Accelerating quantum chemistry

Bogojeski, M. *el al.*, Burke, K. and Müller, K.R. *arXiv* 1811.06255, Efficient prediction of 3D electron densities using machine learning, 2018.





Controlling calculations on the fly

Chenru Duan *et. al.* *ChemRxiv* .7616009, "Learning from Failure: Predicting Electronic Structure Calculation Outcomes with Machine Learning Models", 2019.