

# Robust Factorization of Tensor Networks, With Applications in Quantum Chemistry

Edward Valeev  
Department of Chemistry, Virginia Tech

**SIAM PP22**

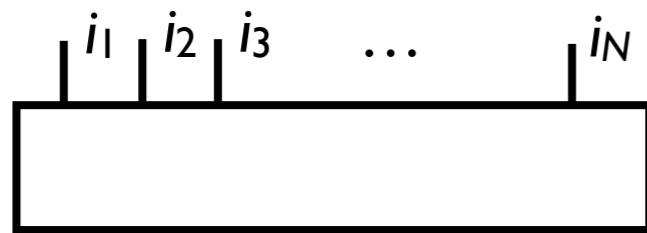
Minisymposium “*Parallel Algorithms for Tensor Computations and their Applications*”

**Feb 26, 2022**

# Why Tensors? Consider $N$ Quantum Particles ...

$$\text{state} = \psi(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_N)$$

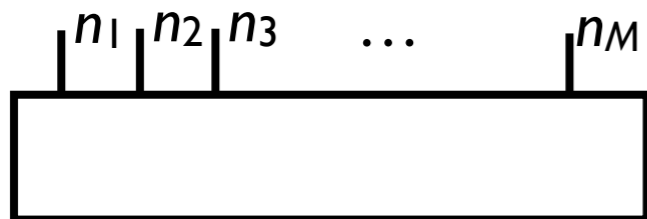
expand in 1-particle basis:  $\psi(\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_N) \approx \sum^M \psi_{i_1 i_2 \dots i_N} \phi_{i_1}(\mathbf{r}_1) \phi_{i_2}(\mathbf{r}_2) \dots \phi_{i_N}(\mathbf{r}_N)$   $M \sim (10) \times N$



$M^N$  elements

encodes probability of finding  $N$  particles in states  $i_1 \dots i_N$   
(joint probability distribution)

or, in occupation number representation (convenient for indistinguishable particles)



$K^M$  elements

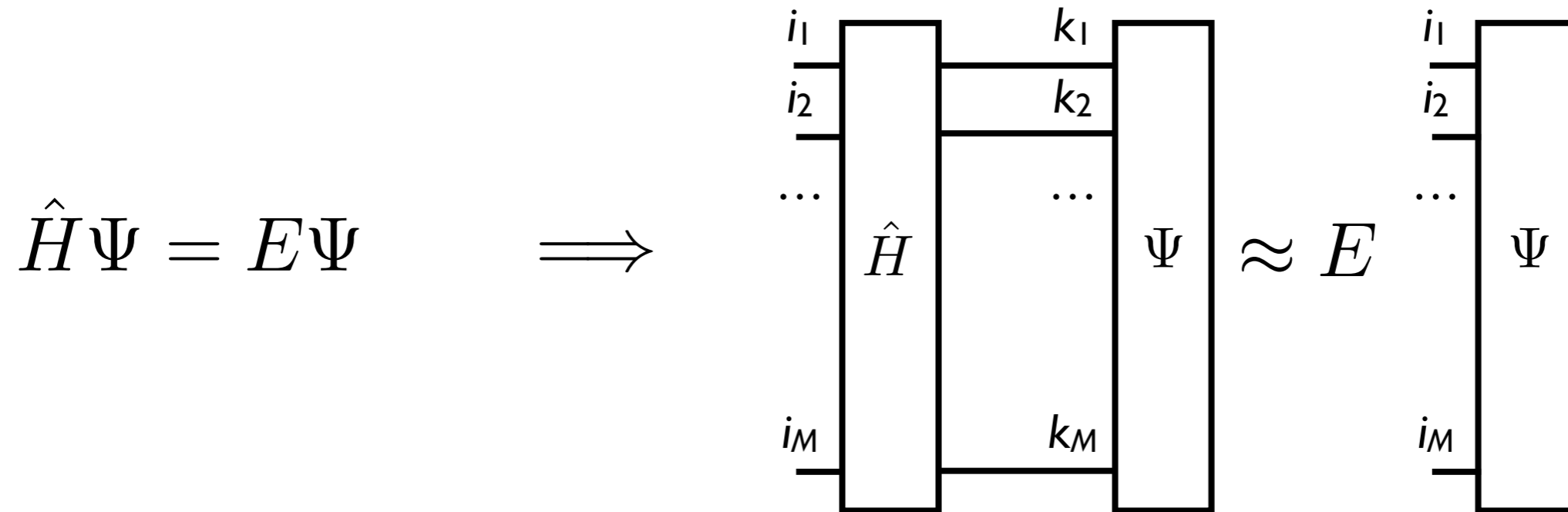
encodes probabilities of specific occupancies of  $M$  states

$K = 2$  or  $4$  for electrons,  $2$  for qubits, etc.

**factorial storage/operation complexities (“curse of dimensionality”)**

# Properties of Quantum States Are Also Tensors

$N$ -Body Schrödinger Equation = Tensor Eigenvalue Problem



Example:  $N_2$  molecule

$N=14$

$M=60$  (cc-pVTZ basis)

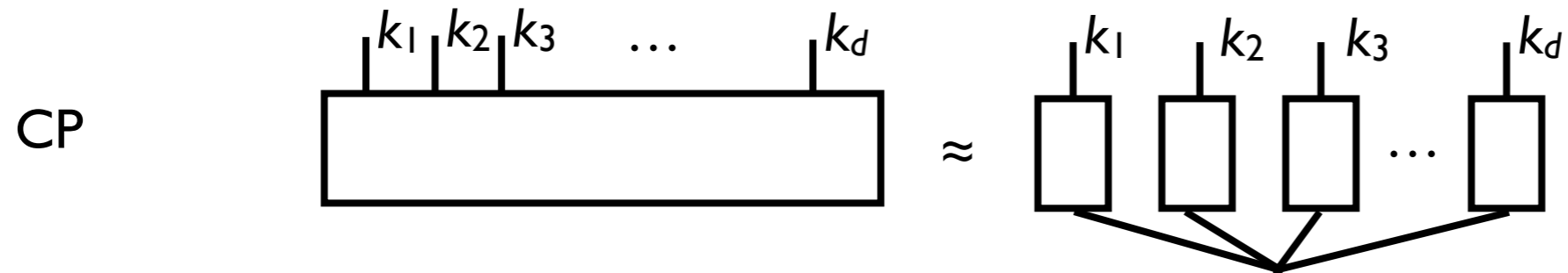
size( $\Psi$ ) =  $1.5 \times 10^{17}$

but only  $< 10^9$  elements are significant!

element sparsity is useful, but it is essential to exploit more general *data sparsity* in  $H$  and  $\Psi$  !

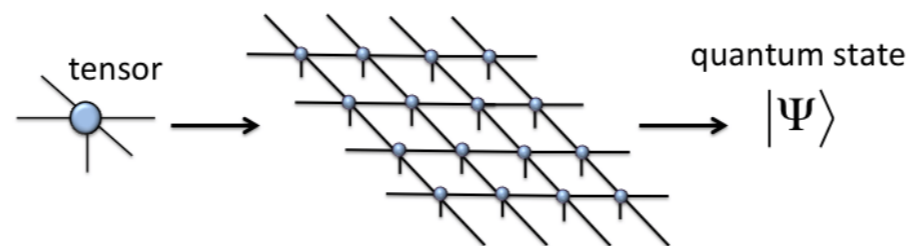
# Tensor Factorization is Key to N-Body Quantum Simulation

## tensor networks



$$A_{k_1 \dots k_d} = \left( U^{(1)} \right)_{r_1}^{k_1} \left( U^{(2)} \right)_{r_1, r_2}^{k_2} \dots \left( U^{(d-1)} \right)_{r_{d-2}, r_{d-1}}^{k_{d-1}} \left( U^{(d)} \right)_{r_{d-1}}^{k_d}$$

PEPS



+ many more (MERA, etc.)

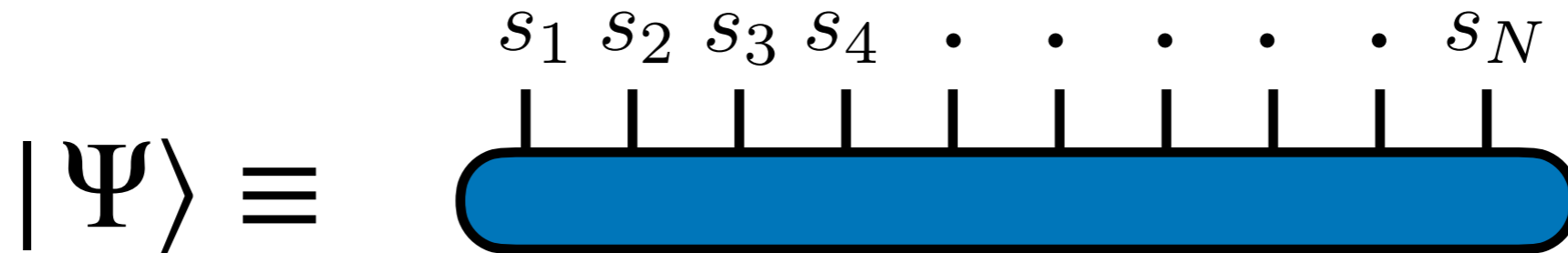
exact when factorization ranks  $\rightarrow \infty$

efficient only for special cases (e.g., DMRG for 1-d systems)

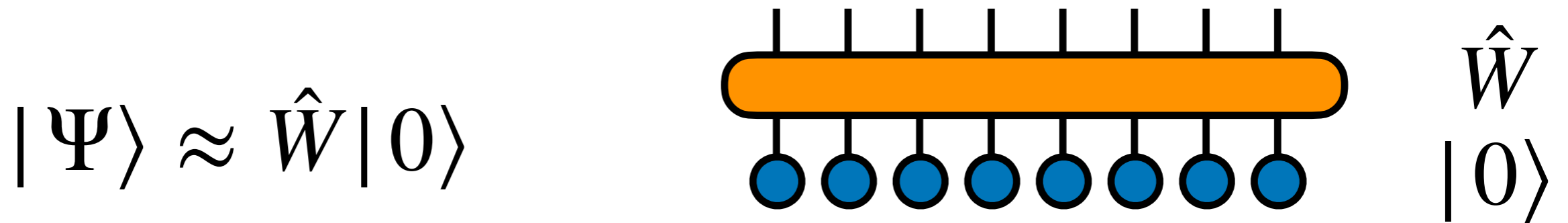


# Tensor Networks via Cumulant/Perturbative Expansion

instead of encoding joint probability amplitudes



encode *differences* in probability amplitudes relative to simple (usually, uncorrelated) state

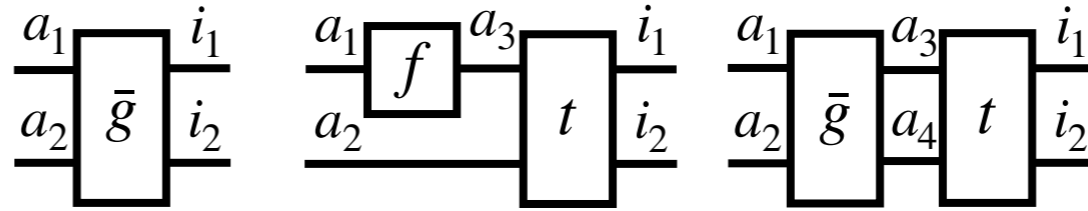


efficient if  $\hat{W}$  limited to a sum of few-body terms (e.g, 2-body in CCSD)

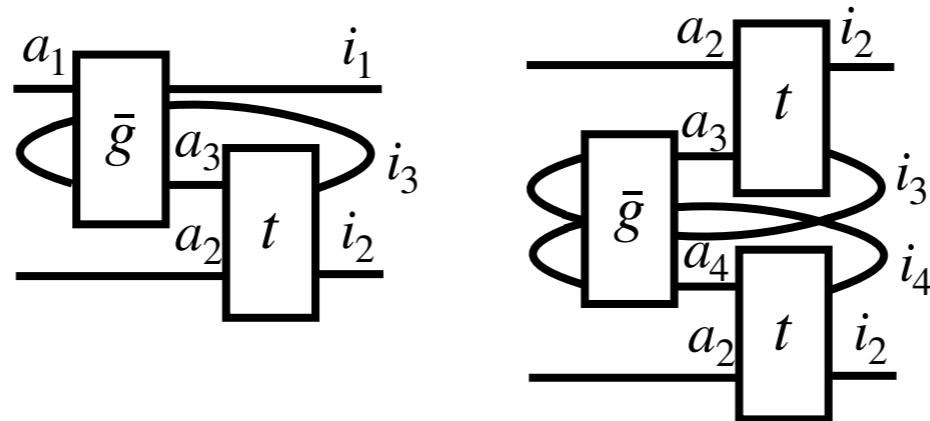
tensor  $\approx$  sum of tensor networks

# Example: CCD Equations

$$0 = \langle \Phi_{i_1 i_2}^{a_1 a_2} | \hat{H} \exp(\hat{T}_2) | 0 \rangle_c = \hat{A}_{i_1 i_2}^{a_1 a_2} \left( \bar{g}_{a_1 a_2}^{i_1 i_2} + f_{a_1 a_3}^{a_3} t_{a_3 a_2}^{i_1 i_2} + \frac{1}{2} \bar{g}_{a_1 a_2}^{a_3 a_4} t_{a_3 a_4}^{i_1 i_2} + \dots \right)$$



$$\bar{g}_{a_1 i_3}^{i_1 a_3} t_{a_3 a_2}^{i_3 i_2} + \frac{1}{2} \bar{g}_{i_3 i_4}^{a_3 a_4} t_{a_1 a_3}^{i_1 i_3} t_{a_4 a_2}^{i_4 i_2} + \dots$$

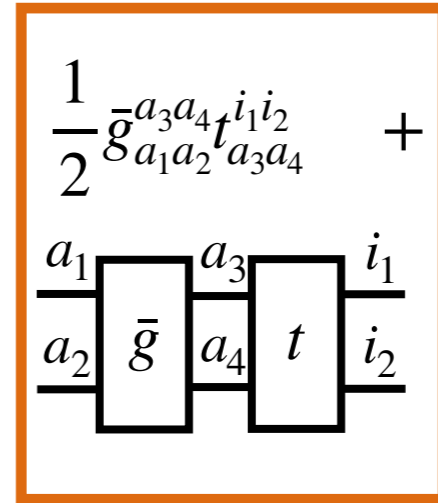
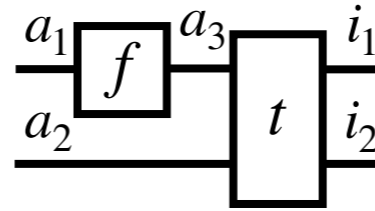
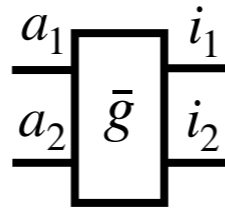


storage =  $O(N^4)$   
 cost =  $O(N^6)$

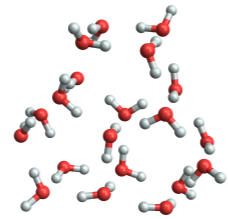
# Example: CCD Equations

dominant tensor contraction

$$0 = \langle \Phi_{i_1 i_2}^{a_1 a_2} | \hat{H} \exp(\hat{T}_2) | 0 \rangle_c = \hat{A}_{i_1 i_2}^{a_1 a_2} \left( \bar{g}_{a_1 a_2}^{i_1 i_2} + f_{a_1}^{a_3} t_{a_3 a_2}^{i_1 i_2} + \frac{1}{2} \bar{g}_{a_1 a_2}^{a_3 a_4} t_{a_3 a_4}^{i_1 i_2} + \dots \right)$$



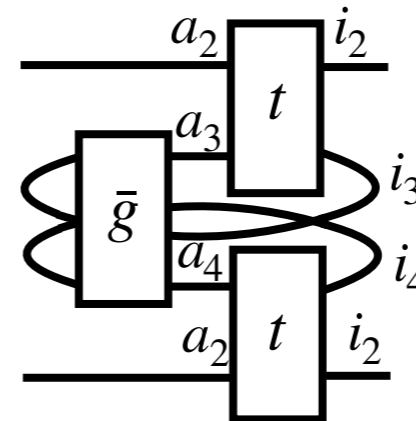
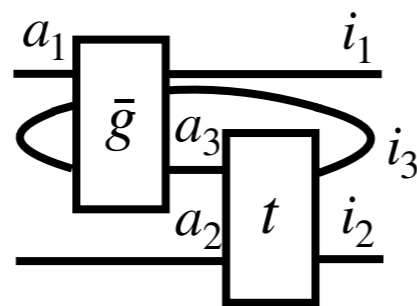
example:



$$\begin{aligned} \text{extent}(i) &= N/2 = 80 \\ \text{extent}(a) &= M - N/2 = 860 \end{aligned}$$

size( $t$ ) = 37.9 GB  
size( $g$ ) = 4.4 TB  
cost  $\sim 3.5 \times 10^{15}$  FLOPs

$$\bar{g}_{a_1 i_3}^{i_1 a_3} t_{a_3 a_2}^{i_3 i_2} + \frac{1}{2} \bar{g}_{i_3 i_4}^{a_3 a_4} t_{a_1 a_3}^{i_1 i_3} t_{a_4 a_2}^{i_4 i_2} + \dots$$

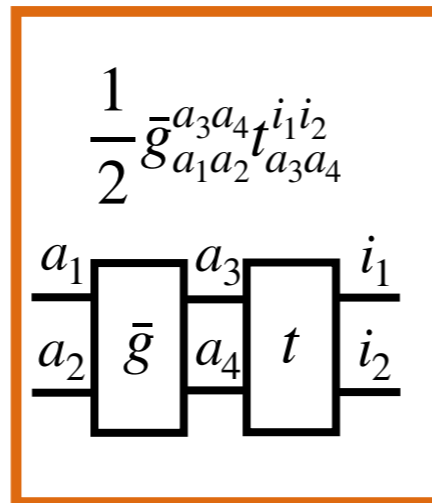


storage =  $O(N^4)$   
cost =  $O(N^6)$



# Our Goal: Complexity Reduction by Factorizing Coulomb Tensor

$O(N^6) \Rightarrow O(N^5)$  by factorizing  $g$

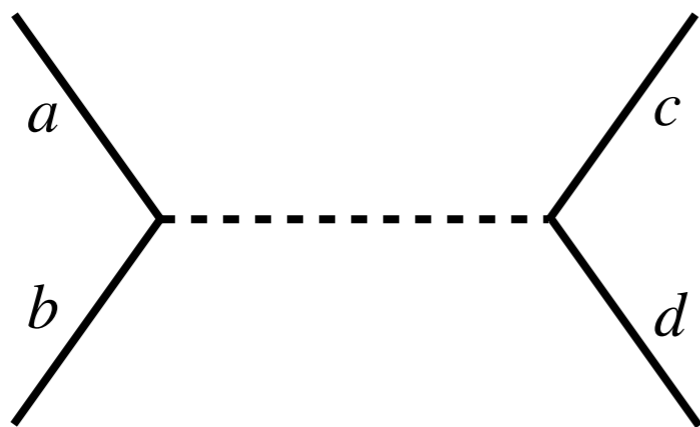


PPL, the dominant “diagram” in CCD, CCSD, and other models

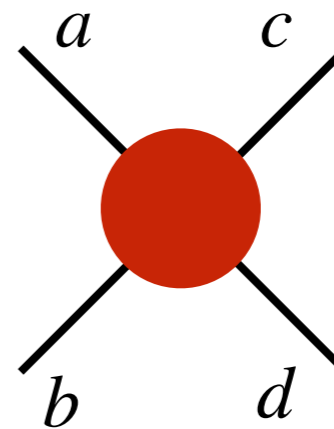
# Coulomb Integral Tensor

$$g_{ab,cd} \equiv (ab | cd) \equiv \int d\mathbf{r} a(\mathbf{r})b(\mathbf{r})\hat{V}cd(\mathbf{r}) \equiv \iint d\mathbf{r} d\mathbf{r}' a(\mathbf{r})b(\mathbf{r})|\mathbf{r} - \mathbf{r}'|^{-1} c(\mathbf{r}')d(\mathbf{r}')$$

$$\hat{V} \equiv \int \frac{d\mathbf{r}'}{|\mathbf{r} - \mathbf{r}'|} \times$$



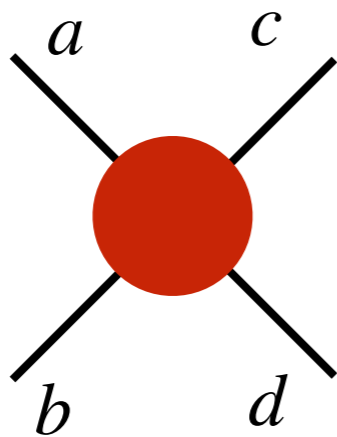
or



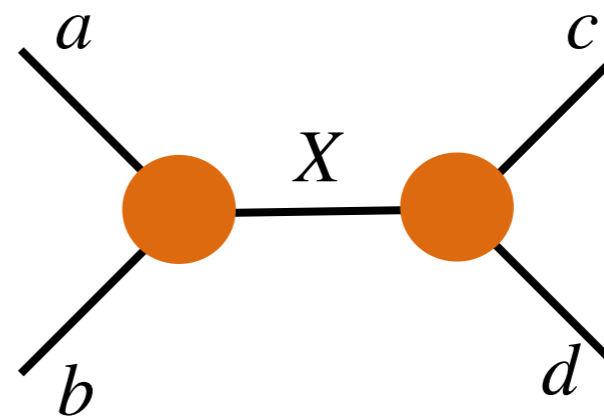
typically never computed explicitly, reconstructed on the fly from factorized form

# “Square Root” Approximations of Coulomb Integrals

$$g_{ab,cd} \stackrel{\text{SQ}}{\approx} \sum_X B_{ab,X} B_{cd,X}$$



$\stackrel{\text{SQ}}{\approx}$



factors computed via physics-based or math-based approximation

(global) density fitting (DF)  
aka resolution-of-identity (RI)

needs empirically-optimized AO basis

Cholesky Decomposition (CD)

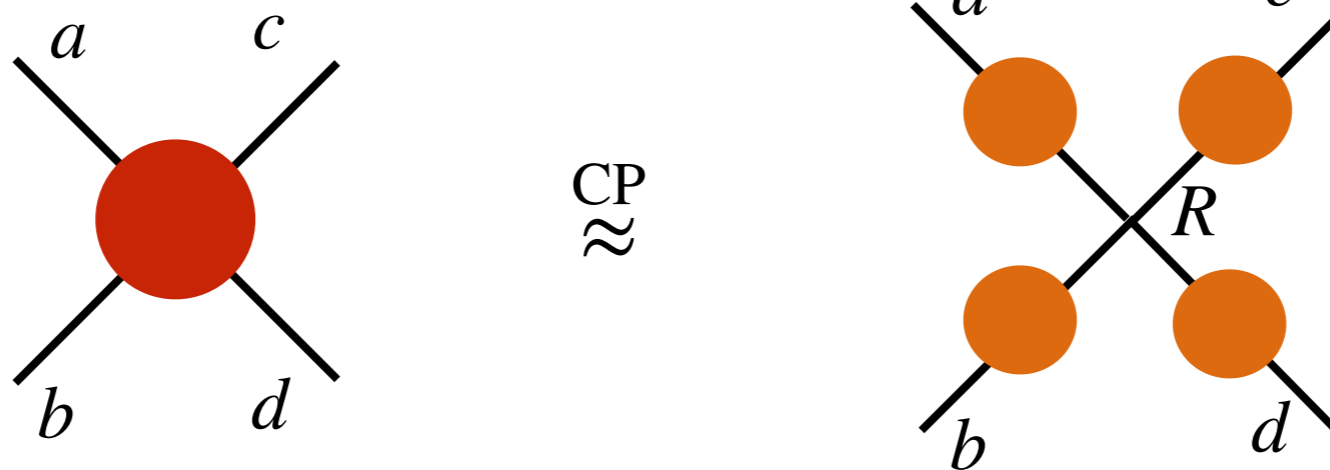
better error control than DF

**does it make sense to use CP directly?**



# CP Approximation of Coulomb Integrals

$$g_{ab,cd} \stackrel{\text{CP}}{\approx} (\mathbf{U}^{(1)})_{a,R} (\mathbf{U}^{(2)})_{b,R} (\mathbf{U}^{(3)})_{c,R} (\mathbf{U}^{(4)})_{d,R}$$

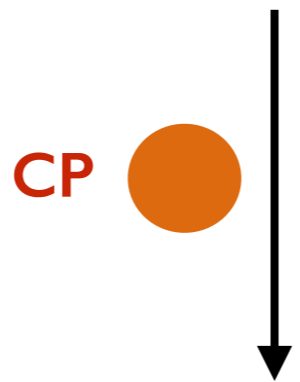
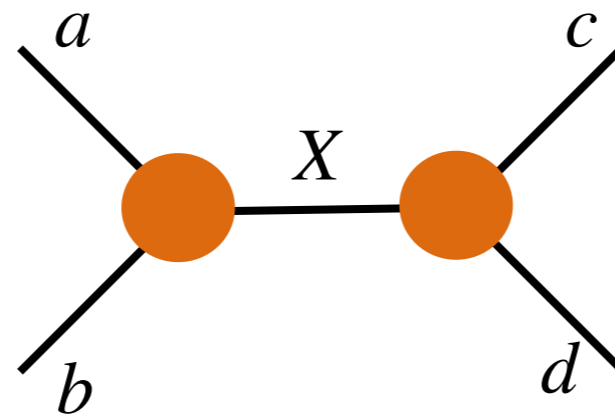


compute by Alternating Least Squares (ALS) or gradient-based methods at  $O(N^5)$  cost

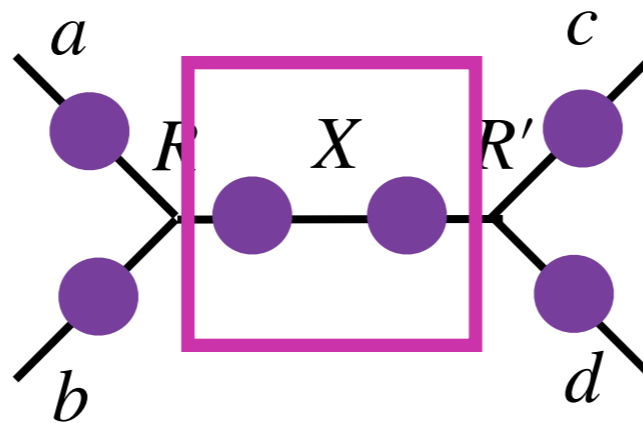
**CP in QC is barely used:** Auer, Espig, et al.; Khoromskaya, Khoromskij, et al.

# In This Talk: Only CP of SQ-Factorized Coulomb Integrals

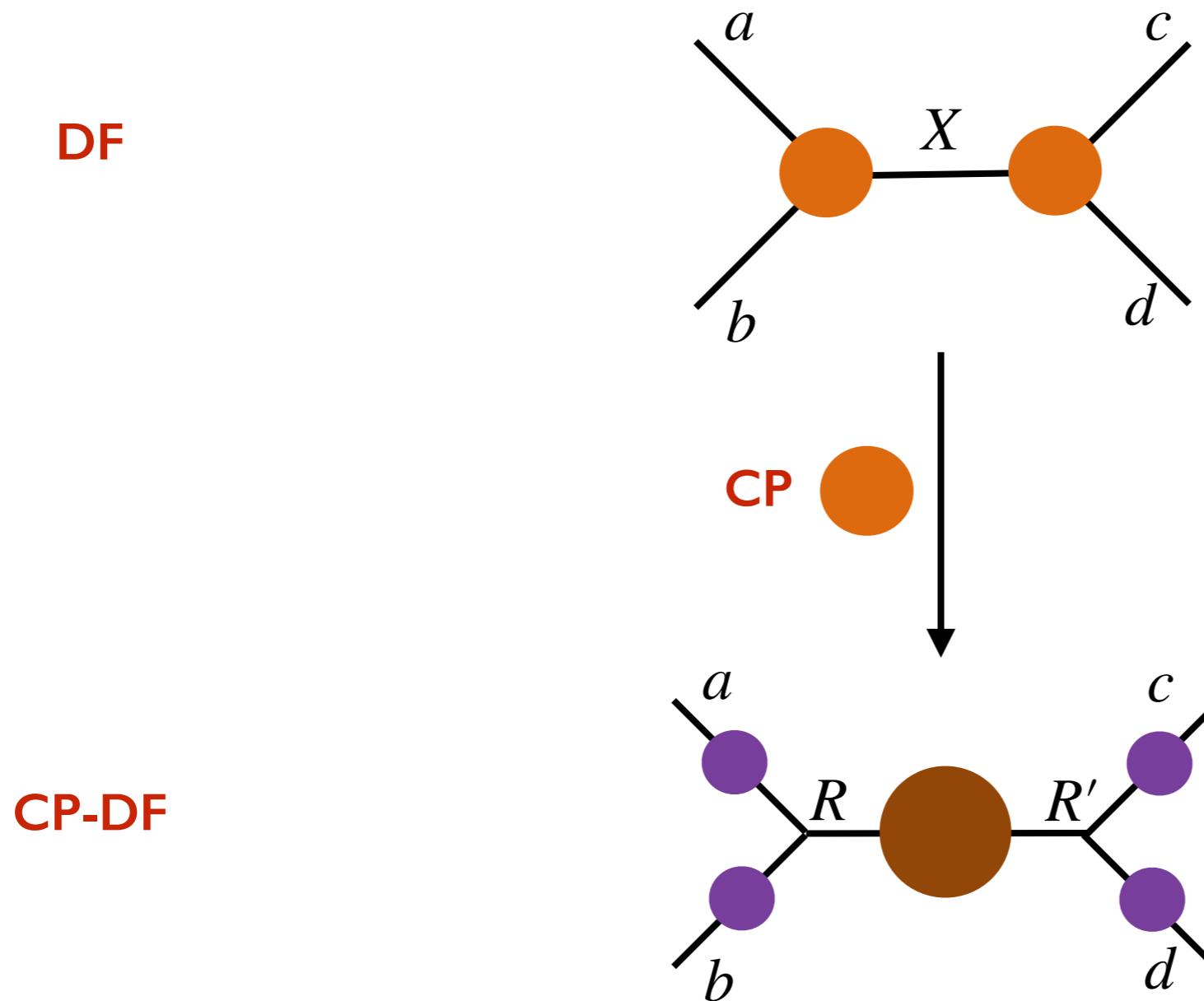
**DF**  
could use any SQ



**CP-DF**



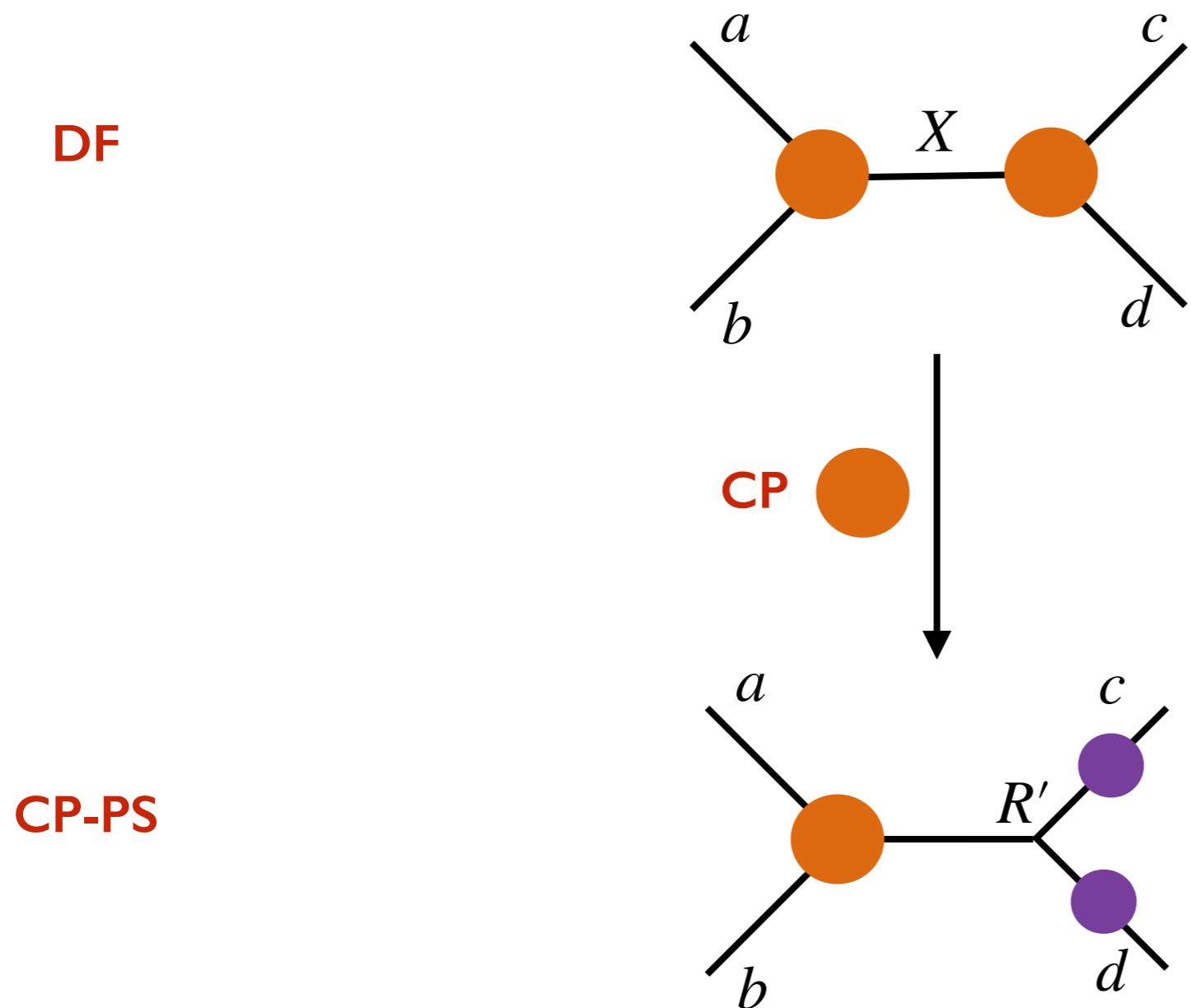
# CP-DF is related to THC



same topology as Tensor Hypercontraction (THC), but purely algebraic!

Related THC work: Hohenstein et al., (2012); Shenvi et al (2014);  
Hummel et al (2017); Schutski et al (2017)

# Another Way: CP-PS



same topology as pseudospectral (PS) factorization, but purely algebraic

Related PS work: Friesner (1985), Carter, Martinez, Ten-no (in F12), Neese (COSX), Klopper, Ochsenfeld (sn-K), ...

# Questions

**How to best use CP: 1 vertex (PS), 2 vertices (THC), or smth else?**

I.e. what's the relationship between errors of PS and THC at same rank?

**How large are CP ranks for reasonable errors?**

I.e. can they be made smaller than the most compact PS/THC grids? (roughly,  $10 \times M$ )

**How practical are CP solvers?**

Notoriously slow convergence typical of simple solvers (ALS)?

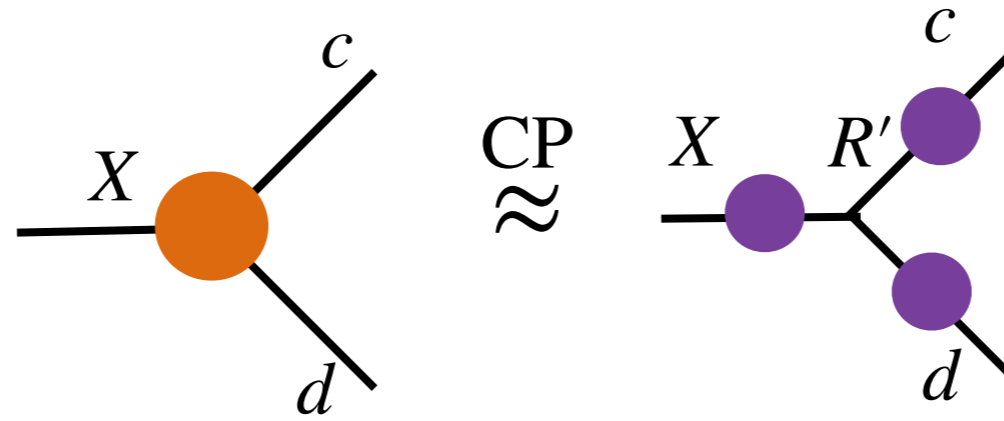
How prone to local minima?

Costs?

**Are there practical benefits?**

Only consider CCSD here

# Error Analysis: PS vs THC



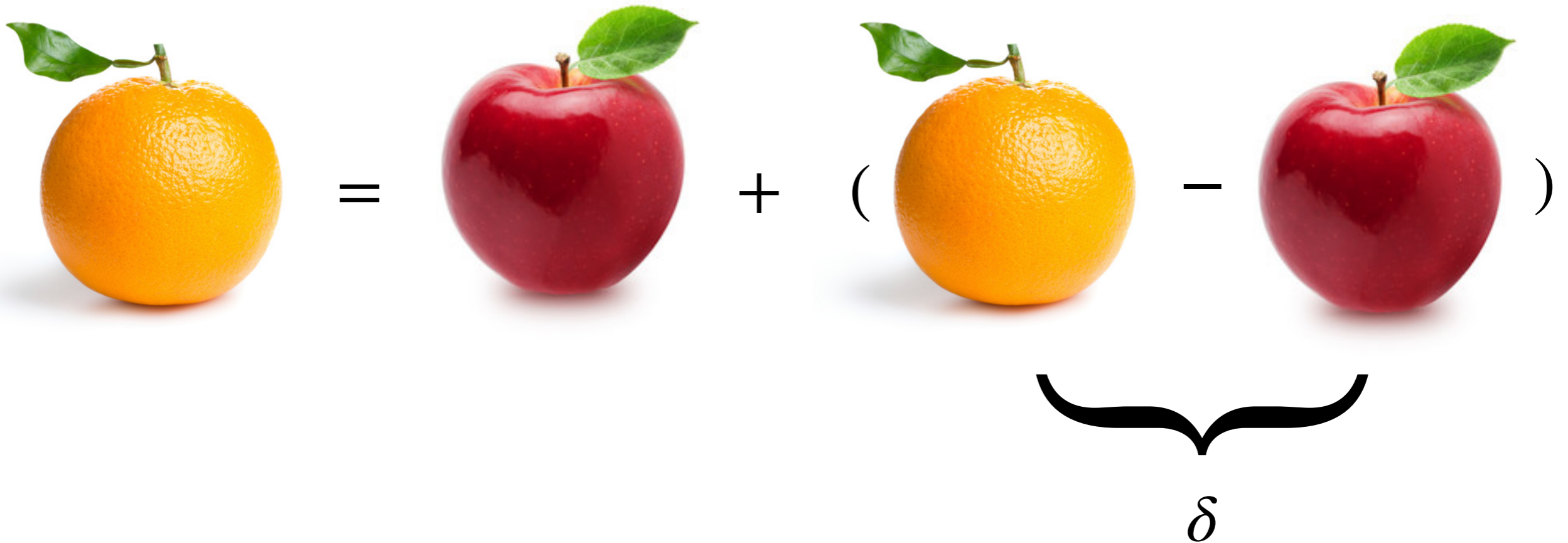
or



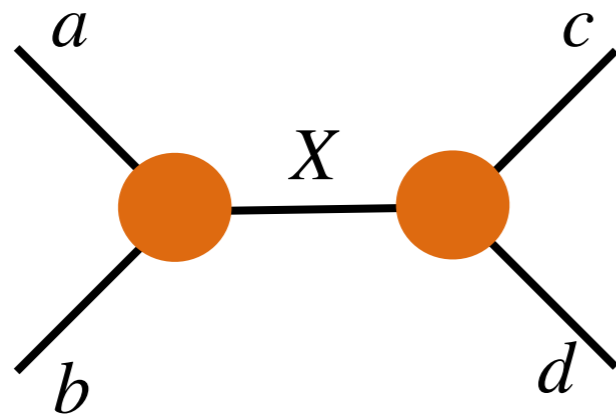
$\approx_{CP}$



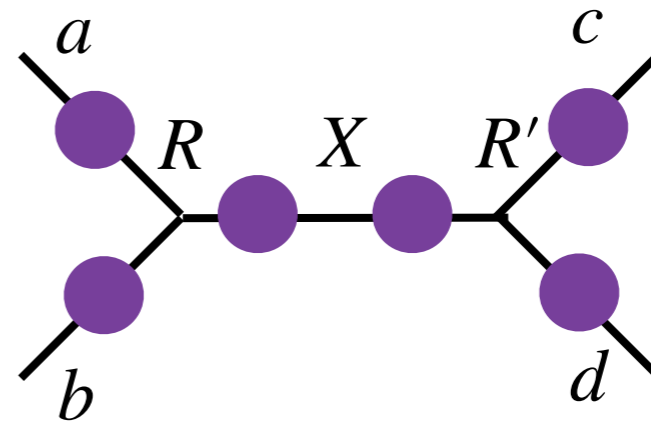
# Error Analysis: PS vs THC



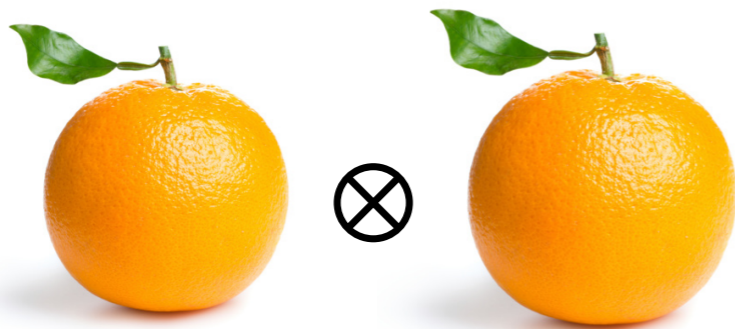
# Error Analysis: PS vs THC



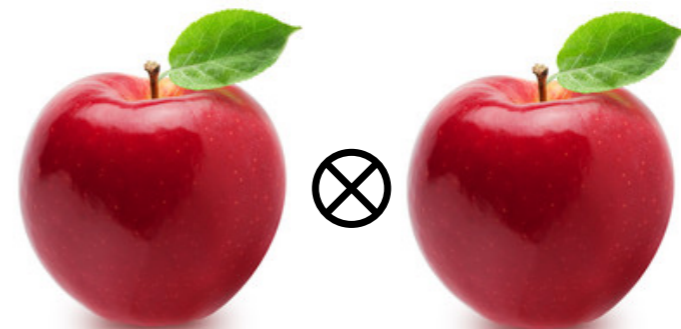
CP-DF  
 $\approx$



or



CP-DF  
 $\approx$





# Error Analysis: PS vs THC

The diagram illustrates the error analysis for PS vs THC using fruit images and mathematical symbols. It shows the decomposition of the product of two images (an orange and an apple) into a sum of terms representing different error components.

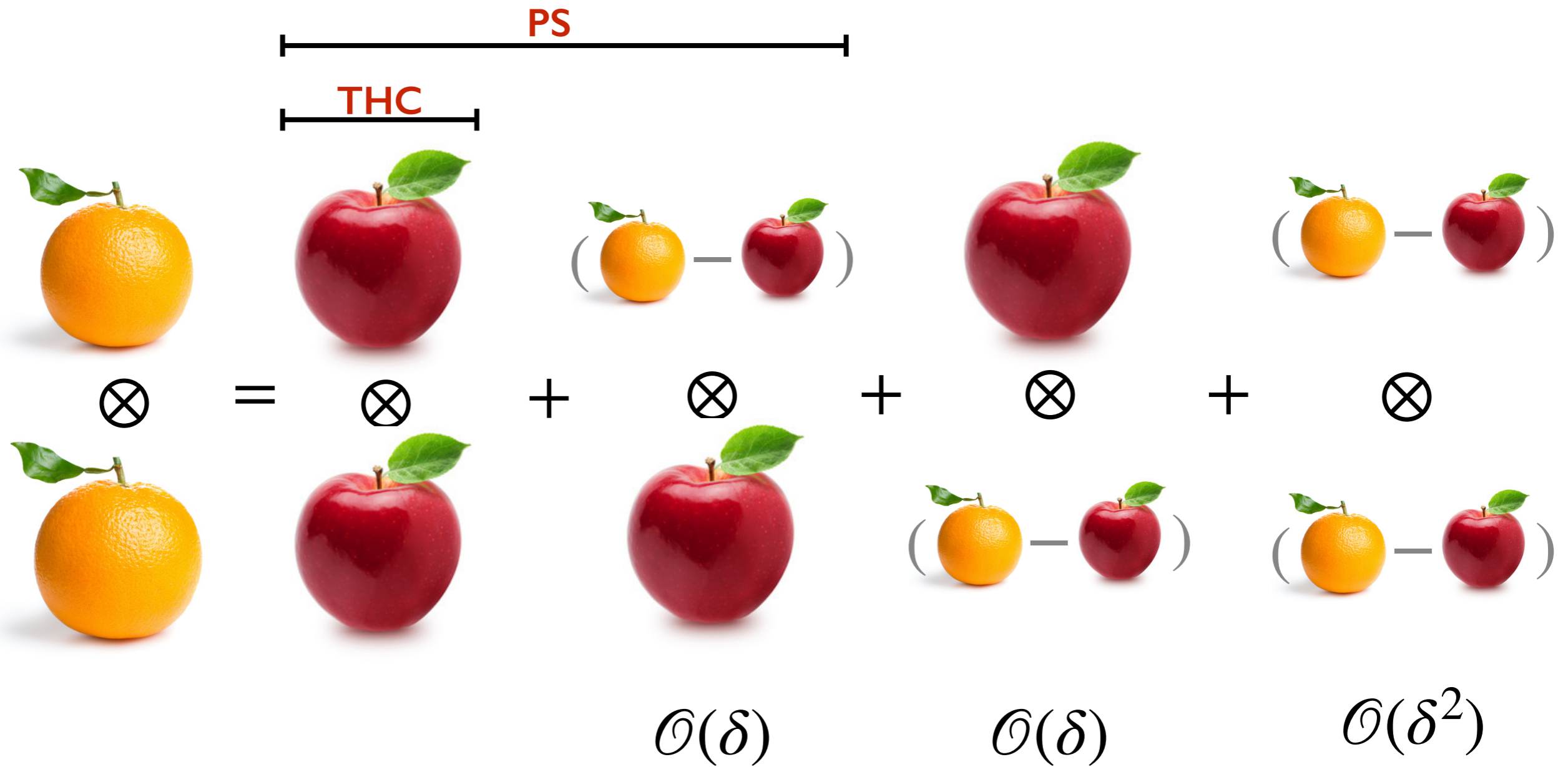
The equation is structured as follows:

$$\begin{aligned} & \text{Orange} \otimes \text{Apple} = \text{Orange} \otimes \text{Apple} + (\text{Orange} - \text{Apple}) \otimes \text{Apple} + \text{Apple} \otimes (\text{Orange} - \text{Apple}) + (\text{Orange} - \text{Apple}) \otimes (\text{Orange} - \text{Apple}) \\ & \otimes = \otimes + \otimes + \otimes + \otimes \\ & \mathcal{O}(\delta) \quad \mathcal{O}(\delta) \quad \mathcal{O}(\delta^2) \end{aligned}$$

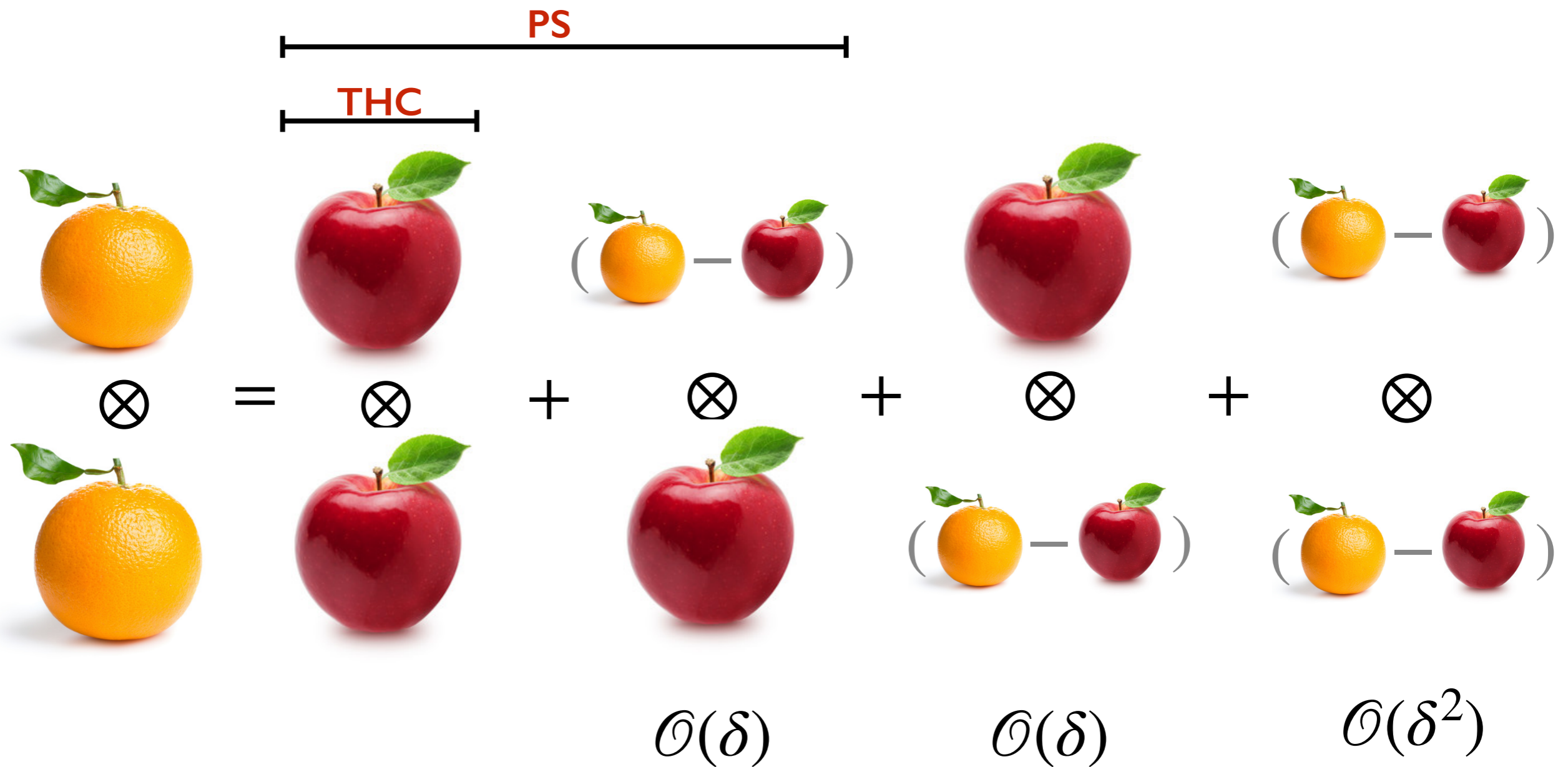
The symbols used are:

- $\otimes$ : Tensor product
- $=$ : Equality
- $+$ : Addition
- $(\text{Orange} - \text{Apple})$ : Difference of the two images
- $\mathcal{O}(\delta)$ : First-order error term
- $\mathcal{O}(\delta^2)$ : Second-order error term

# Error Analysis: PS vs THC

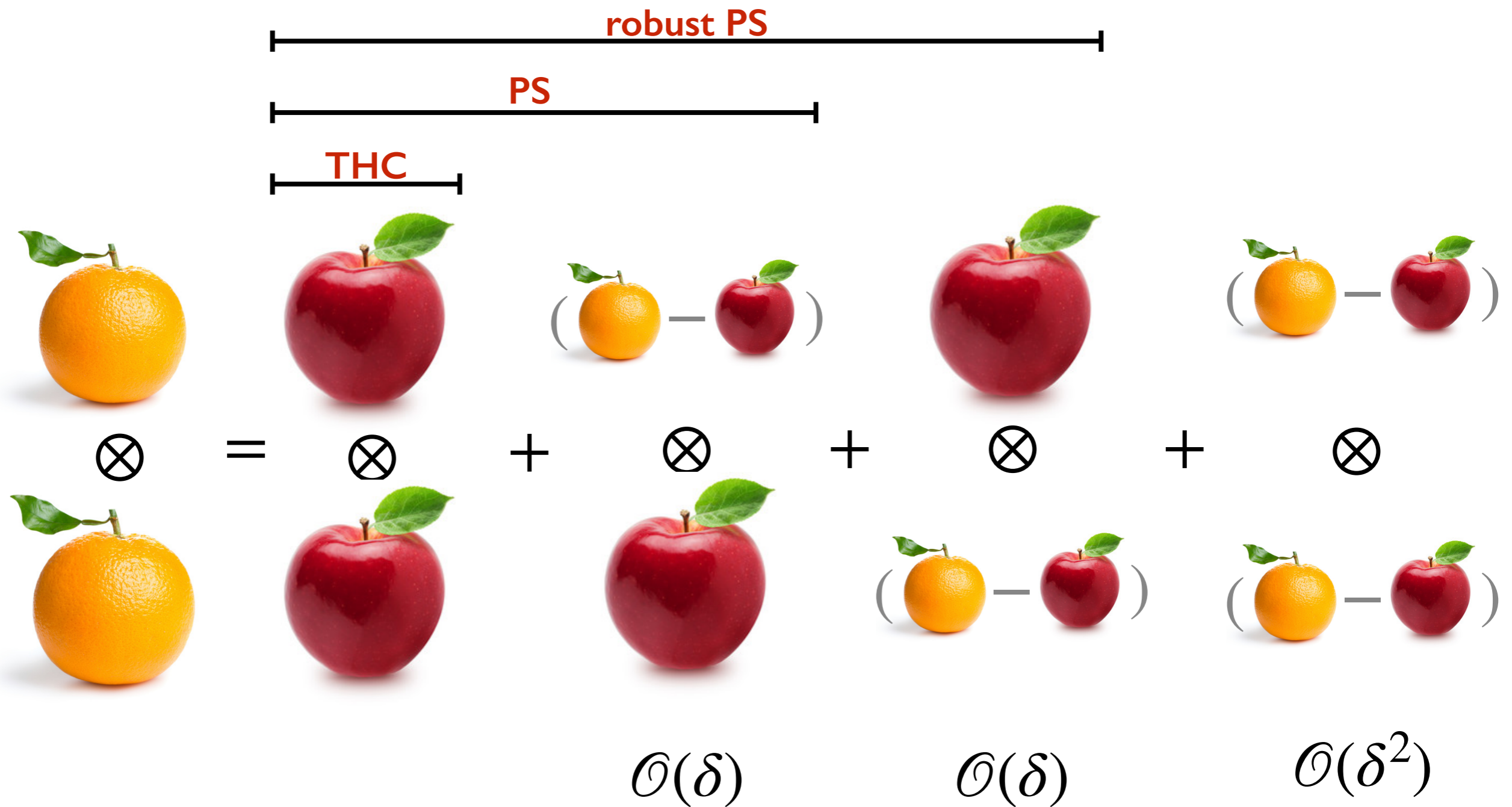


# Error Analysis: PS vs THC



error(THC) ~ 2 x error(PS)

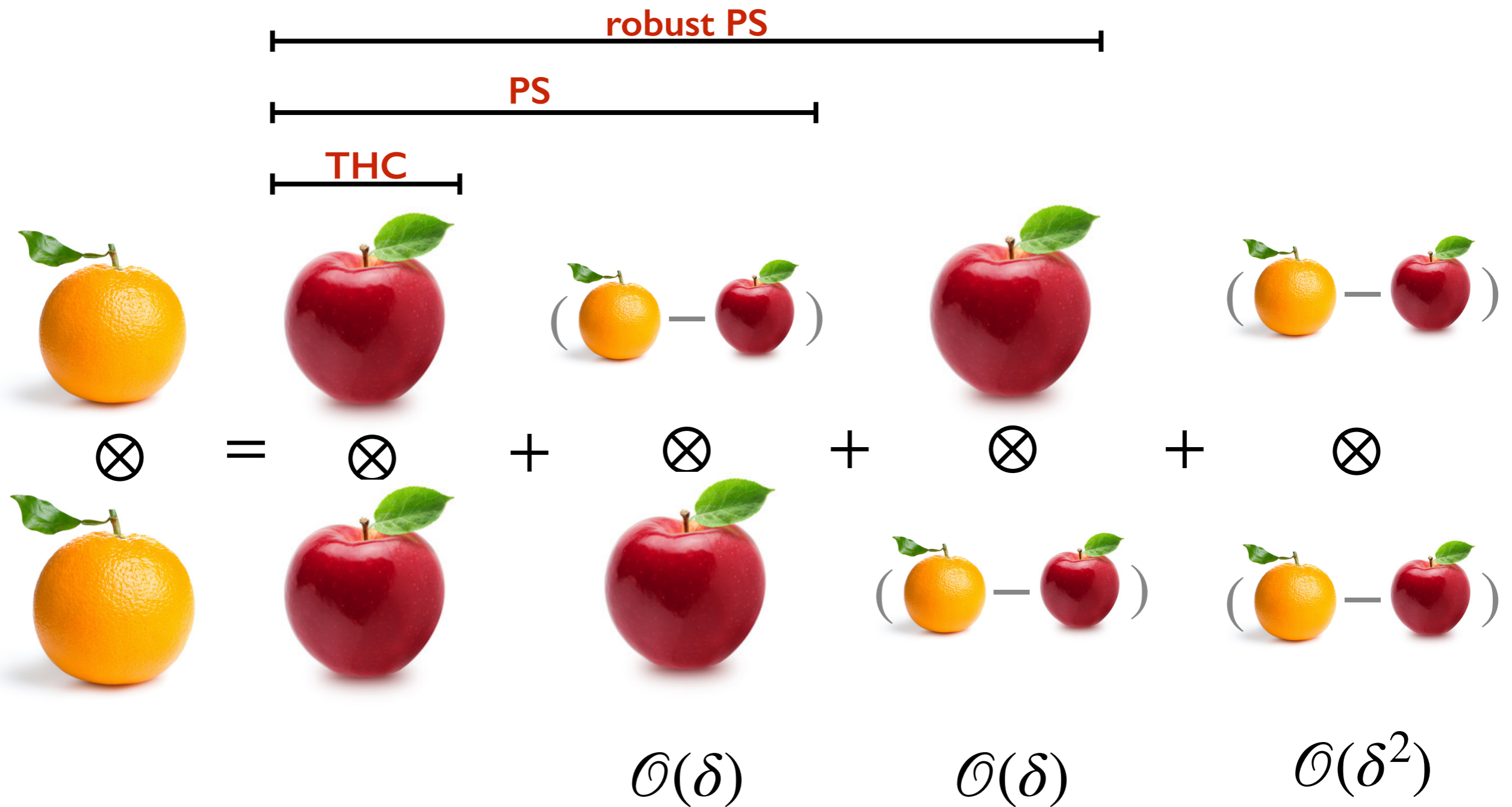
# Error Analysis: PS vs THC



“robust” as in robust DF: Dunlap (2000)

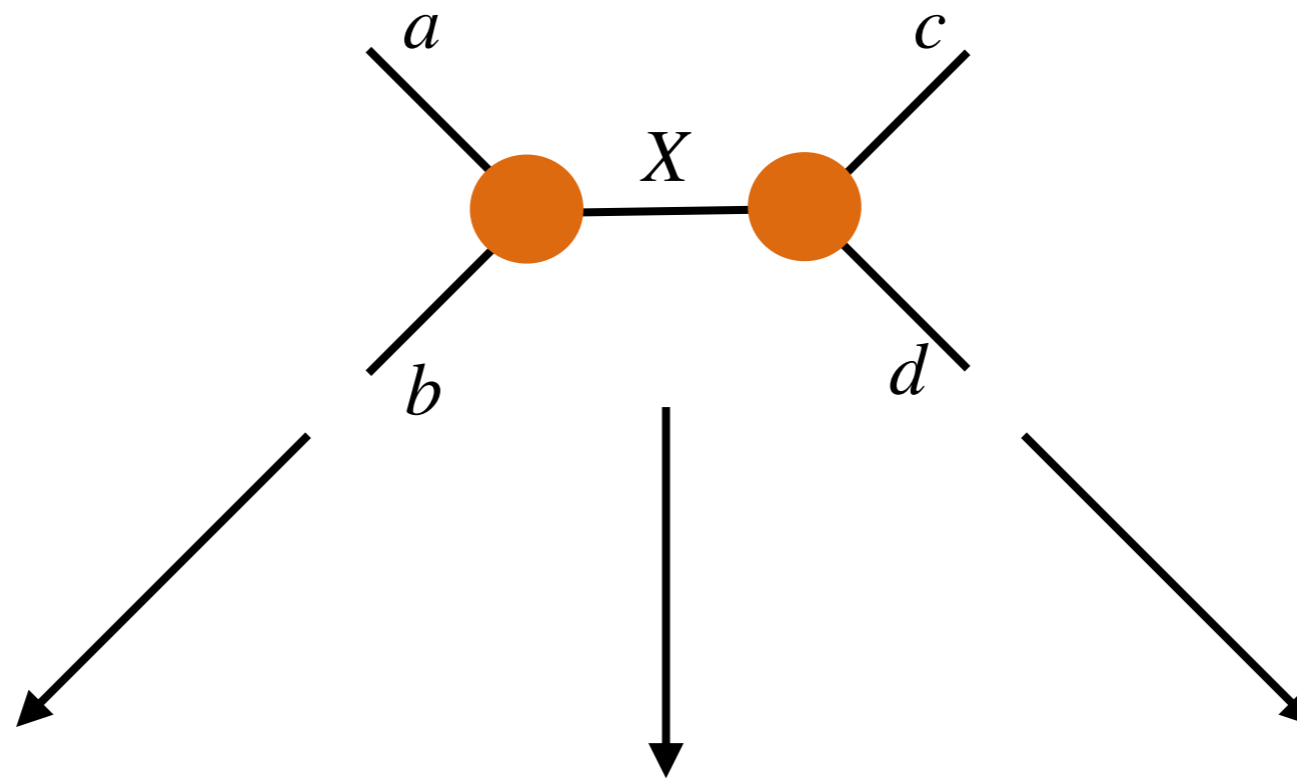


# Error Analysis: PS vs THC



**error(THC) ~ 2 x error(PS) >> error(robust PS)**

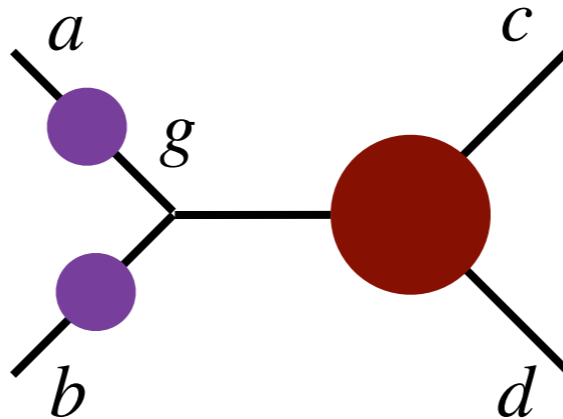
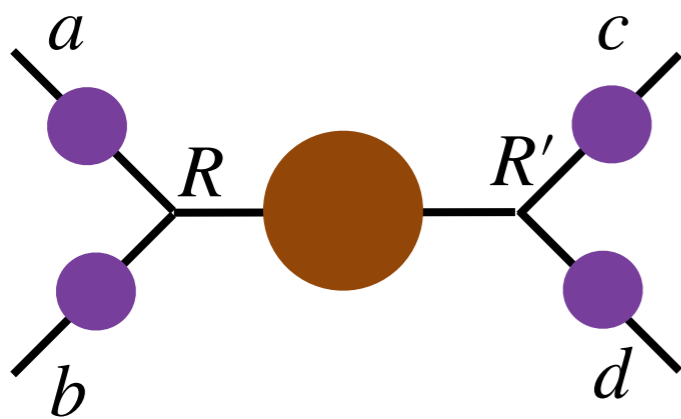
# Error Analysis: PS vs THC



**CP-DF: THC-like**

**CP-PS: PS-like**

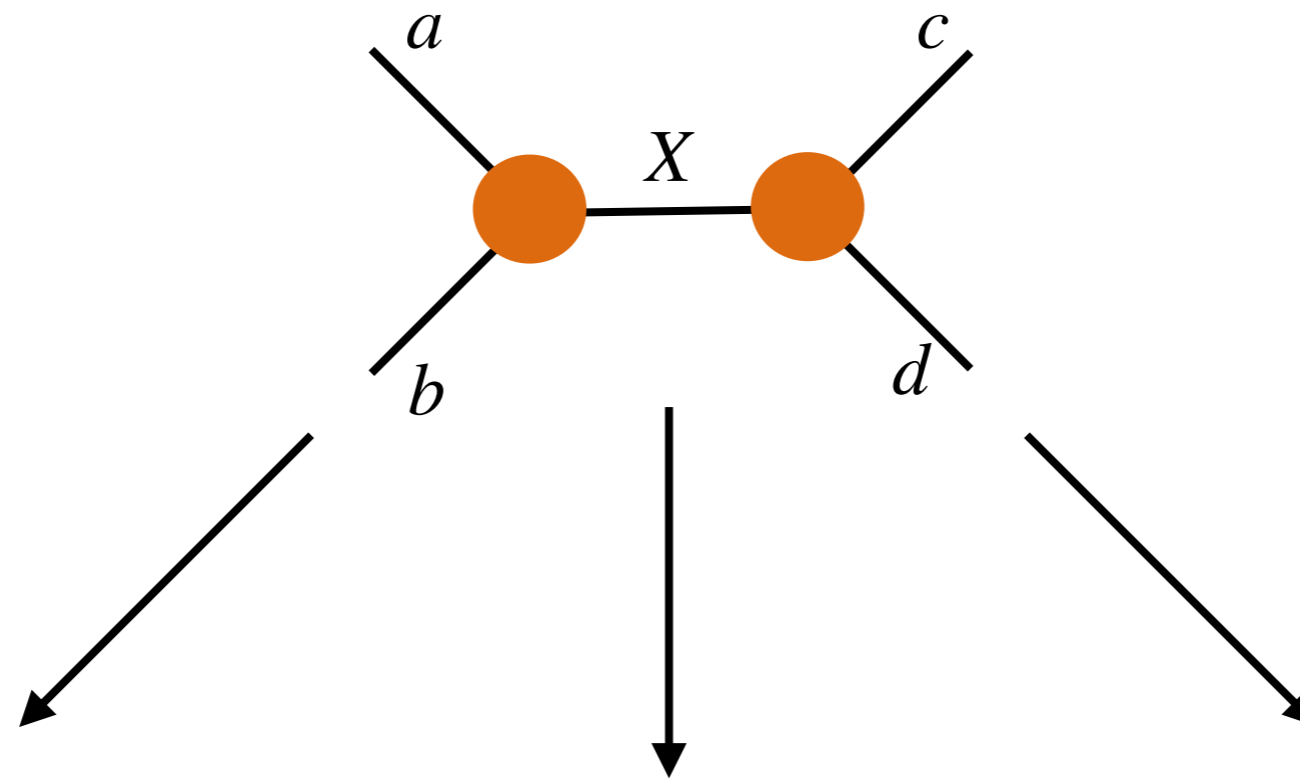
**rCP-DF**



**2 CP-PS - CP-DF**

zero extra cost vs CP-DF/THC

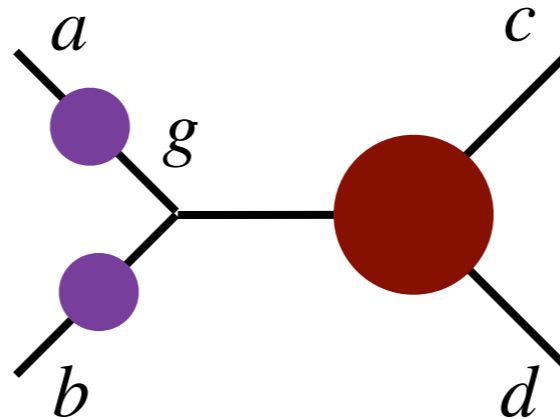
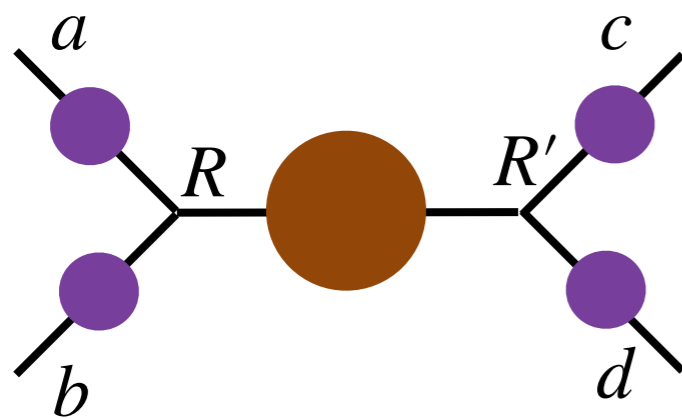
# Error Analysis: PS vs THC



CP-DF: THC-like

CP-PS: PS-like

rCP-DF



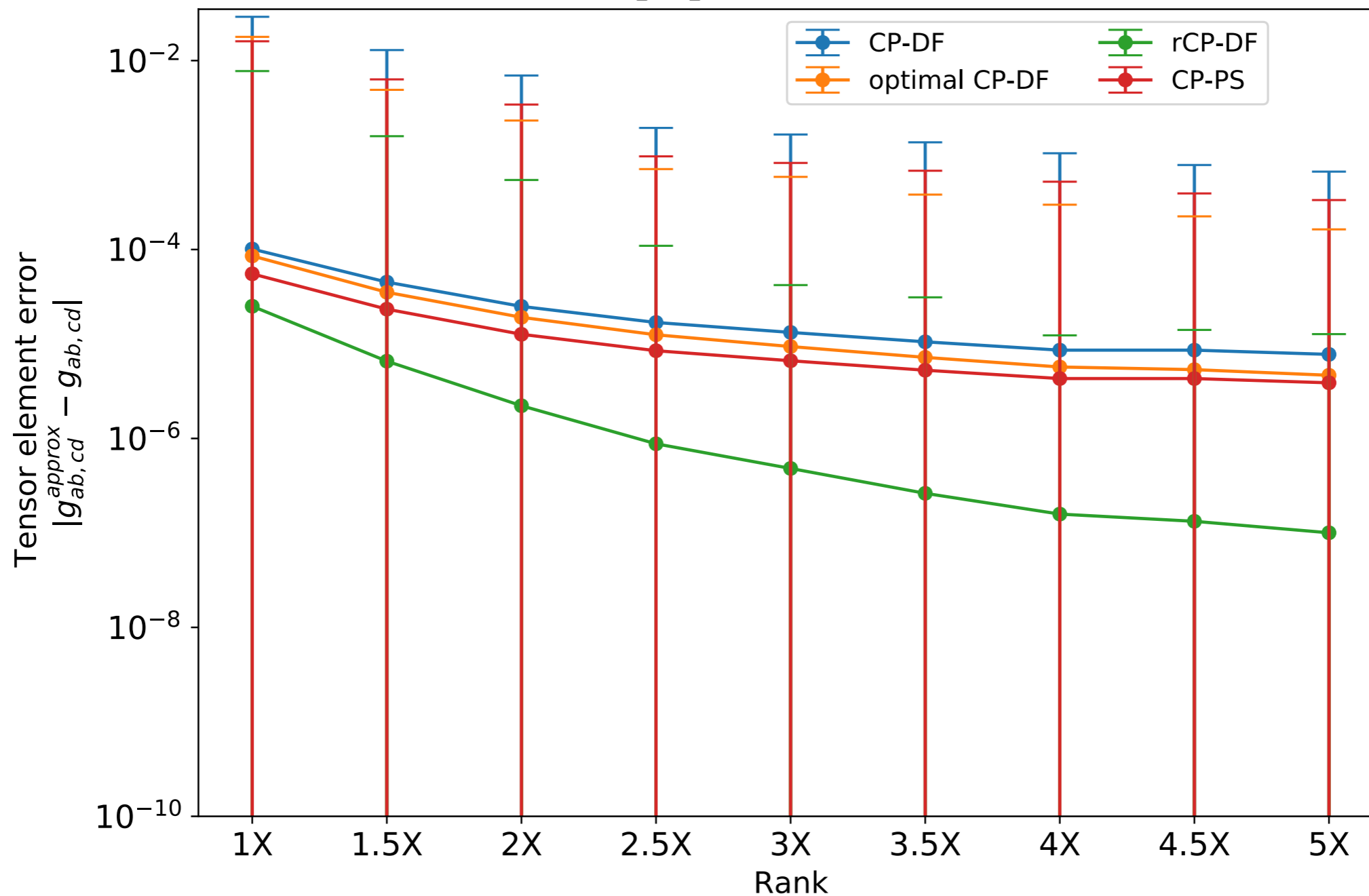
2 CP-PS - CP-DF

zero extra cost vs CP-DF/THC

N.B. can improve by relaxing the CP factors to minimize the error in the full network

# Error Analysis: PS vs THC

(H<sub>2</sub>O)<sub>2</sub>, DZ-F12/aVDZ-RI

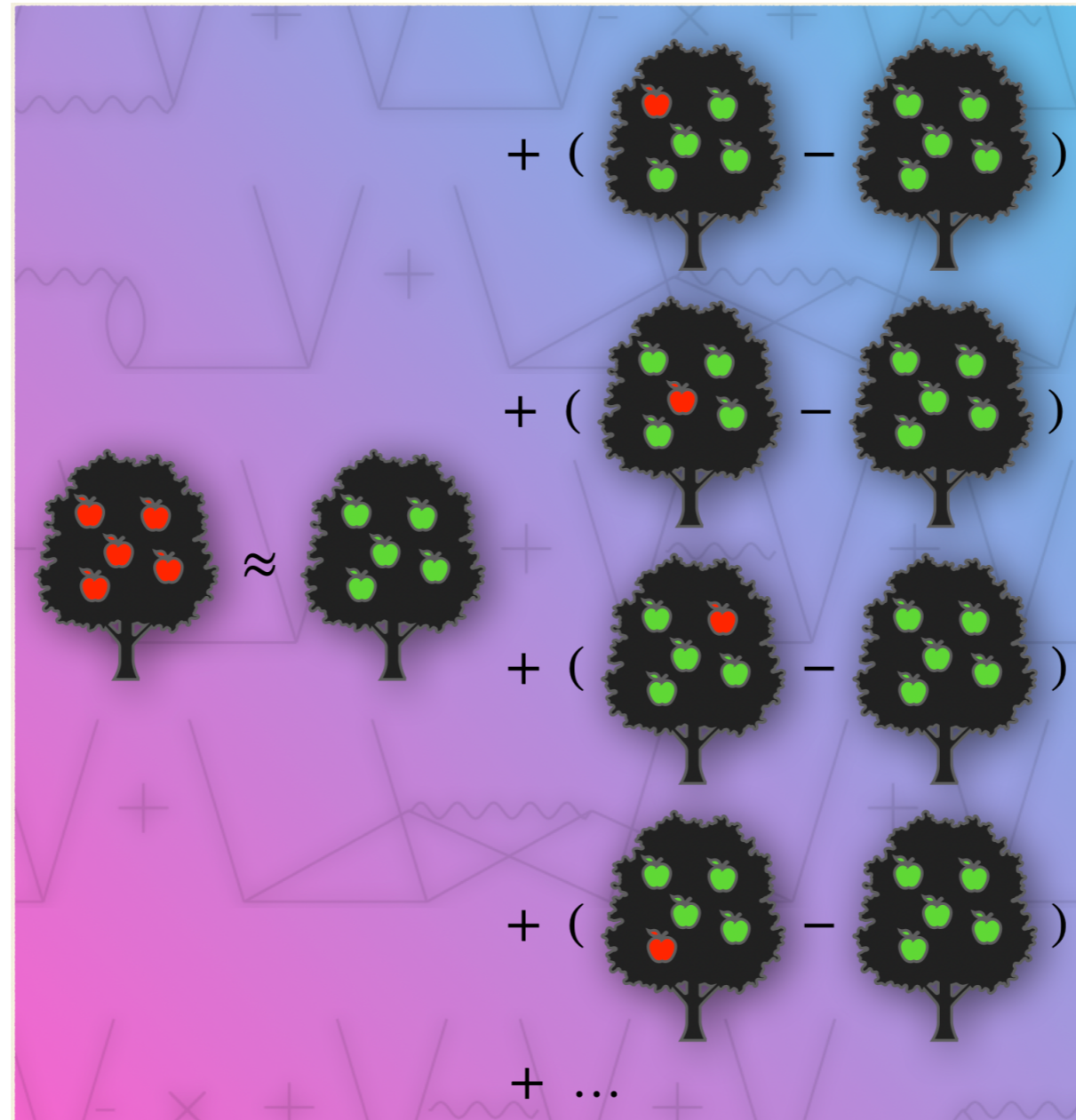


as expected: error(THC)  $\sim$  2 x error(PS)  $\gg$  error(robust PS)

only minor improvement from relaxing CP factors in the CP-DF tensor network

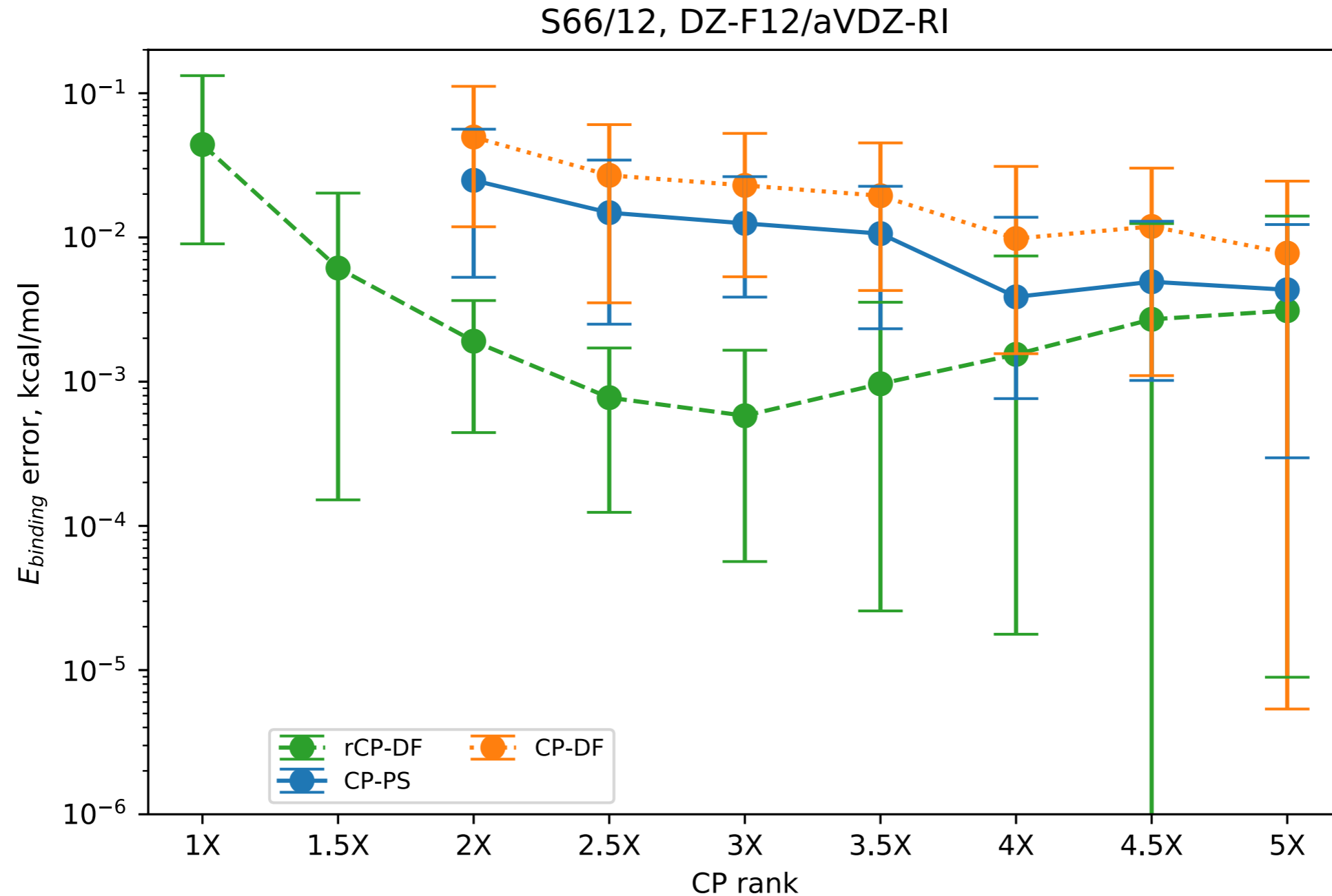


# Bigger Picture: Robust Approximation of Tensor Networks



**application to PPL diagram in CCSD**

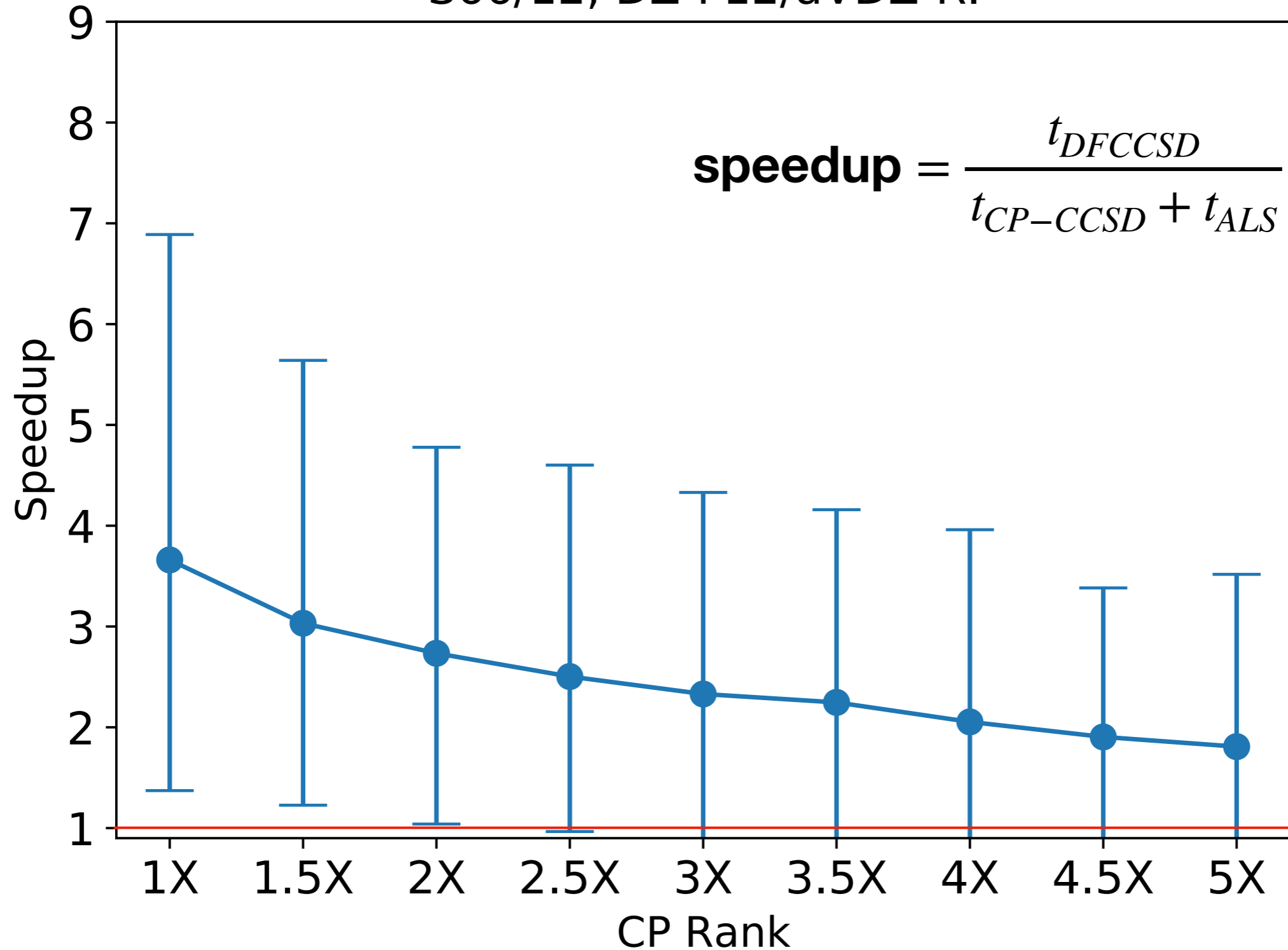
# CP PPL CCSD: Binding Energy Errors vs CCSD



**Robust CP-DF can use CP rank 3-4 times smaller than that used in THC/PS**

# rCP-DF: speedup vs DF-CCSD

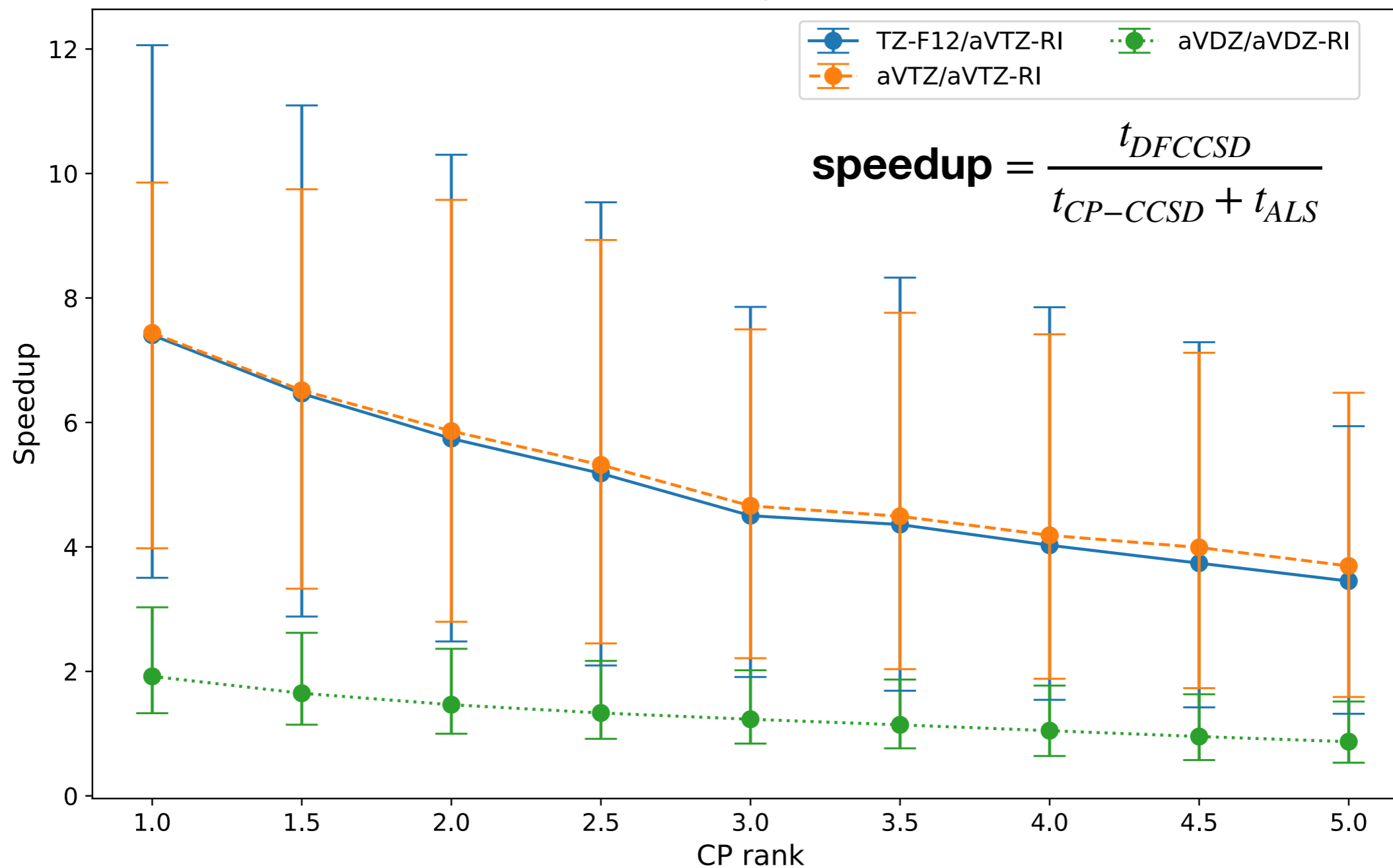
S66/12, DZ-F12/aVDZ-RI



with relevant CP ranks speedup even for a water molecule

# rCP-DF: speedup vs DF-CCSD

S66/7



$$\text{speedup} = \frac{t_{DFCCSD}}{t_{CP-CCSD} + t_{ALS}}$$

greater speedups for larger bases

# Summary

## Robust approximation of tensor networks

compensates for the leading-order errors due to each factor

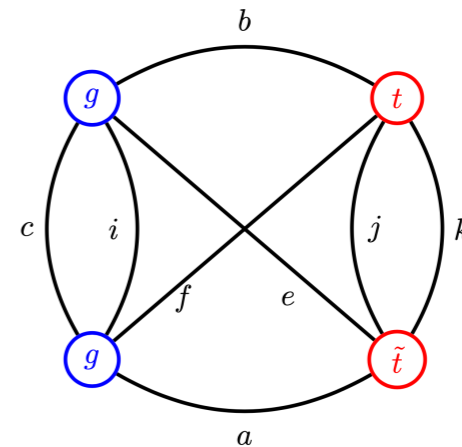
## Robust CP approximation of square-root factorized Coulomb integrals

practical and more accurate at lower ranks than comparable techniques (PS, THC)

## More generally applicable, e.g.

in quantum chemistry: CCSD(T) and CCSDT

eigenvalue solvers using MPS/TT and other tensor networks



Open-Source C++ ALS solvers: [github.com:ValeevGroup/BTAS](https://github.com/ValeevGroup/BTAS)



# The Valeev Group

- ▶ Dr. Andrei Asadchev
- ▶ Dr. Adam Holmes
- ▶ Dr. Karl Pierce
- ▶ Nakul Teke
- ▶ Sam Slattery
- ▶ Bimal Gaudel
- ▶ Conner Masteran
- ▶ Samuel Powell
- ▶ Jaden Yon
- ▶ Ashawini Thakur



## Details

Pierce, Rishi, and Valeev, *J Chem Theor Comp* 2021

JCTC  
Journal of Chemical Theory and Computation

pubs.acs.org/JCTC

Article

### Robust Approximation of Tensor Networks: Application to Grid-Free Tensor Factorization of the Coulomb Interaction

Karl Pierce, Varun Rishi, and Edward F. Valeev\*

Cite This: <https://doi.org/10.1021/acs.jctc.0c01310>

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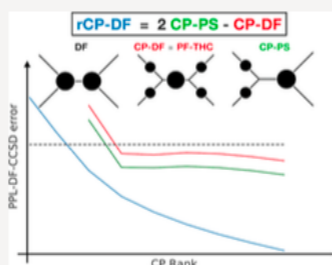
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Supporting Information

**ABSTRACT:** Approximation of a tensor network by approximating (e.g., factorizing) one or more of its constituent tensors can be improved by canceling the leading-order error due to the constituents' approximation. The utility of such robust approximation is demonstrated for robust canonical polyadic (CP) approximation of a (density-fitting) factorized two-particle Coulomb interaction tensor. The resulting algebraic (grid-free) approximation for the Coulomb tensor, closely related to the factorization appearing in pseudospectral and tensor hypercontraction approaches, is efficient and accurate, with significantly reduced rank compared to the naive (nonrobust) approximation. Application of the robust approximation to the particle–particle ladder term in the coupled-cluster singles and doubles reduces the size complexity from  $O(N^6)$  to  $O(N^5)$  with robustness ensuring negligible errors in chemically relevant energy differences using CP ranks approximately equal to the size of the density-fitting basis.



## Resources

