# Are O-PLS Models Really More Interpretable?

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# O-PLS

- Originally formulated as sequential algorithm (NIPALS based)
- Since shown to be obtainable from postprocessing conventional PLS model
- Does not improve prediction
- Claim is that model is more interpretable

E.K. Kemsley and H.S. Tapp, "OPLS filtered data can be obtained directly from non-orthogonalized PLS1," J. Chemo, 23, 263-264, 2009
R. Ergon, "PLS post-processing by similarity transformation (PLS+ST): a simple alternative to OPLS," J. Chemo, 19, 1-4, 2005
J. Trygg and S. Wold, "Orthogonal Projections to Latent Structures (O-PLS)," J. Chemo, 16, 119-128, 2002.



# **Orthogonalize Model**

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Variable	LV	Cum	LV	Cum	-				
1	99.08	99.08	39.05	39.05		0			
2	0.76	99.84	19.26	58.31					
3	0.06	99.90	23.49	81.79					
4	0.03	99.93	14.25	96.04					
5	0.03	99.96	2.24	98.28					
6	0.01	99.98	1.00	99.28<-	- S	uggested			
7	0.01	99.98	0.31	99.59					
8	0.01	99.99	0.09	99.68					
9	0.00	99.99	0.16	99.83					
10	0.00	100.00	0.02	99.85					
11	0.00	100.00	0.09	99.94					
12	0.00	100.00	0.02	99.96		~			
13	0.00	100.00	0.01	99.97					
14	0.00	100.00	0.00	99.97					
15 16	0.00	100.00	0.00	99.98 99.98		* *			

Analysis - PLS 6 LVs - m5spec, propvals									
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Latent	Percent X-Bl	Variance	Captured by Y-Blo	Model ock					
Variable	LV	Cum	LV	Cum					
1	96.86	96.86	99.28	99.28					
2	2.73	99.60	0.00	99.28					
3	0.20	99.80	0.00	99.28					
4	0.10	99.90	0.00	99.28					
5	0.06	99.95	0.00	99.28					
6	0.02	99.98	0.00	99.28	<- Suggested				
7	0.01	99.98	0.31	99.59					
8	0.01	99.99	0.09	99.68					
9	0.00	99.99	0.16	99.83					
10	0.00	100.00	0.02	99.85					
11	0.00	100.00	0.09	99.94					
12	0.00	100.00	0.02	99.96	- -				
13	0.00	100.00	0.01	99.97					
15	0.00	100.00	0.00	99.97					
15	0.00	100.00	0.00	99.98 99.98	A				
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# Questions:

- What do we need to be aware of when interpreting O-PLS recovered components?
- What kinds of sensitivities does O-PLS have to noise, rotational ambiguity, and correlated concentrations?

**Method:** Use well-characterized and/or carefully constructed simple systems to study OPLS



# NIR of Pseudo-gasoline Samples



# **PLS Model of Heptane**





# Regular PLS and O-PLS Filtered Regression Vectors





# Simple System Example

- Synthetic example of three constituents
- Evenly spaced Gaussian peaks, analyte in middle
- Vary correlation between analyte and interferents





### **Gaussian Peaks Scenarios**

- Start with orthogonal concentrations
  - 1) Go from orthogonal to positively correlated concentrations
  - 2) One interferent positively correlated, one negatively correlations



#### **Scenario 1-First O-PLS Loading**



#### **Scenario 1-Regression Vector**



### Scenario 2-First O-PLS Loading



# Pseudo-gasoline Example

- 5 component mixture measured by NIR
- Solve for pure components via CLS
- Use pure spectra to create synthetic scenarios



## **Pseudo-gas Scenarios**

- Start with orthogonal concentraions
  - 3) All analytes positively correlated
  - 4) One interferents positive, three negative



# Scenario 3-First O-PLS Loading



#### **Scenario 4-First O-PLS Loading**



# **Binary Expression Simulation**

- 10 Expressed Proteins (variables), 500 Subjects
- 1 "primary" effect with loading:

1 2 3 4 5 6 7 8 9 10

(must have  $\square$ , cannot have  $\square$ , 0 have no effect)

- 7 "background" effects (rank 1 patterns with positive and negative correlations as for primary)
- Only samples with primary loading expression for 1-4 (after mixing all effects) will exhibit property of interest (e.g. disease)



#### **Example Map of Expression**





### ...Sorted by Property of Interest













#### Example Set 3

#### **OPLS** Component **PLS Regression** Ũ 0.8 0.6 We Can Ignore.. Should be 0 0.4 0.2 0 -0.2 Ĵ -0.4 2 3 6 8 9 10 5 7 3 7 9 1 4 5 1



# Conclusions

- O-PLS does simplify regression vectors. It is CLOSER to underlying bilinear response...
- … HOWEVER, result generally not the same as a first principles model.
- O-PLS results strong function of correlation in concentrations
- O-PLS recovered component is more sensitive to chance correlation than is regression vector (Problem seen even with 500, 1000, or 2000 samples!)

