

Combining Instrument Standardization and Data Preprocessing Methods: What Methods, and What Order?

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Original Abstract

Combining Instrument Standardization and Calibration Transfer Methods: What Methods, and What Order?

Note title change--we're going to look at just prepro and transfer methods at this point, not combined transfer methods.

Abstract: Spectroscopic instrument differences can be mitigated by data preprocessing methods (e.g. baselining, derivitization, multiplicative scatter correction) and standardization methods (e.g. piece-wise direct standardization, orthogonal signal correction, generalized least squares weighting). Each of these methods has strengths and weaknesses in the face of different types of instrument non-idealities. Can these methods be used in combinations that are more effective than single approaches? This talk discussed how combinations of techniques can be used. Approaches are tested on 3 NIR data sets with different issues.



Outline

- The calibration transfer problem
 - Instrument differences, drift, environment changes
- Data sets
 - Pseudo gasoline
 - Corn
- Standardization approaches
 - Generalized Least Squares (GLS) preprocessing
 - Piece-wise Direct Standardization (PDS)
- Preprocessing approaches
 - Multiplicative scatter correction (MSC)
 - Standard normal variate (SNV)
 - Second derivative
- Study Design
- Comparison of results
- Conclusions

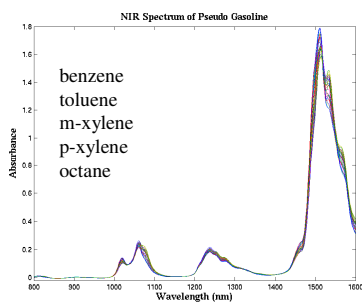


Reasons for Calibration Transfer

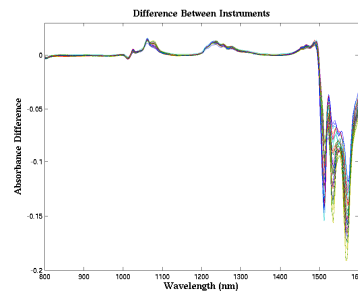
- No two instruments identical
 - Some calibrations depend on very small changes in data
- Single instruments often drift
 - Aging parts, dirt, part replacements
 - Temperature, humidity
 - *Standardization*
- New interferences in samples

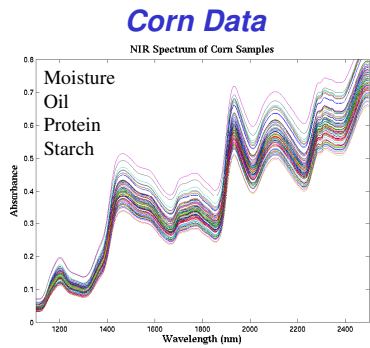


Pseudo Gasoline Data

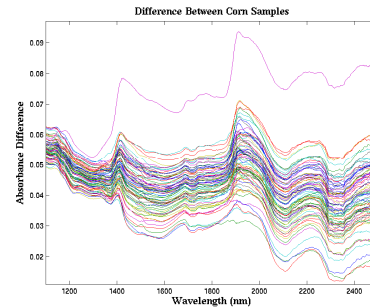


Difference Between Instruments





Difference Between Instruments

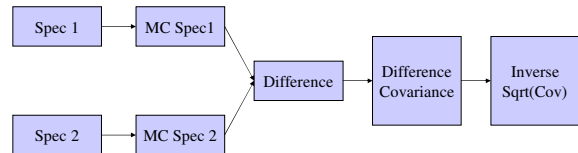


Selection of Transfer Samples

- Transfer samples should
 - be “high leverage”
 - span the space of differences
- Several ways to choose
 - Hand select (based on PC scores, etc.)
 - Find high leverage in PCA
 - Find high leverage based on calibration model



Development of GLS Weighting Matrix



Difference Covariance

$$\mathbf{X}_d = (\mathbf{X}_{1,tr} - \bar{\mathbf{x}}_{1,tr}) - (\mathbf{X}_{2,tr} - \bar{\mathbf{x}}_{2,tr})$$

$$\mathbf{C} = \frac{\mathbf{X}_d^T \mathbf{X}_d}{N-1}$$



Covariance to Weighting Matrix

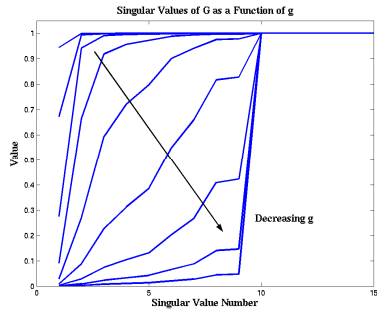
$$\mathbf{C} = \mathbf{V} \mathbf{S}^2 \mathbf{V}^T$$

$$\mathbf{G} = \mathbf{V} \mathbf{D}^{-1} \mathbf{V}^T$$

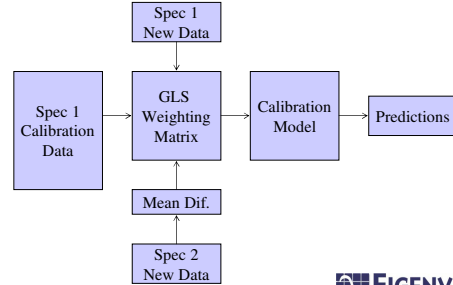
$$s_{i,i}^{-1} = \frac{1}{\sqrt{s_{i,i}^2}} \quad d_{i,i}^{-1} = \frac{1}{\sqrt{\frac{s_{i,i}^2}{g^2} + 1}}$$



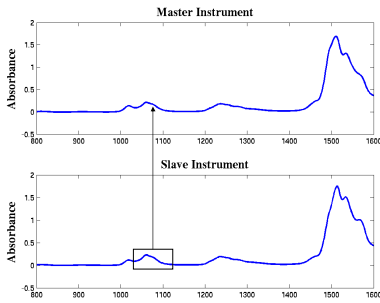
Effect of Parameter g



Application of GLS Weighting Matrix

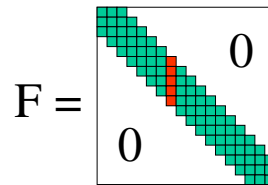


Piece-wise Direct Standardization



PDS Model

$$\mathbf{X}_1 = \mathbf{X}_2\mathbf{F} + \mathbf{1}b_{2-1}$$

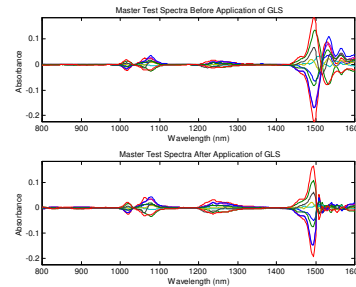


Orthogonal Signal Correction

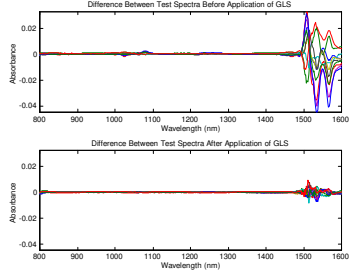
- Determine factor which describes large amounts of variance in \mathbf{X} while being orthogonal to \mathbf{Y}
- Deflate \mathbf{X}
- Build PLS model that predicts scores of deflation factor
- Use PLS model to estimate amount of factor to remove from new \mathbf{X}



Pseudo Gasoline Master Before and After GLS



Pseudo Gasoline Difference Before and After GLS



⇒ movie



Comparison of Methods for Corn Data

- Available data
 - 80 samples split 60/20
 - 3 instruments
 - 4 analytes
- 10 Transfer samples selected
 - Based on model inverse for PDS
 - Based on PCA leverage for GLS
- Tested both methods on all combinations of instrument and analyte



Corn Study Design

- 4 analytes
 - moisture, oil, protein, starch
- 6 ways to transfer
 - between 3 instruments: m5, mp5, mp6
- 2 methods tested
 - PDS and GLS
- 7 preprocessing options
 - SNV, 2nd deriv, and MSC, before and after, or none
- 336 transfers total (4x6x2x7)

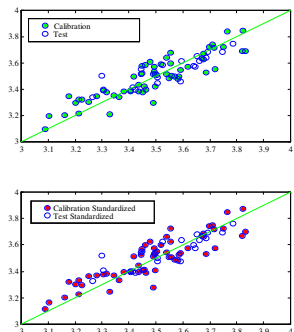


Issues with Meta-parameters

- GLS has only one parameter, g
- PDS
 - Window width
 - Parameters for sub models (LVs or tolerance)
- OSC
 - Number of OSC LVs
 - Tolerance of initial iterations
 - Tolerance on reconstruction
- Number of LVs in PLS calibration models
 - *Try to shown each technique in best light!*



Typical Calibration and Test Data



Standardizing MP5 to M5 for Corn moisture

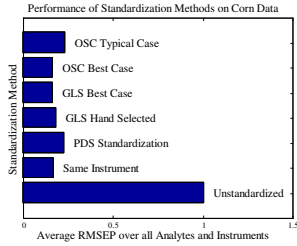


Results from Previous Study on Corn Data

	Prediction Instrument												Average
	Moisture			Oil			Protein			Starch			
Preds	MS	MP5	MP6	MS	MP5	MP6	MS	MP5	MP6	MS	MP5	MP6	
MS	0.0107	1.4166	1.3123	0.2081	0.1274	0.1588	0.1202	1.3685	1.2241	0.2077	2.0589	1.8011	
MP5	1.1622	0.1460	0.2627	0.2731	0.0020	0.1016	1.2719	0.1720	0.2762	2.6274	0.0001	0.5119	
MP6	1.0021	0.2849	0.1657	0.3148	0.1926	0.0819	0.2882	0.2403	0.1876	1.1885	0.8754	0.4031	
PDS Standardization													
MS	-	0.2601	0.4671	-	0.0932	0.0755	-	0.1699	0.1949	-	0.3382	0.3710	
MP5	0.2342	-	0.1749	0.0876	-	0.0944	0.1481	-	0.1880	0.2485	-	0.3972	
MP6	0.2068	0.1801	-	0.0920	0.1035	-	0.1033	0.1770	-	0.4147	0.4286	-	
GLS Standardization, LVs hand selected													
MS	-	0.1392	0.1696	-	0.0839	0.0662	-	0.1531	0.1679	-	0.3314	0.3400	
MP5	0.1391	-	0.1477	0.0479	-	0.0770	0.1732	-	0.2116	0.2838	-	0.4081	
MP6	0.1995	0.1521	-	0.0603	0.0816	-	0.1887	0.1570	-	0.1873	0.3473	-	
GLS Standardization, best over 5-8 LVs													
MS	-	0.1345	0.1891	-	0.0688	0.0763	-	0.1483	0.1602	-	0.3039	0.3350	
MP5	0.1348	-	0.1258	0.0479	-	0.0686	0.1448	-	0.1721	0.2485	-	0.3709	
MP6	0.1922	0.1177	-	0.0500	0.0733	-	0.1268	0.1570	-	0.1873	0.3316	-	
OSC Standardization, best over all cases, 1-3 OSC, 3-8 LVs													
MS	-	0.1830	0.1723	-	0.0816	0.0710	-	0.1433	0.1592	-	0.3002	0.3293	
MP5	0.1845	-	0.1080	0.0710	-	0.0728	0.1384	-	0.1980	0.2540	-	0.4029	
MP6	0.1465	0.1320	-	0.0607	0.0686	-	0.1368	0.1449	-	0.2283	0.3744	-	
OSC Standardization, best single case, 3 OSC 5 LVs													
MS	-	0.2716	0.2611	-	0.0835	0.0742	-	0.1588	0.1592	-	0.3320	0.3315	
MP5	0.2097	-	0.2776	0.0630	-	0.0824	0.1801	-	0.2038	0.4206	-	0.4206	
MP6	0.2038	0.1379	-	0.0600	0.1187	-	0.1884	0.2154	-	0.2119	0.3363	-	



Results of Previous Study on Corn Data



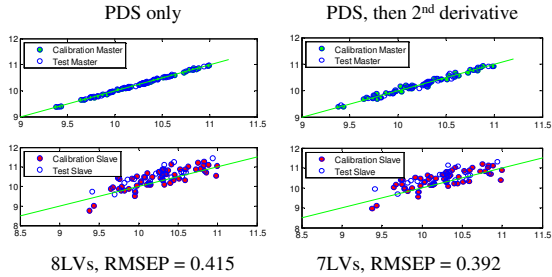
Summary- New Results on Corn Data

	NO standardization		GLS		PDS	
	RMSEP	LV	RMSEP	LV	RMSEP	LV
no preprocessing	1.005	7.1	0.217	7.5	0.236	7.3
MSC after standardization	0.949	5.8	0.228	5.3	0.230	5.4
SNV after standardization	0.887	5.6	0.218	5.5	0.229	5.6
2nd derivative after standardization	0.781	5.8	0.209	4.8	0.224	4.6
MSC before standardization			0.225	5.9	0.280	4.3
SNV before standardization			0.241	5.3	0.230	4.7
2nd derivative before standardization			0.203	4.7	0.220	4.5

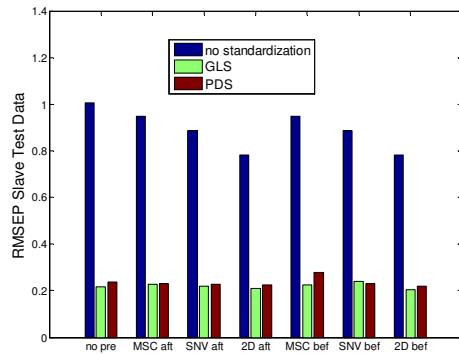


Sample results- corn data

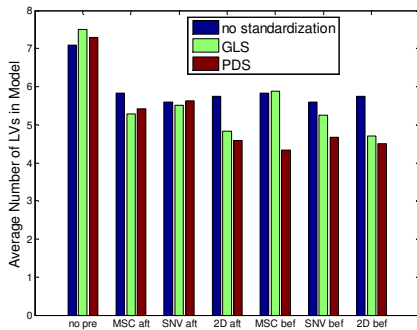
Analyte 1, m5 master/mp5 slave



New Results- Corn Data RMSEP



New Results- Corn Data LVs

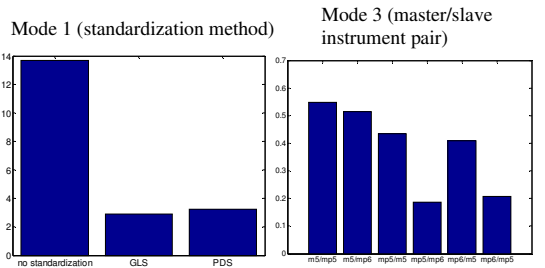


PARAFAC model on Corn RMSEP Results

- 4D array
 - Standardization
 - Preprocessing
 - Master/Slave instrument pair
 - Analyte
- 1 PARAFAC component explains 91.4% of the RMSEP data



PARAFAC loadings

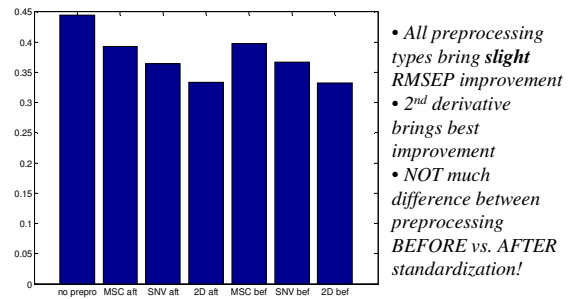


GLS performs slightly better on this data

All transfers involving instrument "m5" have higher RMSEPs



PARAFAC loadings- preprocessing



• All preprocessing types bring *slight* RMSEP improvement
 • 2nd derivative brings best improvement
 • NOT much difference between preprocessing BEFORE vs. AFTER standardization!



Comparison of Methods on Pseudo Gasoline Data

- Available data
 - 30 samples split 20/10
 - 5 analytes
 - 2 instruments
- 5 Transfer samples selected
 - Based on model inverse for PDS
 - Based on PCA leverage for OSC, GLS
- Tested both methods on all combinations of instrument and analyte

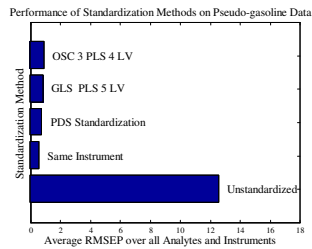


Pseudo Gasoline Study Design

- 5 analytes (moisture, oil, protein, starch)
- 2 ways to transfer (2 instruments)
- 2 methods tested (PDS and GLS)
- 7 preprocessing options (SNV, 2nd deriv, and MSC, before and after, or none)
- 140 transfers total (5x2x2x7)



Results of Previous Study on Pseudo Gasoline Data



New Results for Pseudo Gasoline Data

Ditto results from corn data here.



Other Ways to Apply GLS

- GLS weighting may be applied directly to model
 - Don't have to rebuild model!
 - Works well sometimes, but not always (future work)
- Downweight interferents
 - Requires estimate of effect of interferent
 - Image decluttering
- Upweight analyte of interest



Usability Issues

	Meta-parameters?	Requires Y?	Rebuild calibration model?	Modifies spectra?	Transfer sets function of Y?	Affects net analyte signal?
GLS	1	No	Yes/No	Yes	No	Yes
PDS	2	No	No	No	Yes	No
OSC	3	Yes	Yes	Yes	No	Yes



Conclusions 1/2

- GLS preprocessing is a simple, effective method for eliminating spectral differences
 - "designed" for correlated sampling issues
 - Can be used in several ways
 - Only one adjustable parameter
 - Potential loss of net analyte signal
- PDS
 - designed to account for instrument differences



Conclusions 2/2

- GLS slightly better than PDS for corn data, PDS slightly better than GLS for gasoline data
 - More sampling/scattering issues in corn data than gasoline data
- Preprocessing reduces number of LVs needed, and *slightly* reduces the RMSEP (slave test data)
 - 2nd derivative gave best improvement
 - For all preprocessing types studied
 - no significant difference observed for preprocessing applied *before* vs. *after* standardization
- All transfers involving instrument "m5" resulted in higher prediction errors
 - Unique response biases vs. other two instruments studied



Future Work

- Complete analysis of pseudo-gasoline data
- Expand study to include
 - PDS first to account for instrument differences followed by GLS to handle sampling variance
 - Additional Data Sets



Bibliography

- [1] H. Martens, M. Høy, B.M. Wise, R. Bro and P.B. Brockhoff, "GLS Preprocessing of Multivariate Data," submitted to J. Chemometrics, May 2001.
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