

Review on Multiway Analysis in Chemistry—2000–2005

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This review describes advances in multiway analysis during the period 2000–2005. Multiway analysis started to take off in chemistry in the 1980s, but only in recent years has it been broadly applied to many diverse kinds of data. This review reflects how the field has matured and how the methods have been applied to more and more difficult types of data in new research areas. Multiway analysis is described in terms of different types of data, different areas of applications as well as more fundamental and theoretical results throughout the period. It is evident from this review that multiway analysis is presently a generally accepted and used tool whose full potential is far from reached.

Keywords PARAFAC, tucker, tensor, three-way

INTRODUCTION

Multiway analysis is concerned with the analysis of higher order data as defined, e.g., by Henk Kiers (1). Higher-order data is data that can be arranged in boxes as opposed to two-way data, matrices, that can be arranged in tables. Interestingly, the paper by Kiers, describes the first suggestion for a standardized notation for multiway analysis not only applicable in chemistry, but in data analysis in general. It is advised to use these suggestions for notation in order to make communication across and within different disciplines more straightforward.

Multiway data occurs frequently due to modern instrumental developments, so it is quite typical that multiway data analysis in recent years has been applied to new advanced instrumental data. But the maturing of the area has also led to a situation where multiway tools are more frequently used for other types of data such as process data, sensory data, etc. In certain situations, multiway data are rearranged into matrices and analyzed using ordinary multivariate data analysis, two-way analysis. This review does not go into such extensions of two-way analysis, but focuses on the tools that work directly on the three-way data or in general multiway data. Multiway analysis started in psychometrics in the 1960s and 1970s (2–5) partly based on problems in factor analysis dating back to the 1940s (6). Since then there has been an increasing collaboration between psychometricians and chemometricians on both fundamental and applied issues. In later years, multiway analysis has started to be used in signal processing and mathematics, but most results from these areas will not be covered in this review as they are of little relevance to chemical applications.

As an indication of the growth in multiway analysis, the period that this a review deals with has also witnessed a whole special issue of the *Journal of Chemometrics* devoted to multiway analysis (7) as well as the first book on multiway analysis (8) in chemistry. A review covering the 10-year period 1985 to 1995 contained 126 references (9) whereas this 5-year review contains more than 300 papers.

In the following the literature on multiway analysis is described in terms of three different types of areas. The first part of the review describes applications in terms types of data, while the second part describes multiway analysis in terms of different areas of application, and finally more theoretical aspects of multiway analysis are described.

DATA TYPES

Fluorescence Spectroscopy

Fluorescence spectroscopy is by far the most abundant type of data used for multiway analysis (10). This is undoubtedly due to the close relationship between the unique PARAFAC model and the fundamental structure of common fluorescence spectroscopic data. Andersen and Bro (11) gave an overview of the use of fluorescence excitation-emission spectroscopy and how to perform valid multiway analysis of such data. One of the most interesting aspects of using the PARAFAC model is that it enables the so-called second order advantage (12). That is, the possibility of doing quantitative chemical analytes even in the presence of uncalibrated interferents. A number of papers have dealt with this issue for different types of applications. Moberg et al. (13, 14) used PARAFAC to quantitate different chlorophylls and derived analytes. The PARAFAC based calibration method was shown to be superior to two-way techniques such as classical least squares. PARAFAC was used to perform quantitative

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analysis of pesticides using a fluorescent dye, with detection down to parts-per-trillion (15, 16). Fluorescence and second-order calibration was used to predict sulfathiazole in honey (17) and to quantify catecholamines (less successful) (18, 19). Using the kinetic development of fluorescence it was possible to quantify methotrexate and leucovorin in human urine using four-way PARAFAC modeling (20). There are numerous other examples on the use of fluorescence data and second order calibration: carbendazim, fuberidazole and thiabendazole (21), naphthalenesulfonates using non fully resolved chromatographic analysis (22), doxorubicin (23), ciprofloxacin (24, 25), flumequine and oxolinic acid (26), enrofloxacin (27), verapamil (28), carbendazim, fuberidazole, and thiabendazole (29). An LED-based fluorescence instrument was developed and tested for calibration in the parts-per-billion to parts-per-trillion range for compounds such as 9,10-bis(phenylethynyl)-anthracene and rhodamine B using PARAFAC (30). PARAFAC was used to resolve drug mixtures of propranolol, dipyridamole and amiloride in aqueous solution (31), carbamazepine in serum (32), norfloxacin, enoxacin, and ofloxacin (33, 34), and different drugs in plasma (35).

In some applications, the second-order advantage is not a crucial aspect for solving the calibration problem; It should be "may be because the data is not possible to describe, in a chemically meaningful way, with PARAFAC" or because the components are only indirectly related to the dependent variable. The PARAFAC model may still be used similarly to how the principal component analysis can be used in principal component regression, but it is also possible to use alternative multiway methods. Pedersen et al. (36) showed that they got chemically meaningful PARAFAC models from fluorescence data of fish oil, and that they could use the resulting models for predicting the dioxin content.

Besides the use of fluorescence data for calibration purposes, it is also often used for qualitative analysis, classification, exploratory analysis etc. A fair part of these applications deal with food analysis and environmental analysis. Guimet and coworkers have performed a number of experiments on olive oils characterizing these using fluorescence spectroscopy as well as PARAFAC modeling for verifying possible adulteration (37–39). The multiway N-PLS regression approach was used to predict quality parameters such as peroxide values. Baunsgaard and coworkers on the other hand have published a number of papers on the use of fluorescence for understanding the quality of sugar as well as its intermediate products (40–42) showing how the chemical insight gained from PARAFAC models enabled a deeper understanding of e.g., the formation of colorants. Fluorescence was also used to monitor the quality of dry-cured Parma ham (43) and in yogurt (44) providing chemically meaningful information on major chemical/physical changes during processing. Fluorescence has also been used together with PARAFAC modeling for monitoring light-induced oxidation and changes in cheese with storage (45, 46). PARAFAC models were used to characterize the interaction of chlorpromazine hydrochloride and Neutral Red with DNA (47) and for single-cell temporal analysis of intracellular Ca^{2+} concentration and pH (48).

PARAFAC in combination with fluorescence spectroscopy has also proven useful for various types of applications within environmental analysis such as characterizing oil spills (49) based on fingerprinting polycyclic aromatic compounds (50, 51); characterizing stress by measuring hormones in urine (18); and resolving polycyclic aromatic hydrocarbons (52, 53). Also in environmental analysis, a new approach for chemical identification of dissolved organic matter for tracing pollution has been suggested, based on the use of fluorescence in combination with PARAFAC modeling (54). Finally Haack et al. (55) used PARAFAC and two- and three-way PLS to describe the chemistry and quality of cultivations with *Saccharomyces cerevisiae*.

Although, some view fluorescence excitation-emission data as the ideal type of data for, PARAFAC modeling, for example, there are in fact, a number of problems with typical fluorescence data that complicates practical application of PARAFAC. Most notably, different kinds of scattering signals pose a problem as the scattering signals do not follow the PARAFAC as well as not containing any chemical information. Several approaches have been tested to remedy the bad influence of scattering by downweighting the scatter, setting it to zero or modeling it (11, 56–61).

CHROMATOGRAPHY

Another area where multiway analysis has been extensively used is in chromatography. Ideally, a chromatographic experiment leads to perfect separation of chemical analytes and the resulting chromatograms can be directly converted to e.g., areas or concentrations and used for further analysis. Sometimes, though, it is not possible to achieve perfect separation, either because of the complexity of the samples or because faster chromatographic runs are preferred. In such situations, overlapping peaks result and data analysis can be used for further achieving selectivity by mathematical means or simply for fingerprinting the elution profiles (62). In gas chromatography (GC) multiway analysis has been used for a number of purposes. It has been shown that careful implementation of GC×GC provides data that can be subsequently analyzed by multiway methods enabling high-speed GC systems for complex process or food analysis (63–66). Quantitative and qualitative analysis of naphtha samples were demonstrated using comprehensive high-speed two-dimensional gas chromatography analyzed using N-PLS to predict the aromatic and naphthene (cycloalkanes) content of naphtha samples (67). Tucker and PARAFAC models were used to analyze GC data from Maillard reactions experiments (68). Gas chromatography-mass spectrometry (GCMS) was used for analyzing data from fuels that have undergone various levels of thermally induced oxidation. Regions of the GC-MS data were modeled with PARAFAC providing the mass spectra of individual fuel constituents (69). Also the eigenvalue based algorithm GRAM was used for analyzing GC × GC data of jet fuels (70, 71). Sinha et al. has shown how GC × GC coupled to time-of-flight mass spectrometry (GC × GC-TOFMS) and

combined with PARAFAC provides a powerful analytical methodology where partially resolved components in complex mixtures can be identified directly. It was found that deconvolution results were best with selectivities above 0.18 (72, 73). Garcia et al. (74) compared traditional analytical quantification with the use of PARAFAC, PARAFAC2, Tucker and N-PLS on GCMS data for determining Clenbuterol bovine hair and urine. Five hormonal growth promoters (diethylstilbestrol, hexestrol, dienestrol, 17-beta-estradiol and 17-ethynylestradiol) were similarly analyzed and in addition the use of PARAFAC2 was tested for handling variations in elution time across chromatographic runs (75). For quantification using GC \times GC, the use of GRAM is compared to two traditional peak integration methods providing substantial improvements in quantification precision, accuracy, and limit of detection (76).

As for GC, LC systems also provide data where multiway methods can be helpful. HPLC with infrared spectroscopic detection can be hampered by strong absorption bands of the eluent. It was shown that a modified PARAFAC or PARAFAC2 model that specifically models the eluent could alleviate the problem (77). An iterative approach to resolving overlapping peaks was suggested by Wang et al. (78) and an approach for extraction and quantification of sulfamethoxy-pyridazine, sulfamethoxazole and sulfadimethoxine in porcine kidney by HPLC-DAD was developed using PARAFAC to resolve overlapping peaks (79). PARAFAC was shown to be able to resolve partly separated peaks into their pure chromatographic, spectral and concentration profiles, even with severely overlapping spectra using a system of lidocaine and prilocaine analyzed by LC-DAD (80) and overlapping LC \times LC data were resolved by Fraga and Corley (81).

FLOW INJECTION

In flow injection, threeway data often occur (82–84) and there are often problems with so-called rank overlap because of the lack of separation in the time mode. Least squares-based and eigenvalue-based algorithms were tested for calibration in FIA systems with a pH profile induced and with rank overlap (85). Benzoic and sorbic acids were determined in commercial orange juices using a flow injection system with pH gradient generation, diode array spectrophotometric detection, and PARAFAC as well as multivariate curve resolution (86). Levodopa and benserazide were quantified in pharmaceutical formulations based on the N-PLS modeling of kinetic-spectrophotometric data from a spectrally detected stopped-flow injection method where the analytes reacted with periodate (87).

MAGNETIC RESONANCE

Both low-field and high-field NMR is gaining momentum in new types of applications. And while the data structures are quite different, multiway analysis has been extensively used for both types of data. In low-field NMR, the use of multiway analysis arises from the often multi-exponential nature of the data. As shown initially by Antalek and Windig (88–90)

such data can be modeled by rearranging the data appropriately (slicing) and then fit a PARAFAC model to the rearranged data. The resulting models provide direct access to the quantitative and qualitative information of the underlying exponentials. Often, the use of least squares fitting through alternating least squares is replaced by faster approximate methods based on eigenvalue decompositions (GRAM, TLD etc.). These methods are particularly useful for low-field NMR because the signal-to-noise ratio is high and the model error low leading to excellent performance of these methods. A refined algorithm for fitting low-field NMR called PowerSlicing was proposed by Engelsen and Bro (91–93). The method was used to determine fat content in minced meat as well as characterizing preslaughter stress in processed meat (94), predicting sensory attributes of potato samples (95) and for exploring properties of cod muscle (96). Nordon et al. (97) showed the superiority of the multiway approach both with respect to accuracy and possible automation in analysis of a glycerol-based polyether polyol (98). Multiway analysis has been used in a number of different types of high-field NMR applications. A PARAFAC-based method called MUNIN has been applied to deal with huge-size multidimensional NMR data (99–102). Three- and four-way PARAFAC models were used to model fMRI data from multiple runs of a bilateral finger-tapping paradigm (103). Independent component analysis and PARAFAC was used to model multisubject FMRI analysis (104). Dyrby et al. (91, 105–107) used PARAFAC for curve-resolution, Tucker models for exploratory studies and N-PLS for quantitative models of various metabonomic data.

EEG

EEG data was acquired during the testing phase of a new drug expected to have effect on the brain activity. The implemented test program (several patients followed in time, different doses, conditions, etc.) led to a six-way data set and Tucker modeling was shown to provide detailed information on the underlying phenomena (108). Multiway partial least squares regression was used to model EEG and fMRI data uniquely as a sum of “atoms” (109, 110) and PARAFAC was used to find the underlying structure of multichannel EEG recordings (111, 112).

Other

Geladi et al. has shown how NIR batch data can be modeled using multiway analysis (113, 114). Nielsen et al. (115) used an approach called COMDIM to characterize relations between NIR spectra, particle size distributions and chemical parameters of wheat flours. PARAFAC was used to model UV/Vis kinetic spectra studying amino acid transport through liquid membranes (116). Rank annihilation factor analysis (RAFA) was used for UV/Vis spectrophotometric studies of complex formation (117). Mixtures of acetylsalicylic acid and ascorbic acid were studied by UV/Vis spectra using a pH range and estimating spectra and pK_a values. N-PLS regression was performed to predict the content of the analytes in pharmaceutical samples (118). UV/Vis

spectra were acquired as a function of time of an alkaline hydrolysis reaction of the antihypertensor Nifedipine. PARAFAC and PARAFAC2 methods were used for building calibration models (119).

Microsynchrotron radiation X-ray fluorescence were modeled with PARAFAC (120). Data from electronic nose data was modeled using PARAFAC2 for handling shifted time-profiles. The resulting data were used to classify samples of licorice (121). N-PLS was used to classify electronic nose data of microorganisms relevant for diagnosis of pneumonia (122). Water samples containing varying mixtures of toluene, ethyl benzene, and cumene were analyzed by purge-and-trap/direct sampling mass spectrometry. N-PLS and PARAFAC was employed for quantitative purposes and the PARAFAC models were shown to be able to predict samples that contained unmodeled, interfering compounds (123). PARAFAC was used to analyze both the time-dependent and polarization-angle-dependent IR spectra (124). PARAFAC has been used for modeling data from ICP-AES in order to gain better fundamental understanding of stability, robustness, etc. (125, 126). The use of voltabsorptometric determination of *o*-tolidine in presence of high concentration of ferrocyanide was as a model system for multiway calibration (127). PARAFAC of full skin impedance spectra was used to investigate human skin properties (128). The use of multi-way analysis for image analysis has also been discussed (129, 130).

APPLICATION AREAS

Calibration

Calibration is one of the major fields of application in chemometrics and also using multi-way methods (8, 131, 132). Several papers describe and compare different theoretical approaches to calibration (133–139) and a large number of applications especially within analytical chemistry has been published e.g., for determining creatinine in serum (140), flavilium cation, quinoidal basen, and E and Z ionized chalcones (141), dimethylphenol isomers (142), naphthalene, 1-naphthol and 2-naphthol (143), lorazepam (144), piroxicam (145), aromatic sulfonates (146), salicylate in plasma (147), verapamil (28), ciprofloxacin (25), trace levels of Cu, Zn, Co, Ni and Fe (148), pyridines (149), naproxen-salicylic acid-salicylic acid mixtures (139). In QSAR there have been a number of approaches suggested often involving the use of N-PLS (150–156) and N-PLS was also used for predicting grain yield and protein content in wheat and barley (157). The method bilinear least-squares was used for quantifying various juice colorants from spectral-pH three-way arrays (158). Quantification of tetrachloro-dibenzoparadiioxin was performed by solid-liquid extraction laser-excited time-resolved Shpol'skii spectroscopy using four-way PARAFAC (159).

MSPC

Multivariate statistical process control often involves multiway data and hence applications of multiway analysis have appeared especially in recent years (160–166). Experimental

results from a pilot-scale paper mill filtration application was modeled using PARAFAC (167), PARAFAC2 was used for fault detection and diagnosis in a semiconductor etching (168), N-PLS was used to model the performance of an industrial fed-batch fermentation process (169), while a modified Tucker3 model was used for modeling first-order chemical batch reactions monitored by UV/Vis spectroscopy (170). PARAFAC and N-PLS was used to model dynamic behavior in an on-line batch process (171). Finally, PARAFAC was developed for on-line monitoring of batch processes (172). Other models based on multidimensional scaling have also been proposed (173).

Metabonomics

Metabonomic data are often multiway of structure. Dyrby et al. (107) showed how a traditional dose-response experiment could be properly explored using Tucker3 models and PARAFAC was used for similar data (174). Idborg et al. (175) exemplified the use of PARAFAC and N-PLS in handling metabolite screening using liquid chromatography/electrospray ionization mass spectrometry. Lipoprotein characterization using 2D diffusion-edited NMR spectroscopy was analyzed with PARAFAC providing chemically meaningful spectra (106).

Environmental Analysis

Chemical analyses (dissolved oxygen, nitrates, etc.), physical data (turbidity, temperature, COND), and biological monitors (total and faecal coliforms, faecal streptococci) were monitored monthly during four years on freshwaters sampled at seven sites in northeastern Italy. Tucker models were used to explore patterns of information reflecting the environmental quality of the monitored freshwaters (176). A number of similar studies has shown and discussed the utility of particularly Tucker but also PARAFAC in environmental analysis (177–183). N-PLS was used for predicting average air temperature, dew temperature and precipitation (184) while PARAFAC was used to characterize polycyclic aromatic hydrocarbons (53). The availability and mobility of trace elements and heavy metals were analyzed using PARAFAC (185). Monitoring of photocatalytic degradation of phenol in aqueous suspensions of TiO₂ was based on fluorescence spectroscopy and PARAFAC (186). A multilinear model was developed for the analysis of the spatial patterns and possible sources affecting haze and its visual effects in the southwestern United States (187) and chemical composition data was analyzed using a mixed two-way/three-way model (188). There have been a number of projects related to characterizing dissolved organic matter from diverse aquatic environments with PARAFAC. The PARAFAC approach is used to replace more manual evaluations of the fluorescence measurements and a high number of papers are appearing on this (49, 54, 189–191). Modified versions of Tucker3 and PARAFAC have been developed for optimally handling interval-valued data and are used for analyzing air pollution data (192) and three-way environmental data are analyzed with STATIS, Tucker and PARAFAC2 (193).

Kinetics

Incorporation of kinetic constraints in PARAFAC-like models (194, 195) have been published as well as reports on the suitability of threeway methods for kinetic modeling (196, 197). Often times, direct application of multiway methods such as PARAFAC are hampered by the changes in actual shapes of kinetic profiles, yet there have been experiments where PARAFAC2 was used to overcome this problem (198). Kinetic-spectrophotometric analysis for quantification of nitrite in water and meat samples using PARAFAC (199) and simultaneous degradations of chlorophyll a and b was studied by fluorescence spectroscopy and resolved by PARAFAC (200). Kinetic calibration models were developed for carbaryl and while curveresolution and PARAFAC was able to predict new samples with unknown interferents, N-PLS was shown not to be able to as is expected from its regression properties. Bijlsma et al. have developed several models for describing various kinetic systems (201, 202) using combinations of hard and soft models (203). Rank annihilation was used for determining rate constants (204) and N-PLS used to predict levodopa and benserazide from kinetic-spectrophotometric data (87, 205). Time-dependent activity data of laccase enzyme was analyzed using Tucker3 (206, 207).

Sensory Analysis

Chewing sounds of different types of dry-crisp snacks were analysed by N-PLS, Tucker and PARAFAC in order to classify the samples (208). Time-intensity measurements of flavor release were modeled by a number of methods including PARAFAC2 (209). Scores from PARAFAC models were used as predictors to predict sensory qualities of different potatoes (95) as well as to predict sensory properties of hams (43). Tucker and PARAFAC was also used to model sensory profiling data (8, 68). Effects of oil type, lipid antioxidants on oxidative flavor stability of fish oil-enriched milk were evaluated using PARAFAC (210). GEMANOVA, a method for analyzing higher-order interactions in complex data was used for monitoring changes in fresh beef during storage (211).

Classification

Very little work has been done on dedicated multiway classification, although some new types of classification models have been suggested (212–214, 215). PARAFAC was used in trying to discriminate between phytoplankton classes using fluorescence spectra (216) and PARAFAC as well as N-PLS was used for distinguishing five species of *Penicillium* (217). Allosio et al. (218) used time-dependent NIR reflectance spectroscopy and PARAFAC to model a malting process. PARAFAC fluorescence analysis of olive oils was used to discriminate between non-adulterated and adulterated samples (38) while the chewing sound was used to detect differences in foods (208). Particle sizes were arranged as histograms for 21 size classes and analyzed with PARAFAC (219). Tucker3 modeling was used to study differences in patterns of nutritional content of foodstuffs (220).

THEORETICAL

In this last section, more theoretical papers on multiway analysis are described. There are a number of papers describing the general use and utility of multiway methods as well as proper notation (1, 8, 11, 131, 221–225). The use of Procrustes analysis for multiway analysis was described in an introductory tutorial (226) and robust versions of Tucker3 and PARAFAC have been developed (227, 228). Several methods have been proposed for second-order calibration (20, 229, 230). Generalized rank annihilation–GRAM–has been thoroughly described and used in recent years (231–236). Multiway multiblock component and covariates regression models are described by Smilde et al. (237) and new models have been developed for handling shifts in data (238–240). New methods for determining the optimal number of components in PARAFAC have been proposed (241–245).

The PARAFAC model has the very attractive uniqueness properties; a fact that has been one of the main reasons for its success. Yet, the identifiability conditions are still far from fully understood as explained recently (246, 247). Basic properties of multiway models are important also in practical applications. Many results arise from the tensor properties of multiway arrays (248–254). The rank of multiway arrays is not as simple a topic as for two-way matrices. New concepts arise and many aspects are not understood in detail (255–260). Plotting of parameters from multiway models was described in detail (261, 262). New notations and operations for multiway analysis have also been suggested (1, 224, 225).

In order to perform sensible analysis, preprocessing of the data is often mandatory. Preprocessing can range from simple centering and scaling to e.g., variable selection. The theory of centering and scaling was thoroughly addressed by Bro and Smilde (263) as well as tested in practical applications in multiway regression (156). Bylund et al. used warping for aligning chromatographic data prior to the application of PARAFAC (264) while Comas et al. performed a similar operation based on a time shifting operation (138). For reducing the amount of data without losing essential information, it has been proposed to perform an initial variable selection based on genetic algorithms (265). With the increasing popularity of the PARAFAC model, a number of suggestions have been made for improved algorithms (266–275). Two papers have compared the many different existing algorithms (276, 277). New approaches to imposing smoothness constraints were suggested (278, 279) and dealing with missing values in PARAFAC was evaluated (280). A general algorithm for fitting different kinds of multiway models was developed based on the conjugate gradient method (281).

Several algorithms have been modified to enable a maximum likelihood fitting rather than the usual least squares fitting (53, 282–286). Jackknifing of PARAFAC was shown to be able to help identifying outliers as well as providing uncertainty estimates in PARAFAC (287) and bootstrapping was used for building confidence intervals (288, 289). Other papers have dealt with

general statistical aspects of multiway models (234, 290, 291). Different approaches to getting sample-specific prediction errors have been developed for both PARAFAC and N-PLS (292–296). Various papers have dealt with figures of merit (297, 298).

Software

Several software packages are available for performing multiway analysis. The N-way toolbox (www.models.kvl.dk) is a free MATLAB toolbox that performs PARAFAC, Tucker, N-PLS, GRAM, TLD (299–301). Also at (www.models.kvl.dk), the following multiway methods and tools are available: PARAFAC2 (302, 303), PowerSlicing for low-field NMR data (92), Jackknifing of PARAFAC (287), alternative implementation of algorithms for PARAFAC (e.g., Levenberg Marquadt) in Matlab (276), PARAFAC for complex-valued arrays (304), MILES for maximum likelihood fitting of PARAFAC (286), GEMANOVA for multiplicative ANOVA models (211), and SENSABLE, a graphical user interface for analyzing data from electronic noses and tongues (121). At (csmr.ca.sandia.gov/~tgkolda/pubs), a free MATLAB Tensor toolbox is available for performing basic mathematical operations on multiway arrays. There are several commercial programs with multiway methods included. At (www.multid.se), DATAN containing PARAFAC is available and at (www.eigenvector.com), PLS_Toolbox can be acquired giving access to PARAFAC, PARAFAC2, Tucker, N-PLS, GRAM, TLD as well as a number of additional multiway tools for preprocessing and handling. The Unscrambler available at (www.camo.com) contains N-PLS. At (<http://three-mode.leidenuniv.nl/>) an extensive list of available software is available.

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