



Using Analytic Solver Platform

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What We'll Cover Today



- Introduction
 - Session II beta training program goals
 - Brief overview of XLMiner
- Overfitting problem
- Partitioning the data
- Supervised learning classification





Session II Online Beta Training Goals

- To empower you to achieve success
 - State of the art tools
 - Online educational training
 - Training documents and demos
- To familiarize you with the following concepts:
 - Understanding the ideas behind the classification techniques
 - Fitting classification models to data
 - Assessing the performance of methods
 - Applying the models to predict unseen test cases



Data Mining Steps







Unsupervised Learning Algorithms



- No outcome variable in the data set, just a set of variables (features) measured on a set of samples.
 - Market basket analysis.
 - Social network analysis.





Supervised Learning Algorithms



- For each record:
 - Outcome measurement y (dependent variable, response, target).
 - Vector of predictor measurements x (feature vector consisting of independent variables).

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- Prediction:
 - Housing market: Price.
 - Product: Demand.
- Classification:
 - Online Transactions: Fraudulent (Yes / No)?
 - Email: Spam / Not Spam?
 - Insurance Applicant: High / Medium / Low Risk?



Brief Overview of XLMiner





Data Analysis

- Draw a sample of data from a spreadsheet, or from external database (MS-Access, SQL Server, Oracle, PowerPivot)
- Explore your data, identify outliers, verify the accuracy, and completeness of the data
- Transform your data, define appropriate way to represent variables, find the simplest way to convey maximum useful information
- Identify relationships between observations, segment observations



Brief Overview of XLMiner





Time Series

- Forecast the future values of a time series from current and past values
- Smooth out the variations to reveal underlying trends in data
 - Economic and business planning
 - Sales forecasting
 - Inventory and production planning



Brief Overview of XLMiner





Data Mining

- Partition the data so a model can be fitted and then evaluated
- Classify a categorical outcome good/bad credit risk
- Predict a value for a continuous outcome house prices
- Find groups of similar observations market basket analysis



Chapter 6 - Part I Classification Methods

Using XLMiner







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The Problem of Overfitting



• If we have a complicated model, the model may fit and explain the training data very well, yet fails to generalize to new data.



Underfit

 x_2

 $f(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_1^2 + \alpha_4 x_2^2 + \alpha_5 x_1 x_2)$



 $f(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_1^2 + \alpha_3 x_1^2 x_2 +$ $\alpha_4 x_1^2 x_2^2 + \alpha_5 x_1^2 x_2^3 + \alpha_6 x_1^3 x_2 + ...)$ Overfit

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Partitioning the Database



- Helps to avoid overfitting by testing the model on validation part.
- Partitioning is segmenting the data into following groups.
 - **Training set:** used for learning the parameters of model.
 - Validation set: used for evaluating the model error and tuning parameters.
 - **Test set (optional):** used for a final, independent test of the performance of the model on new data that was not part of the model building.



Partitioning the Database XLMiner

- Standard Partitioning
 - Random partitioning
 - User-defined Partitioning
- Partitioning with Oversampling
 - Use Oversampling when there are only two categories and the group of interest is rare.
 - Example: Universal Bank data personal loans solicitations.





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Summary- Partitioning with Oversampling Using XLMiner

 Click any cell within the dataset, then click
 Partition – Partition with
 Oversampling (in the Data Mining section of the XLMiner ribbon).

Partition	Classify	Predict	Associate	Sco	re	Help
	Standard	l Partitio	on		Тос	ols
	Partition	with O	versamplin	9		J

Select all variables in
the Variables list box
then click > to move all
variables to the
Variables in the
partitioned data listbox

 Workbook: Catalog_multi.xlsx Worksheet: Data Data range: \$A\$1:\$V\$58206 # Rows in data: 58205 # Columns in data: First row contains headers Variables ariables in the partitioned data Target dependent variable:buy Total LTD Orders Total 24 Month Orders Days Since Last Purchase Days Since First Purchase Number of Divisns w/ Purchas Number of Credit Cards Used Output variable Choose one of the selected variable 12345 Specify Success class: Specify % Success in training set Specify % validation data to be taken away as test data QK Cance es of all the worksheets available in the selected workhor





Highlight the target variable in the Variables in the partitioned data listbox then click the > to the left of Output variable to designate
this variable as the output variable, then click OK.

Data sourc	e	
Worksheet:	Data	▼ Workbook: Catalog_multi.xlsx
Data range:	\$A\$1:\$V\$58206	
# Rows in da	ata: 58205	# Columns in data:
Variables -		
 Eirst row 	contains headers	
⊻ariables		Variables in the partitioned data
		Target dependent variable:bu Total LTD Orders Total 24 Month Orders Days Since Last Purchase Days Since First Purchase
		Number of Divisns w/ Purchas Number of Credit Cards Used Customer Gender
Randomiza Set seed	tion options	Number of Divisns w/ Purchas Number of Credit Cards Used Customer Gender Qutput variable: Chgose one of the selected va < Target dependent variable:bi
Randomizai Set seed Output opt # Classes:	tion options	Number of Divisns wij Purchas Number of Craft Craft Used Customer Gender Quitput variable: Choose one of the selected va Choose one of the selected va Choose one of the selected va
Randomizal Set seed Output opt # Classes: % Success Specify % S Specify % y	tion options I 12345 In data set:	Number of Divises vi Putters Number of Credit Card Used Customer Gredit Card Used Customer Gredit Card Used Card Dised Card Dised
Randomizal Set seed Output opt # Classes: % Success Specify % S Specify % v	tion options 12345 ions in data set: 0.5 iuccess in training set raildation data to be to	Number of Divisity of Particles Number of Credit Card Used Customer Gender Quitput Vaniable: Choose one of the selected value Z Specify Success class: 1 aken away as test data:

Classification Using XLMiner

- Discriminant Analysis
- Logistic Regression
- k-Nearest Neighbor
- Classification Tree
- Naïve Bayes
- Neural Networks







Discriminant Analysis (DA)



- Estimates the probabilities that a given record falls into one of the possible classes.
- Estimates means and covariance(s) of groups using training data.
- Models distribution of each group separately.
- Bayes theorem posterior probabilities (adjusted with prior frequencies of classes).
- Independent variables are assumed to be normally distributed.
- Linear discriminant analysis (LDA) linear decision boundaries.
- Quadratic discriminant analysis (QDA) quadratic decision boundaries.



Scoring New Data

- XLMiner's dialogs for classification routines provide an option to score new data in a database or from worksheet.
- In the Discriminant Analysis Step 3 of 3 dialog.
- Score new data in a database using XLMiner : MS-Access, SQL Server, Oracle.
 - Example: Scoring to MS-Access Database
- XLMiner's "Score" in the Tools group, will allow you to score new data after you have fitted your model. XLMiner produces Stored Worksheet with saved model.



Discriminant An	alysis - Step 3 of 3 🛛 🗙		
Output option	gs		
Score training data	Score training data Score validation data		
Detailed report	Detailed report		
Summary report	Summary report		
Lift charts	🗖 Lift charts		
Canonical Scores	Canonical Scores		
Score test data	Score new data in		
Detailed report	Worksheet		
Summary report	Detailed report		
Lift charts	Canonical Scores		
Canonical Scores	🗖 Data <u>b</u> ase		
Help Cancel <	Back Next Einish		
If checked, output will includ	e Canonical variate loadings.		
J			





Summary-Scoring to a Database

 In the Discriminant Analysis method, this feature is found on the Step 3 of 3 dialog.

Discriminant Analysis - Sten	3 of 3				
Discriminant Analysis - Step					
Output option					
Canonical variate loading	15				
Score training data	— Score validation data				
✓ Detailed report	✓ Detailed report				
Summary report	Summary report				
🔽 Lift charts	🔽 Lift charts				
✓ Canonical Scores	Canonical Scores				
Score test data	Score new data in				
Detailed report	Worksheet				
Summary report	Detailed report				
🗖 Lift chart <u>s</u>	Canonical Scores				
Canonical Scores	🗆 Data <u>b</u> ase				
Help Cancel <	Back Next Einish				
If checked, output will include data set.	canonical scores on validation				

- In the Score new data in group, select **Database**. The Scoring to Database
- The first step on this dialog is to select the **Data source**.
- Once the *Data source* is selected, **Connect to a** database... will be enabled.
- Enter the appropriate details, then click OK to be connected to the database.

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OK.

– Database Conne	tion		
Data source	MS-Access	- Connect	to a database
<u>Select</u> table/view	Bostan_Housing	← # Records	506 # Fields 17
Input data Eields in table CRIM ZN INDUS CWS	Variables in I CRIM ZN INDUS NOX	input data	Match CRIM <> CRIM
NOX RM AGE DIS	AGE DIS RAD TAX	-	selected variable
Match the Output field C Select output C Add new field	ch verieble(s) with s : first 11 <u>v</u> ariables in : fileki) > [d før output	ame name(s) the same sequence	
Heb Cick this to unmate	h all the matched va	riables from the input	Cancel

Summary-Score Test Data Using DA Model



 Click Score on the XLMiner ribbon.



 Select the new data and the Stored Model worksheets.

Select New Data Sheet & Stored Model sheet-Step 1
Data to be scored Worksheet: Sheet12
Data range: \$A\$1:\$K\$13
✓ First row contains headers # Data Rows: 12 # Data Columns: 11
Stored Model Wgrksheet: Workbook Boston_Housing.xlsx
Help Next Cancel
Specifies names of all the worksheets available in the selected workbook.

- Click **Next**. XLMiner will open the *Match* variables – Step 2 dialog.
- Match the Input variables to the New Data variables using Match variable(s) with same names(s) or Match variables in stored model in

same sequence.

• Then click **OK**.

Variables in ne CRIM ZN INDUS CHAS	w data Va	rjables in stored i CRIM_Scr ZN_Scr INDUS_Scr CHAS_Scr CHAS_Scr	nodel	Match the two selected variables
RM AGE DI5 RAD	-	NGA_JO RM_SCr AGE_Scr DIS_Scr RAD_Scr	_	Unmatch the selected variable Unmatch All
Match	Match variable n variable <u>s</u> in st	o(s) <u>w</u> ith same na ored model in sar	me(s) ne sequence	
Help This is the list of picked from the	' variables you new data rang	can choose from e.	Back These have beer	OK Cancel

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Strengths and Weaknesses of Discriminant Analysis



Strengths:

- Very fast even for large data.
- Useful and well-interpretable number of features is not large.
- Perfect fit normal group distributions.
- Stable model well-separated groups.
- Multiclass learning can explain data in lower dimensions.
 - Similar to PCA, but in a supervised way.



Strengths and Weaknesses of Discriminant Analysis



Weaknesses:

- Does not apply number of features exceeds number of records.
- Overcomplicated and less stable high-dimensional data.
- May fail to capture structure of the data highly non-Normal distributions.



Summary-Discriminant Analysis

Data source Worksheet: Data_Partition

Rows In training set:

CRIM

ZN INDUS

INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO

B LSTAT

Help

Classes in the output varial

Specifies number of columns in selected data range

Variables in input data

- Partition the data.
- Select a cell on the Data_Partition1 worksheet then click
 Classify – Discriminant Analysis.



• Select the Output variable and Input Variables.

Discriminant Analysis - Step 1 of 3

405 In validation set: 101

-

Specify "Success" dass (for Lift Chart

Cancel

Workbook:

Input variable

Output variable

Boston Housing, xlsx

– # Columns: 15

Next > Einish

• Click **Next** and select the desired method of computing *Prior class probabilities.*

Discriminant Analysis - Step 2 of 3

Use equal prior probabilities

Cancel

classes found in the training data

User specified prior probabilities
 Misclassification Costs Of

1

This option will assign equal probability to all

According to relative occurrences in training data

Failure(0):

< <u>B</u>ack

 $\underline{N}ext >$

Prior class probabilities

Success(1):

Help

X

1

Einish



 Select the output and score training and validation data options.

Discriminant An	alysis - Step 3 of 3 🛛 🗙		
Output option Canonical <u>v</u> ariate loading	js		
Score training data	Score validation data		
Detailed report	Detailed report		
Summary report	Summary report		
Lift charts	Lift charts		
Canonical Scores	Canonical Scores		
- Score test data	Score new data in		
De <u>t</u> ailed report	Worksheet		
Summary report	Detailed report		
Lift charts	Can <u>o</u> nical Scores		
Canonical Scores	🗌 Data <u>b</u> ase		
Help Cancel <	Bac <u>k</u> Next <u>F</u> inish		
If checked, output will includ	e Canonical variate loadings.		

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Classification Using XLMiner

- Discriminant Analysis
- Logistic Regression
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Logistic Regression (LR)



- Extremely powerful and widely used.
- Extends Linear Regression.
- XLMiner binary classification problems.
- Fitted parameters estimate the probability of given records belonging to one of two possible groups.







• Models *Logit* transformation – linear combination of predictors:

$$Logit(P\{success|x\}) = b_0 + b_1 x_{i1} + b_2 x_{i2} + \dots + b_p x_{ip}$$

- LR conditional probabilities (generative learning)
- DA joint probabilities (discriminative learning)



Strengths and Weaknesses of Logistic Regression



Strengths:

- Very popular 2 classes.
- No assumption distribution of independent variables.
- Unlike Linear Regression error terms are not assumed to be normally distributed.
- No assumption linear relationship between independent and response variables.
- Performs well data containing categorical predictors.
- Handles large high-dimensional datasets.



Strengths and Weaknesses of Logistic Regression



Weaknesses:

- Less stable low dimensional data where classes are well-separated.
 - Discriminant Analysis.
- Less efficient number of records are less than number of features and when collinearity is present.
 - XLMiner embedded variable selection and best subset.



Summary-Logistic Regression



 Select a cell on the *Data_Partition1* output worksheet, then click Classify – Logistic Regression on the XLMiner ribbon.



- Choose input and output variables.
- Choose the value that will be the indicator of "Success" by clicking the down arrow next to Specify "Success" class (necessary).
- Specify the initial cutoff probability for success, and Click Next.

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Logistic Regression - Step 1 of 3
Worksheet: Data_Partition1 vorkbook: Charles_BookClub.xlsx v
Data range: # Columns: 18
Rows
Variables
✓ First row contains headers
Variables in input data Input variables
Seq# ID# B F FirstPurch ChildBks YouthBks VouthBks
Classes in the output variable
Classes: 2 🔽 Specify "Success" class (necessary): 1
Specify initial cutoff probability value for success: 0.5
Help Cancel < Back

Summary-Logistic Regression

• Set confidence level and Click **Advanced**.



 Select the desired options and Click OK to return to the Step 2 of 3 dialog.

Maximum #	gression - Adva	inced Opti	ons 50
– Initial marq	uardt <u>o</u> vershoot	factor:	1
Collinear	rity Diagnostics – orm Collinearity d of <u>c</u> ollinearity col	iagnostics mponents:	2
Help		ок	Cancel
If checked	d, output will inclu	ude Collinea	rity

- Click Best Subset and Select Perform best subset selection.
- Choose the desired selection procedures for selecting the best subset of variables.

laximum size of best subset:	15 🕂 Number of best subsets: 15 🚆
Selection procedure	C Eorward selection
C Exhaustive search	C Sequential replacement
C Stepwise selection	
FIN:	F <u>o</u> ut;
Help	OK Cancel
Specifies how many best (first	best, second best, etc) of the subsets you





- Click **OK** to return to the *Step 2 of 3* dialog.
- Click **Next** to advance to the *Step 3 of 3* dialog.
- Select Covariance matrix of coefficients, Residuals, reports, and Lift charts, then Click Finish.

Output options on trainin	g data
Covariance matrix of	coefficients 🔽 <u>R</u> esiduals
Score training data	Score validation data
<u>Detailed report</u>	© Detailed report
<u>Summary report</u>	© Summary report
<u>Lift charts</u>	© Lift charts
Score test data	Score new data
Help Cancel	< Back

Classification Using XLMiner

- Discriminant Analysis
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- k-Nearest Neighbors
- Classification Tree
- Naïve Bayes
- Neural Networks









k-Nearest Neighbor



- Very simple powerful algorithm classification decision based on information from neighboring records.
 - k observations most similar.
 - Majority voting most frequent group among the k nearest neighbors.
- No learning stage training data is our model.
- Similarity measure Euclidean Distance.
- Independent variables scaled appropriately.
- Best model assessing the classification error for various values of k.
- Less chance of overfitting validation error.



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• Focus – local structure. • Fails – global picture.

- "Curse of dimensionality."
- Extremely sensitive outliers and noise.
- Poor performance undersampled/oversampled groups.
- Weaknesses: • Expensive – computationally.
- Stable and easily interpretable results.

Strengths: • Very often performs well in practice.





Summary-k-Nearest Neighbor

 Select a cell on the Data_Partition1 worksheet, then click Classify – k-Nearest Neighbors on the XLMiner ribbon.



 Select desired variables under Variables in input data then click > to select as input variables. Select the output variable or the variable to be classified.





- Specify "Success" class and the initial cutoff value, and click Next.
- Select Normalize input data and the reports and input Number of nearest neighbors. Click Finish.



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Classification Using XLMiner



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Classification Tree





- Splitting rules partitions space of independent variables.
 - Tree summarized and visualized process.
- "Best" splits measure (e.g., Gini index, Information Gain).
- Internal node for splitting.
- Branch two subsets of possible values of parent node.
- Leaf nodes value of response.







- Fully grown classification tree overfitting.
- Solution *pruning*.
- Over-pruned tree lose ability to capture structural information.
 - What is the optimal size?
- Optimal pruning techniques reduce size without sacrificing predictive accuracy.



Strengths and Weaknesses of Classification Trees

Strengths:

- Easily interpreted if-then rules.
- Handles raw data.
- Implicit *feature selection*.
- No explicit assumptions underlying relationships.

Weaknesses:

• Greedy heuristic approach – locally optimal solution.





Summary-Classification Tree

 Select a cell on the Data_Partition1 worksheet, then click
 Classify – Classification
 Tree on the XLMiner



• Select Output and Input variables.

• Specify *"Success" class* and Specify *initial cutoff probability*, then click **Next**.



 Select Normalize input data, Minimum #records in a terminal node, and Prune tree, then click Next.
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 Set Maximum # levels to be displayed, select Full tree, Best pruned tree, Minimum error tree, and reports, then click

finish.



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Naïve Bayes



- Bayes rule posterior probabilities.
 - Assign classes MAP (maximum a posteriori).
- Conditional independence of features.
- XLMiner Multivariate Multinomial distribution.
 - XlMiner Bin Continuous Data.
- "Naïve" assumptions yet surprising efficiency.



Strengths and Weaknesses of the Naïve Bayes Algorithm



Strengths:

- Applicable high-dimensional data.
- Parameter estimation small training sample.
- Applicable discrete and continuous data.
- Efficient computationally.
- Robust with irrelevant features.
- Perfect classifier independent features.



Strengths and Weaknesses of the Naïve Bayes Algorithm



Weaknesses:

- Independence assumption strong.
- Multinomial model must contain already observed values.



Naïve Bayes **Data Preparation**: Binning Continuous Data using XLMiner

 Click Transform -- Bin Continuous Data on the XLMiner ribbon.



- Select **Equal Count** for binning the variable.
- Select **Rank** to assign category label to bin intervals.

- Select the continuous variable and enter **#bins** for the variable.
- Click on Apply this option and click on ok.

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Summary- Naïve Bayes

- Partition the Binneddata1.
- Select a cell on the Data_Partition1 worksheet, then click Classify – Naïve Bayes.



- Select Input and Output variables.
- Specify "Success" class and Enter a value between 0 and 1 for Specify the initial cutoff probability for success. Click Next.



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Naive Bayes -	Step 2 of 3
Prior dass probabilities C According to relative occurr C Use equal prior probabilities C User specified prior probabi	ences in training data ties
Help Cancel < Bac	k <u>N</u> ext > <u>F</u> inish
This option will assign equal prob classes found in the training data	ability to all a.

 Select Detailed report, Summary report, and Lift charts. Click Finish.

Score training data	Score validation data	
Detailed report		
Summary report		
🔽 Lift charts		
Score test data		
🗖 Detailed report	In worksheet	
Summary report		
Lift charts	In database	
Help Cancel < B	ack Next > Einish	

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Neural Networks (NN)



- Powerful machine learning technique structure of the human brain.
- XLMiner feed-forward back-propagation.
- Interconnected neurons organized in layers.
- Neurons computational units.
- Internally feature extraction.
- Dependency settings and architecture.



Neural Networks Key Components







- Output layer prediction fed-forwarded information.
- Back-propagated errors learning.
- Epoch processing of all training observations.
- Desired predictive accuracy (training, cross-validation errors) many learning epochs.



Strengths and Weaknesses of Neural Networks



Strengths:

- "Universal Approximators."
- Detects independent and depended variables' nonlinear relationships.
- Detects predictors' relationships.
- Automated Learning less formal modeling.
- Robust model large high-dimensional datasets.
- No strong explicit assumptions.



Strengths and Weaknesses of Neural Networks



Weaknesses:

- "Black-box" learning.
- Expensive computationally.
- Prone to overfitting.
- Dependency architecture, parameters, choice of activation and error functions.
 - XLMiner Automatic Network Architecture option.



Summary-Neural Networks

 Select a cell on the Data_Partition1 worksheet, then click Classify – Neural
 Network.



- Select Input and Output variables.
- Specify "Success" class and Enter a value between 0 and 1 for Specify the initial cutoff probability for success. Click Next.





 Select Normalize input data. Manfully adjust the Network Architecture and

Training options.

Network Architecture <u>A</u> utomatic	Training op # Enorths:	tions 3	
• Manual	Step size for gradient descent:		
# hidden layers (max <u>4</u>): # node <u>s</u> : 3 0 0	1 Weight char 0 Error tolerar Weight deca Weight deca	nge momentum: 0. nce: 0.0 ay:	
Cost function	Hidden layer sigmoid -	Output layer sigmoi	
Guared error	Standard	Standard	
C Cross entropy	C Symmetric	C Symmetric	
C Maximum likelihood			
C Perceptron convergence			
Hele	Canal 4		
Teb	Calce	Back Rexc > Euro	

Select the Reports and click
 Finish.



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Comments on Classification



- No perfect model different predictive power and accuracy.
- Build several models best overall performance.
- Fundamental problems:
 - Overfitting.
 - Choose simple best.
 - Use cross-validation.
 - Curse of dimensionality.
 - Choose algorithm consider dimensions.
 - Reduce data dimension explicitly or use XLMiner's techniques.
- Final independent test use test samples.



Summary



- Classification whether a customer will buy a certain product.
- XLMiner classification techniques.
- Fitting classification models to data.
- Working with output of each method.
- Appling fitted models to classify new observations.







- Vital skill for business analysts use data intelligently.
- Retrieve and combine data from from SQL databases to Web data sources use Excel.
- Visualize and transform your data, apply supervised and unsupervised learning methods – use XLMiner in Excel.
- A complete toolset for descriptive, predictive and prescriptive analytics use Analytic Solver Platform including XLMiner.



Contact Info



- Dr. Sima Maleki
- Best way to contact me: <u>Consulting@Solver.com</u>
- You may also download this presentation from our website.
- You can download a free trial version of XLMiner at http://www.solver.com/xlminer-data-mining



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Q&A



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