Introduction to Data Science

Lecture 4; April 18th, 2016

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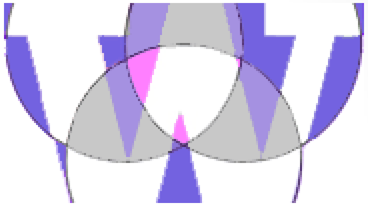
Agenda



- Announcements
  - Encourage Group Homework!
  - For all assignments: Label answers with the pertinent question number and letter (e.g. 3b)
  - Please note that there is an Assignment slide at the end of each Lecture slide deck
  - Guest Lectures in May
    - Business side of Data Science by Marius Marcu on May 9th 2016
    - Data Visualization by Tatyana Yakushev on May 2nd 2016 (?)
    - Building a Data Science Group by TBD
- Review (Homework)
- Quiz 04a (Normalization in K-Means)
- Data and Models in Supervised Learning
- break
- Schema for Classification
- Quiz 04b (Attributes for Supervised Learning)
- Partition Modeling Data
- Break
- Partition Modeling Data (In-class and Homework Assignment)
- Predictive Analytics Iteration Trap (Time Permitting)
- Assignment (Complete all assignments items from all 4 assignment slides)

Review: Normalization in K-Means

- See the posted KMeansNorm_complete.R
  - Normalize Observations
  - Normalize Initial Cluster Centers
  - Use K-Means to find cluster centers of normalized observations
  - De-normalize the cluster centers

Review: Normalization in K-Means

- Z-Normalization applies standard deviation and mean of the observations to the observations and to the initial cluster centers

```
# Determine mean and standard deviation of 1st dimension in observations
mu1 <- mean(observations[,1])
sigma1 <- sd(observations[,1])
# normalize 1st dimension of observations
observations[,1] <- (observations[,1] - mu1)/sigma1
# normalize 1st dimension of clusterCenters
clusterCenters[,1] <- (clusterCenters[,1] - mu1)/sigma1
```

Review: De-Normalization in K-Means

- De-normalization uses the same standard deviation and mean as normalization.

- # denormalize in first dimension
- clusterCenters[,1] <- clusterCenters[,1] * sigma1 + mu1

Review: Homework Questions

3. Answer these questions:
   a) What is the single most obvious difference between the distributions of the first and second dimensions?
   b) Does clustering in Test 1 occur along one or two dimensions? Which dimensions? Why?
   c) Does clustering in Test 2 occur along one or two dimensions? Which dimensions? Why?
   d) Does clustering in Test 3 occur along one or two dimensions? Which dimensions? Why?
   e) Does clustering in Test 4 occur along one or two dimensions? Which dimensions? Why?
4. Why is normalization important in K-means clustering?
   Answer: So that the dimensions (data attributes) have similar scales.
5. How do you encode categorical data in a K-means clustering?
   Answer: Category attributes are binarized
6. Why is clustering un-supervised learning as opposed to supervised learning? **Answer: The algorithm is not told what is observed or what the "goal" is. There is no expert label.**

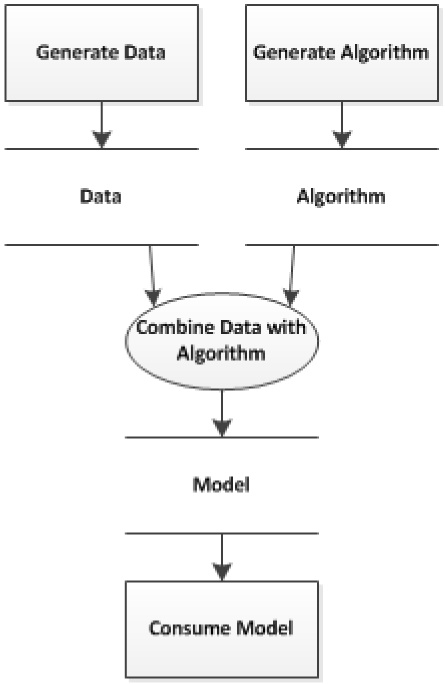
Quiz 04a (Normalization in K-Means)

- Use R if you want (I wouldn't)

Data and Models in Supervised Learning

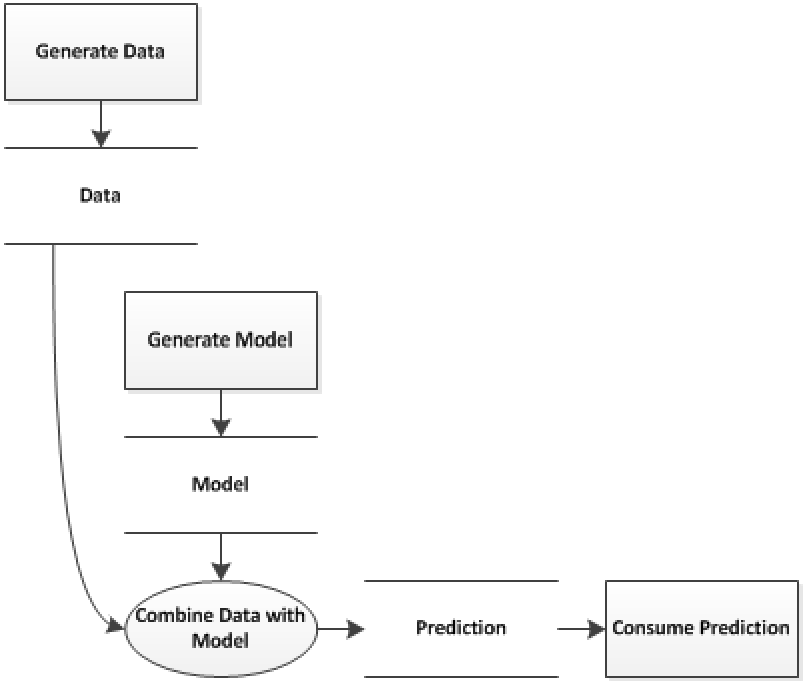
From Data to Predictions (0)

From Data to Predictions (1)



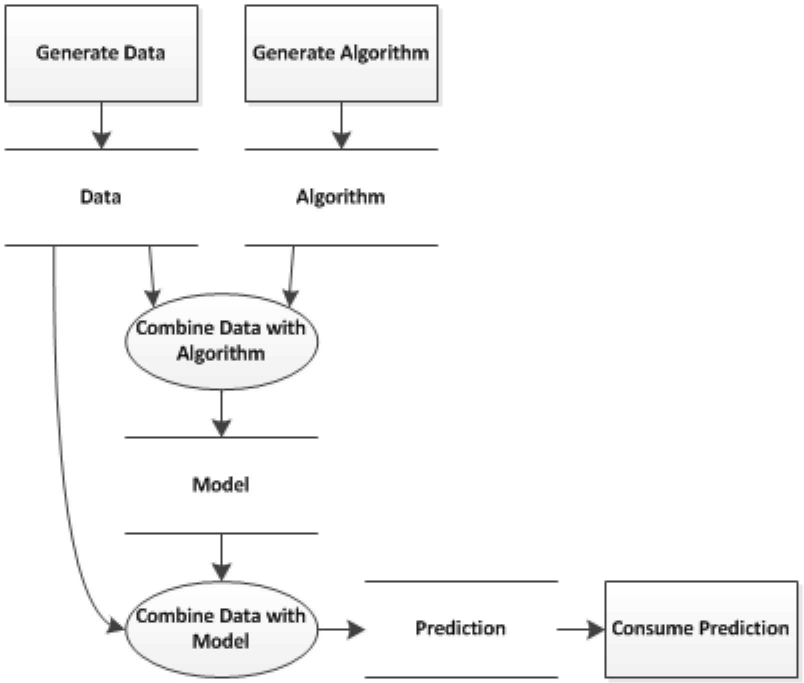
Data + Algorithm → Model

From Data to Predictions (2)



Model + Data → Prediction

From Data to Predictions (3)



Data + Algorithm → Model
Model + Data → Prediction

From Data to Predictions (4)

- Pseudo Assignments (Derivations):
  - Data + Algorithm → Model
  - Model + Data → Prediction

- Create Model from Algorithm and Data
  - Example Algorithm: Logistic Regression
    - Create Model: model <- glm(formula, data=trainSet, family="binomial")
- Predict from Model and Data
    - Predict: prediction <- predict(model, newdata=testSet, type="response")

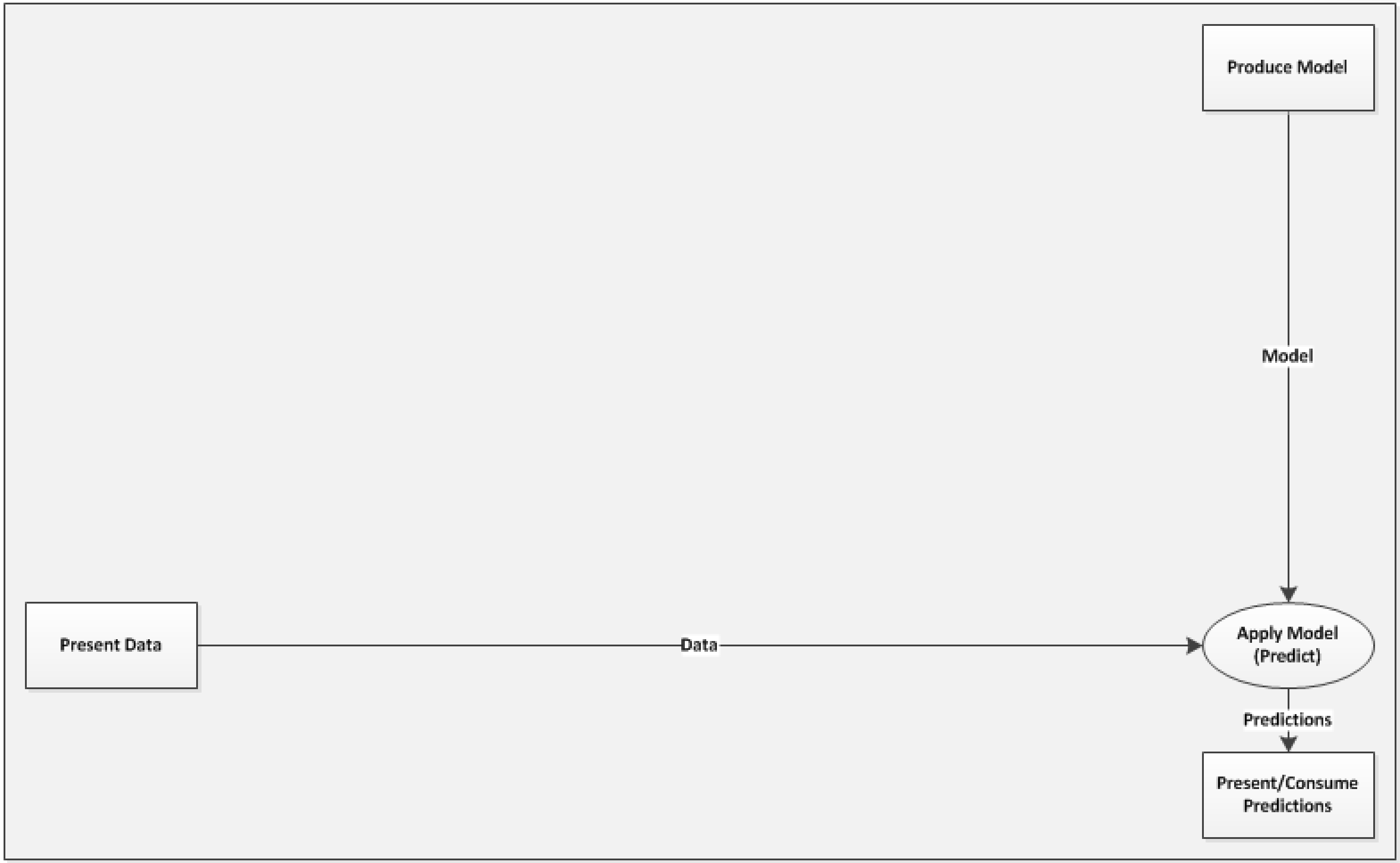
Data + Algorithm → Model
Model + Data → Prediction

From Data to Predictions (5) Review

- A model or hypothesis is (best response)
  - a combination of test data and training data
  - a predictor based on data and algorithm
  - a falsification of a theory
  - a verified theory as long as the model was not falsified
- A model applied to new data leads to a (best response)
  - Prediction
  - Falsification / Verification
  - Hypothesis
  - errors
- A model applied to test data leads to a (best response)
  - Prediction
  - Falsification / Verification
  - Hypothesis
  - errors
- A hypothesis that cannot be tested
  - is a law if the data are consistent
  - is an untested hypothesis
  - is not a hypothesis
  - is a theory

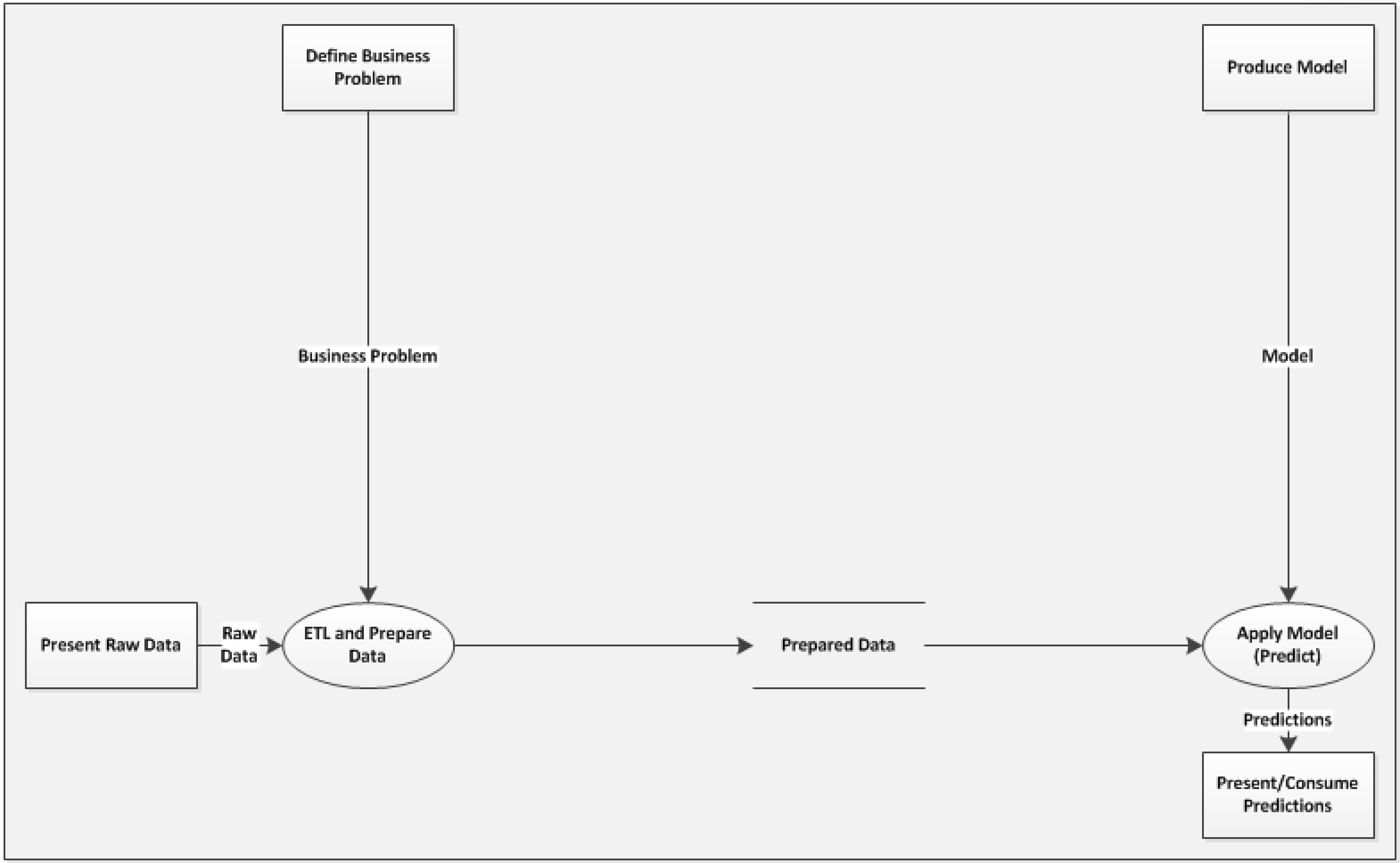
(0) DFD of Supervised Learning

(1) Model Acts on Data



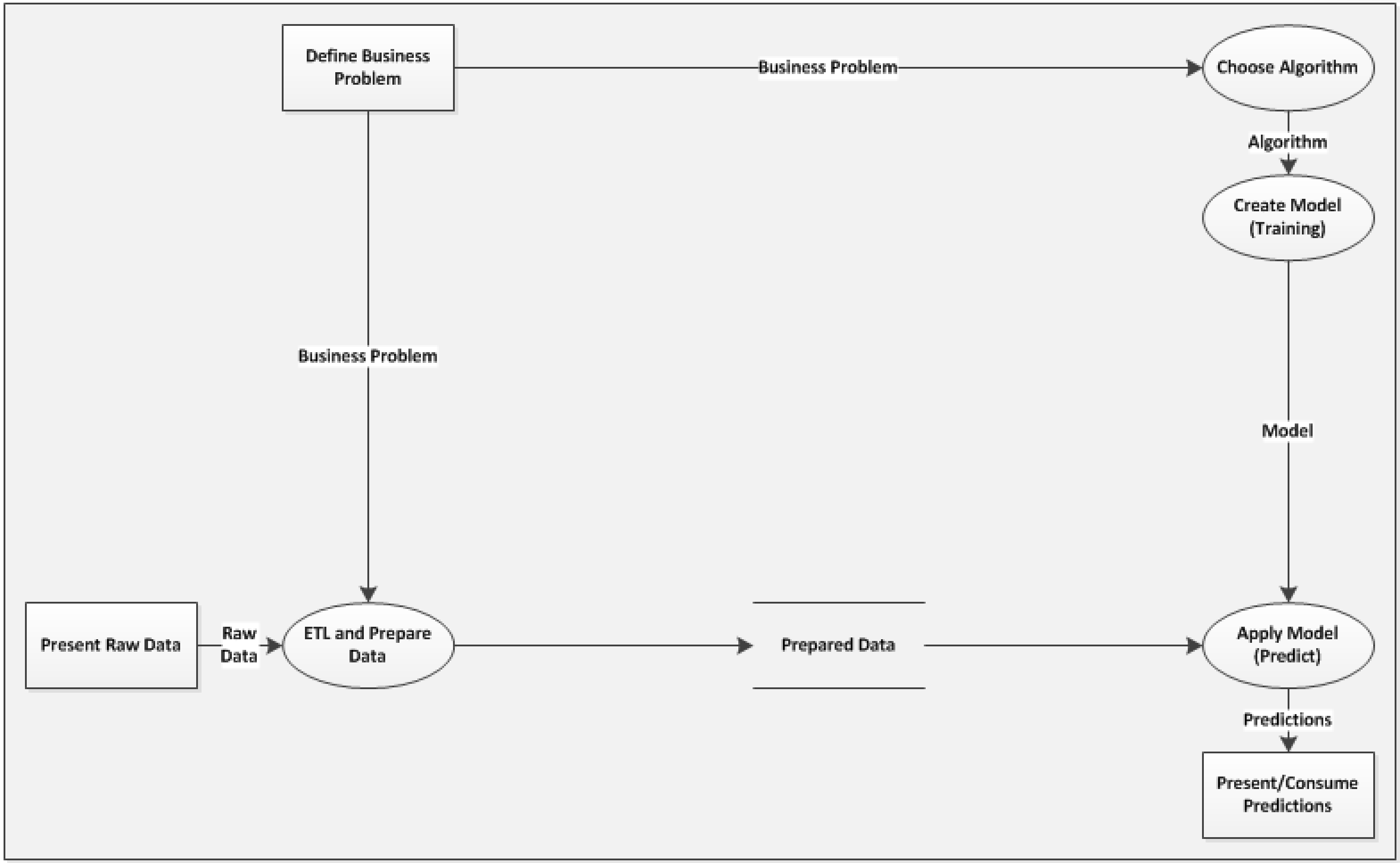
Model + Data → Prediction

(2) Data ETL and Preparation driven by Business Problem



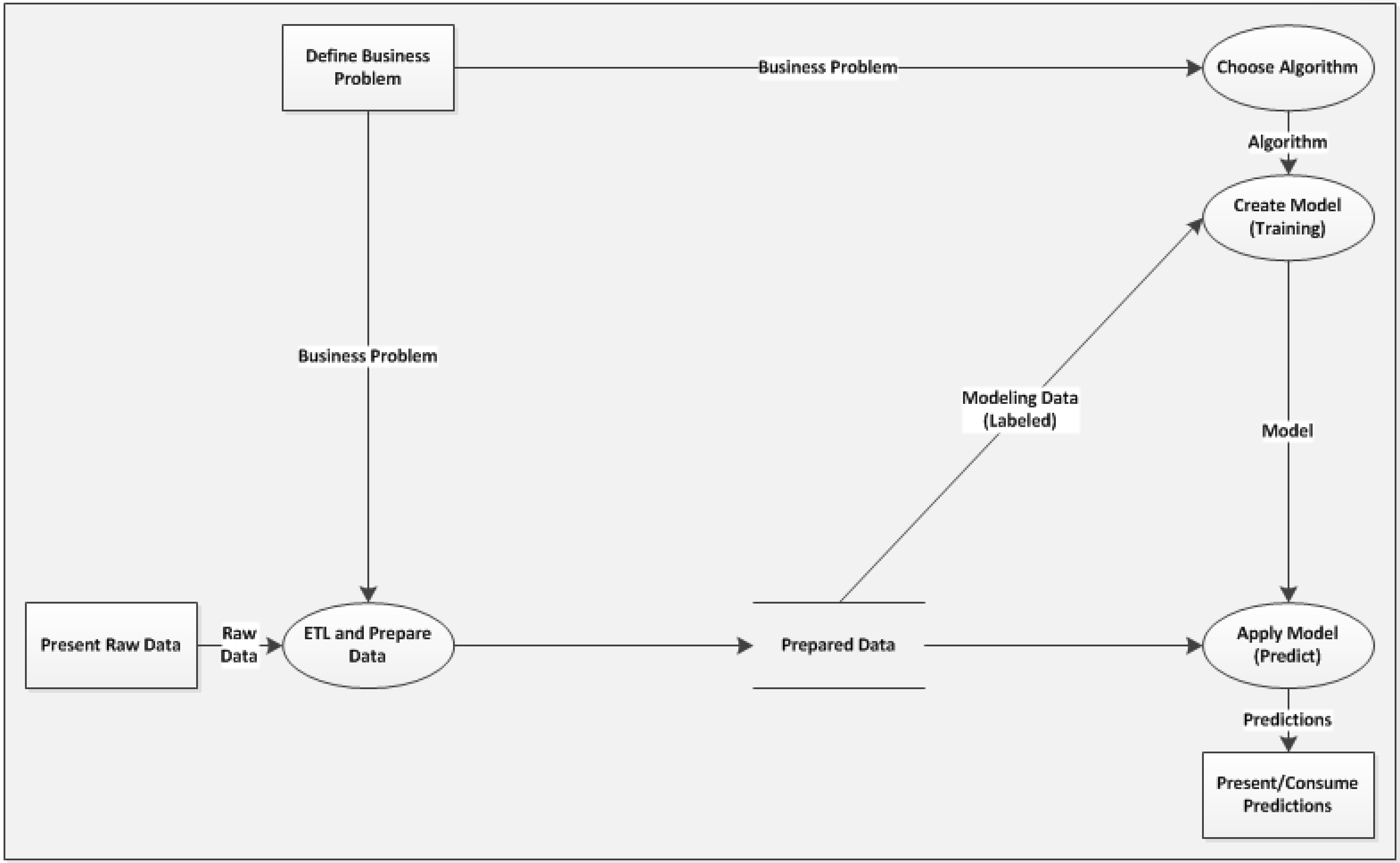
Business Problem determines ETL and Data Prep

(3) Algorithm choice driven by Business Problem



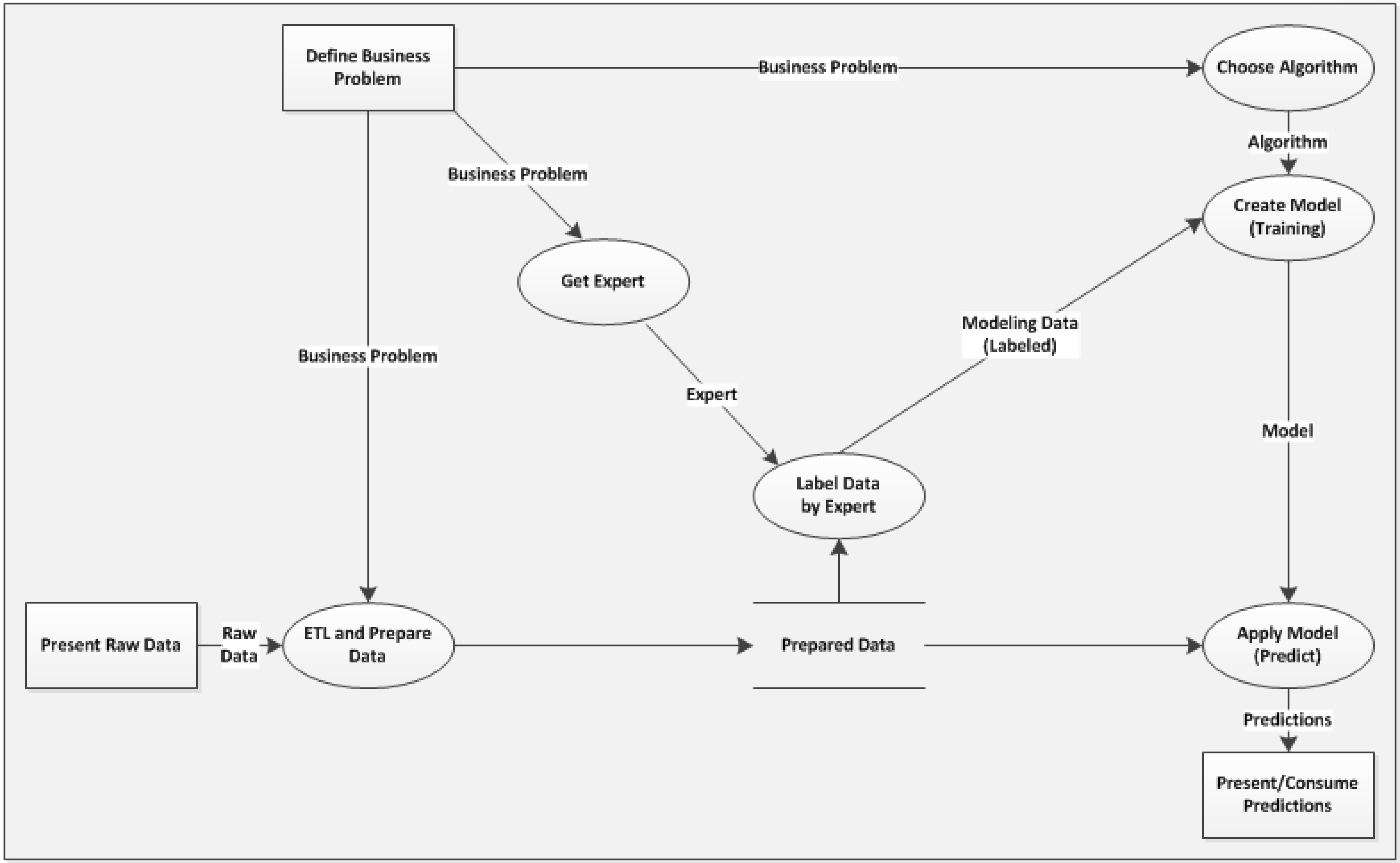
Business Problem determines the choice of Algorithm.

(4) Model Creation needs Data



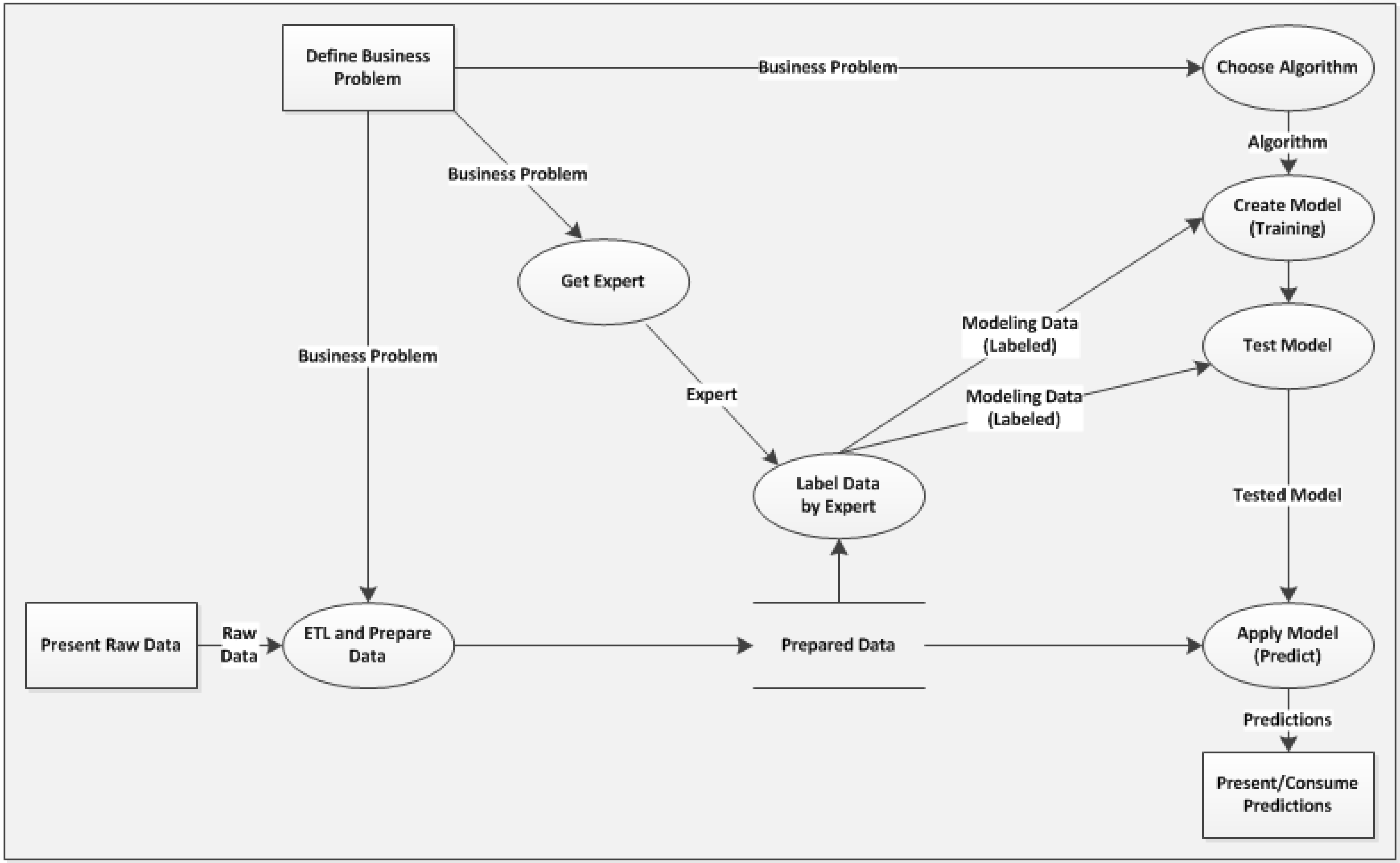
Data + Algorithm → Model

(5) Supervised Training needs Data Labeled with Outcomes



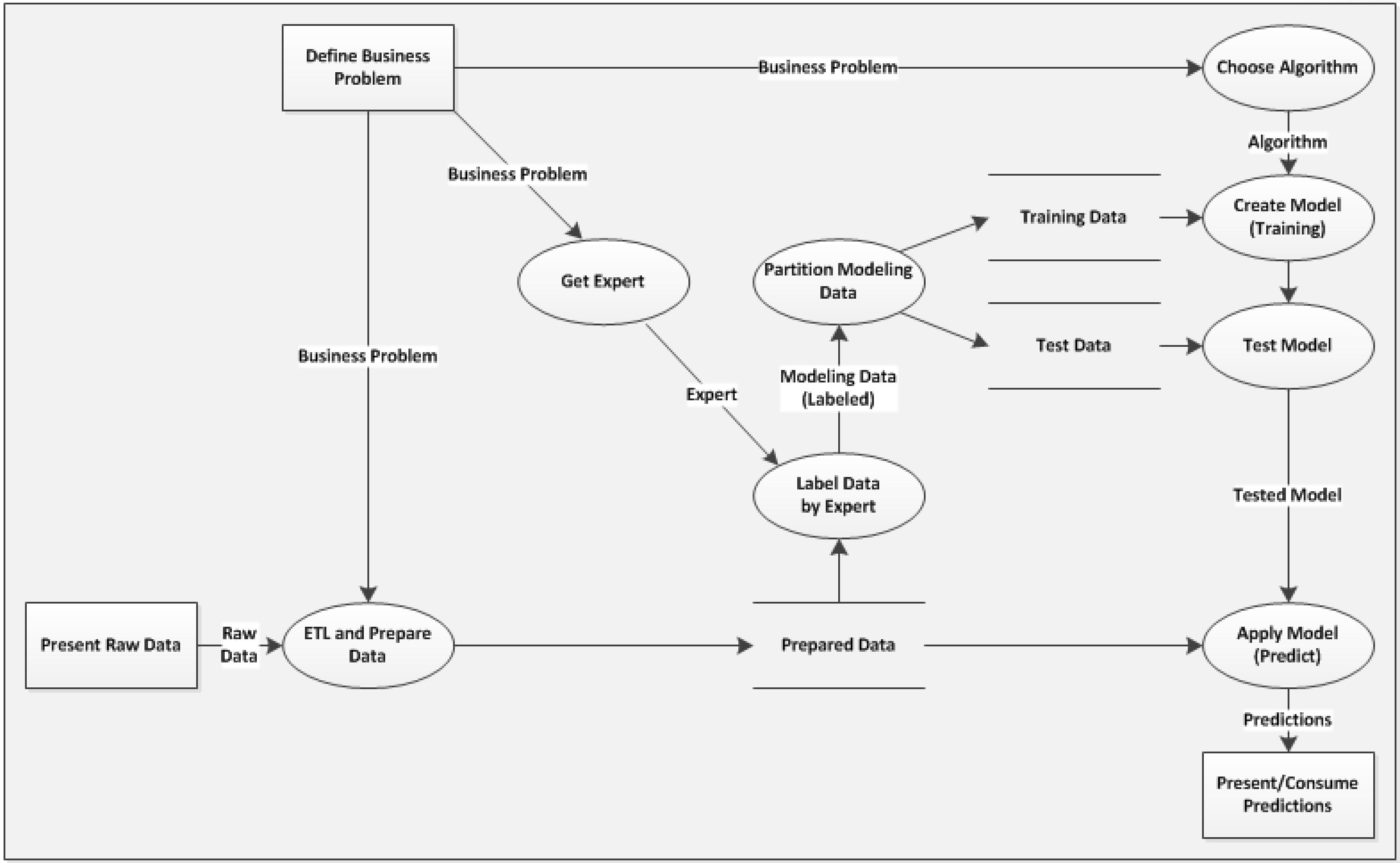
Supervised Learning requires expert labeling of data.

(6) Models need to be Tested



Do not trust predictions from an un-tested model!

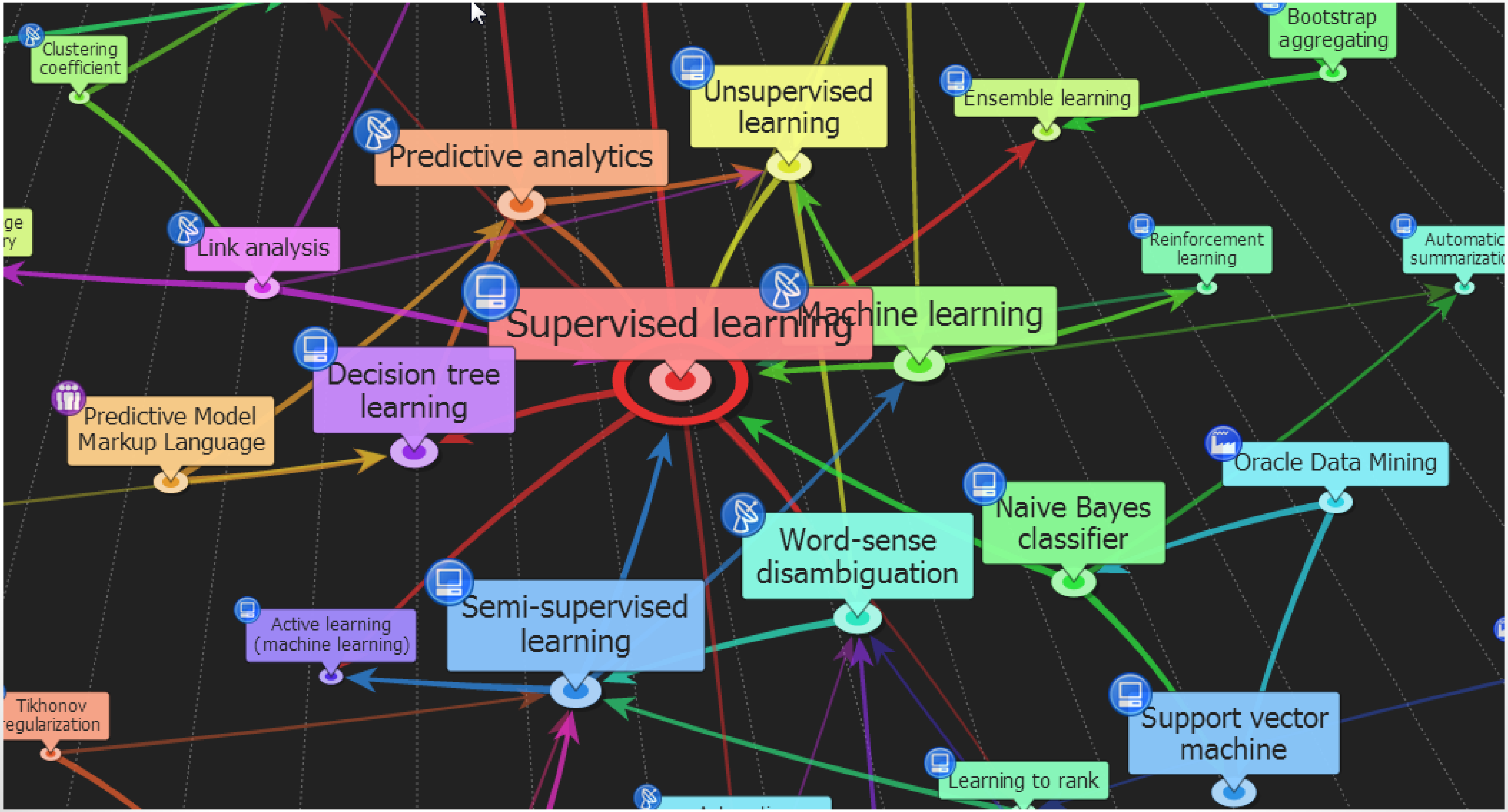
(8) Training & Testing of Model use different Data



Do not test a model using training data!

Data and Models in Supervised Learning

Break


Clustering coefficient
Bootstrap aggregating
Unsupervised learning
Ensemble learning
Predictive analytics
Link analysis
Reinforcement learning
Automatic summarizati
ge
ry
Supervised learning
Machine learning
Decision tree learning
Predictive Model Markup Language
Oracle Data Mining
Naive Bayes classifier
Word-sense disambiguation
Semi-supervised learning
Active learning (machine learning)
Tikhonov regularization
Support vector machine
Learning to rank

Classification Schema

Classification Schema (0)

- Rectangular Modeling Dataset
    - Schema
        - Input columns
        - Output column (target column, outcome)
            - Classification: Category Column
    - Partition For Training and Test Data
    - Incremental Data
- Algorithm
    - Classification
        - Logistic Regression
        - Neural Network
        - Decision Tree
        - Naïve Bayes

Classification Schema (1)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Classification Schema (2)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Here is a rectangular dataset. The table has columns with headers and the data in each column have the same datatype. The data have been prepared and are ready for modeling.

Classification Schema (3)

Column	Column	Column	Column 4	Column 5	Column 6	Column 7
			0.123	red	T	Yes
			0.987	green	T	No
			0.245	blue	F	Yes
			0.254	blue	T	Yes
			0.244	blue	F	No
			0.415	green	F	Maybe
			0.925	red	T	Yes
			0.376	green	F	Yes
			0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Elsewhere, I have new data that do not contain this column. I want to predict categorical values, like these, from this new data. For each row in the new data, I want to use the values from the other columns in the same row to predict the value in the missing column. This predicted value is called the “Target Outcome”.

Target Outcome

Classification Schema (4)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Target Outcome

Classification Schema (5)

Column 1	Column 2	Column 3	Column	Column	Column	Column
330-3141	Seaborg	Good				
330-3150	Seaborg	No				
330-3202	Seaborg	Yes				
415-2008	Seaborg	Yes				
415-2081	Seaborg	Bad				
415-2796	Seaborg					
415-2799	Seaborg	Yes				
415-2913	Seaborg	Yes				
415-3659	Seaborg	Bad				
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Keys and random data should not be used as inputs for predictive analytics. Random data may appear to have patterns, but those patterns are fortuitous and will not be available when needed for predictions. Keys may contain patterns, but these patterns are deceptive and may also not be available when needed.

Random or Keys

Target Outcome

Classification Schema (6)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Random or Keys

Target Outcome

Classification Schema (7)

Column 1	Column 2	Column 3	Column	Column	Column	Column
330-3141	Seaborg	Good	0			
330-3150	Seaborg	No	0			
330-3202	Seaborg	Yes	0			
415-2008	Seaborg	Yes	0			
415-2081	Seaborg	Bad	0			
415-2796	Seaborg		0			
415-2799	Seaborg	Yes	0			
415-2913	Seaborg	Yes	0			
415-3659	Seaborg	Bad	0			
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Columns with constant data are unnecessary. In general, they will not affect the algorithm and therefore the model will be the same. But, they distract from the task. Also, they may increase memory and processing requirements.

Constant

Random or Keys

Target Outcome

Classification Schema (8)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Random or Keys

Constant

Target Outcome

Classification Schema (9)

Column 1	Column 2	Column 3	Column	Column	Column	Column
330-3141	Seaborg	Good	0			
330-3150	Seaborg	No	0			
330-3202	Seaborg	Yes	0			
415-2008	Seaborg	Yes	0			
415-2081	Seaborg	Bad	0			
415-2796	Seaborg		0			
415-2799	Seaborg	Yes	0			
415-2913	Seaborg	Yes	0			
415-3659	Seaborg	Bad	0			
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

A proxy column is a column that was created after the “target” was observed. The proxy contains information that would not be available for predictions. The proxy column correlates well with the target .

Random or Keys

Constant

Proxy

Target Outcome

Classification Schema (10)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Constant

Random or Keys

Proxy

Target Outcome

Classification Schema (11)

Some inputs to supervised learning are continuous attributes, like integers, floats and time.

Some inputs to supervised learning are categories, like strings, binned numbers, and factors.

Some inputs to supervised learning are binary attributes, like categories with only two states and binarized multi-state categories.

Column	Column	Column	Column 4	Column 5	Column 6	Column 7
			0.123	red	T	Yes
			0.987	green	T	No
			0.245	blue	F	Yes
			0.254	blue	T	Yes
			0.244	blue	F	No
			0.415	green	F	Maybe
			0.925	red	T	Yes
			0.376	green	F	Yes
			0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No

Random or Keys

Constant

Proxy

Continuous Input

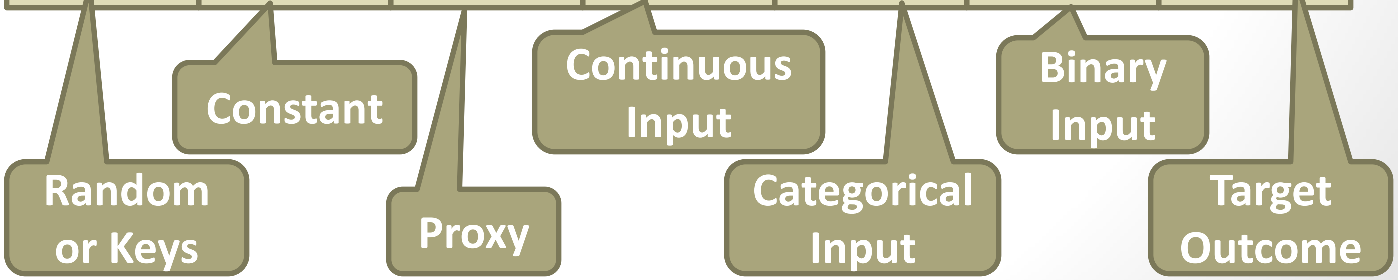
Categorical Input

Binary Input

Target Outcome

Classification Schema (12)

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
330-3141	Seaborg	Good	0.123	red	T	Yes
330-3150	Seaborg	No	0.987	green	T	No
330-3202	Seaborg	Yes	0.245	blue	F	Yes
415-2008	Seaborg	Yes	0.254	blue	T	Yes
415-2081	Seaborg	Bad	0.244	blue	F	No
415-2796	Seaborg		0.415	green	F	Maybe
415-2799	Seaborg	Yes	0.925	red	T	Yes
415-2913	Seaborg	Yes	0.376	green	F	Yes
415-3659	Seaborg	Bad	0.615	green	T	No
595-8413	Seaborg		0.321	blue	F	Maybe
598-1243	Seaborg	No	0.098	green	F	No
598-2454	Seaborg	Bad	0.765	red	T	No



Random or Keys

Constant

Proxy

Continuous Input

Categorical Input

Binary Input

Target Outcome

Classification Schema (13)

[redacted]

Column 4	Column 5	Column 6	Column 7
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Continuous Input

Categorical Input

Binary Input

Target Outcome

Classification Schema (14)

Column 4	Column 5	Column 6	Column 7
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Continuous Input

Categorical Input

Binary Input

Target Outcome

Classification Schema (15)

Outcome ~ Input 1 + Input 2 + Input 3

Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Classification Schema (16)

Outcome ~ Input 1 + Input 2 + Input 3

Modeling Data
(300-100000 rows)

Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Classification Schema (17)

Outcome ~ Input 1 + Input 2 + Input 3

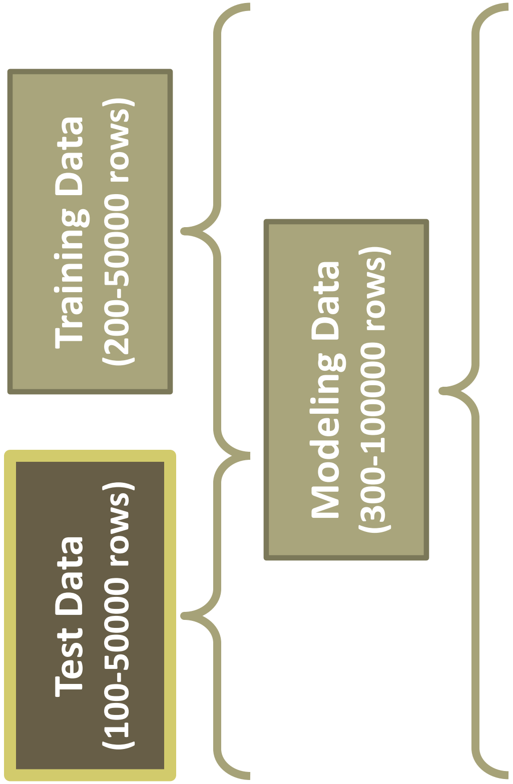
Training Data (200-50000 rows)

Modeling Data (300-100000 rows)

Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Classification Schema (18)

Outcome ~ Input 1 + Input 2 + Input 3



Training Data (200-50000 rows)

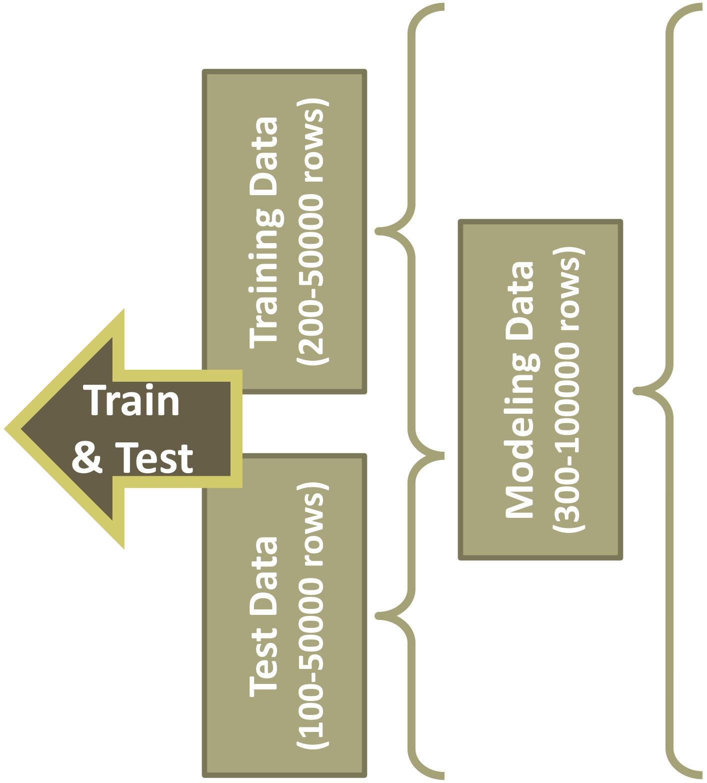
Test Data (100-50000 rows)

Modeling Data (300-100000 rows)

Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	**green**	**F**	**Yes**
0.615	**green**	**T**	**No**
0.321	**blue**	**F**	**Maybe**
0.098	**green**	**F**	**No**
0.765	**red**	**T**	**No**

Classification Schema (19)

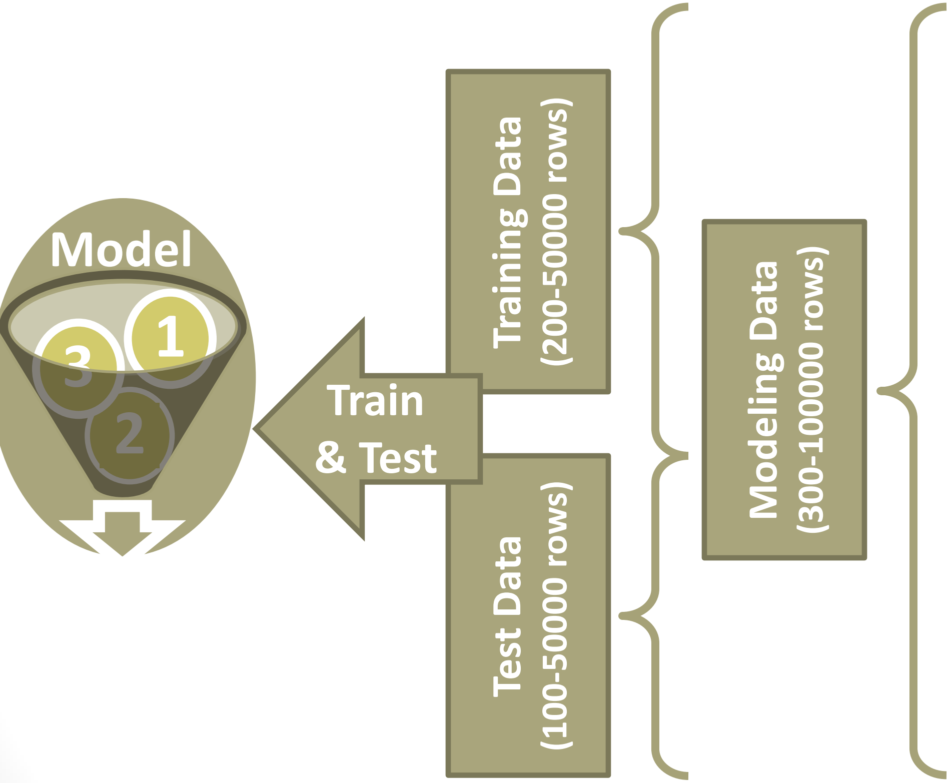
Outcome ~ Input 1 + Input 2 + Input 3



Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Classification Schema (20)

Outcome ~ Input 1 + Input 2 + Input 3



Train & Test

Training Data (200-50000 rows)

Test Data (100-50000 rows)

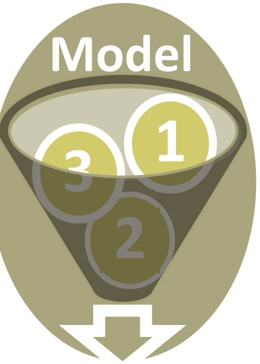
Modeling Data (300-100000 rows)

Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	No
0.321	blue	F	Maybe
0.098	green	F	No
0.765	red	T	No

Classification Schema (21)

Outcome ~ Input 1 + Input 2 + Input 3

Elsewhere, I have new data that do not contain the target outcome. I want to predict categorical values, like these, from this new data. For each row in the new data, I want to use the values from the other columns in the same row to predict the value in the missing column. This predicted value is called the "Target Outcome".



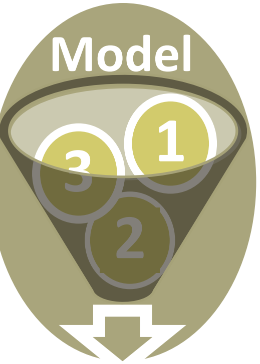
Input 1	Input 2	Input 3	Outcome
0.123	red	T	Yes
0.987	green	T	No
0.245	blue	F	Yes
0.254	blue	T	Yes
0.244	blue	F	No
0.415	green	F	Maybe
0.925	red	T	Yes
0.376	green	F	Yes
0.615	green	T	N
0.321	blue	F	
0.098	green	F	No
0.765	red	T	No
0.234	green	T	
0.567	blue	F	
0.890	green	T	
0.314	red	T	

Target Outcome

Operational Data (1- ∞ rows)

Classification Schema (22)

Outcome ~ Input 1 + Input 2 + Input 3



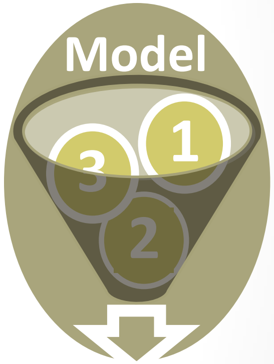
Target Outcome

Operational Data (1- ∞ rows)

Input 1	Input 2	Input 3	Outcome
0.234	green	T	
0.567	blue	F	
0.890	green	T	
0.314	red	T	

Classification Schema (23)

Outcome ~ Input 1 + Input 2 + Input 3

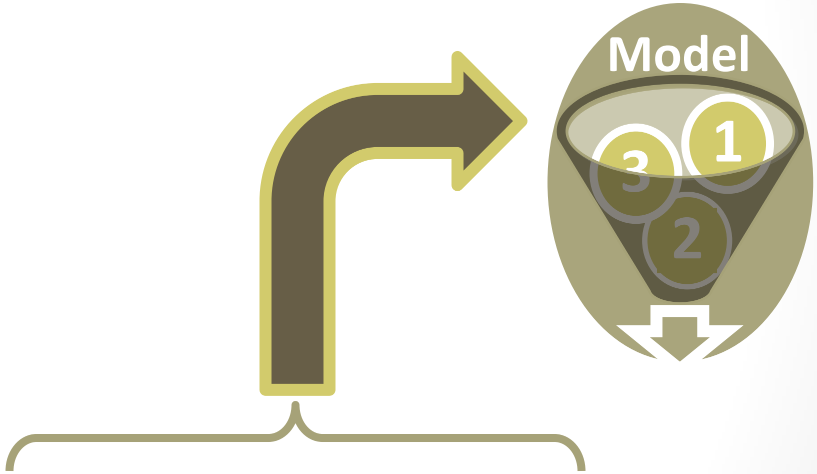


Operational Data (1- ∞ rows)

Input 1	Input 2	Input 3	Outcome
0.234	green	T	
0.567	blue	F	
0.890	green	T	
0.314	red	T	

Classification Schema (24)

Outcome ~ Input 1 + Input 2 + Input 3

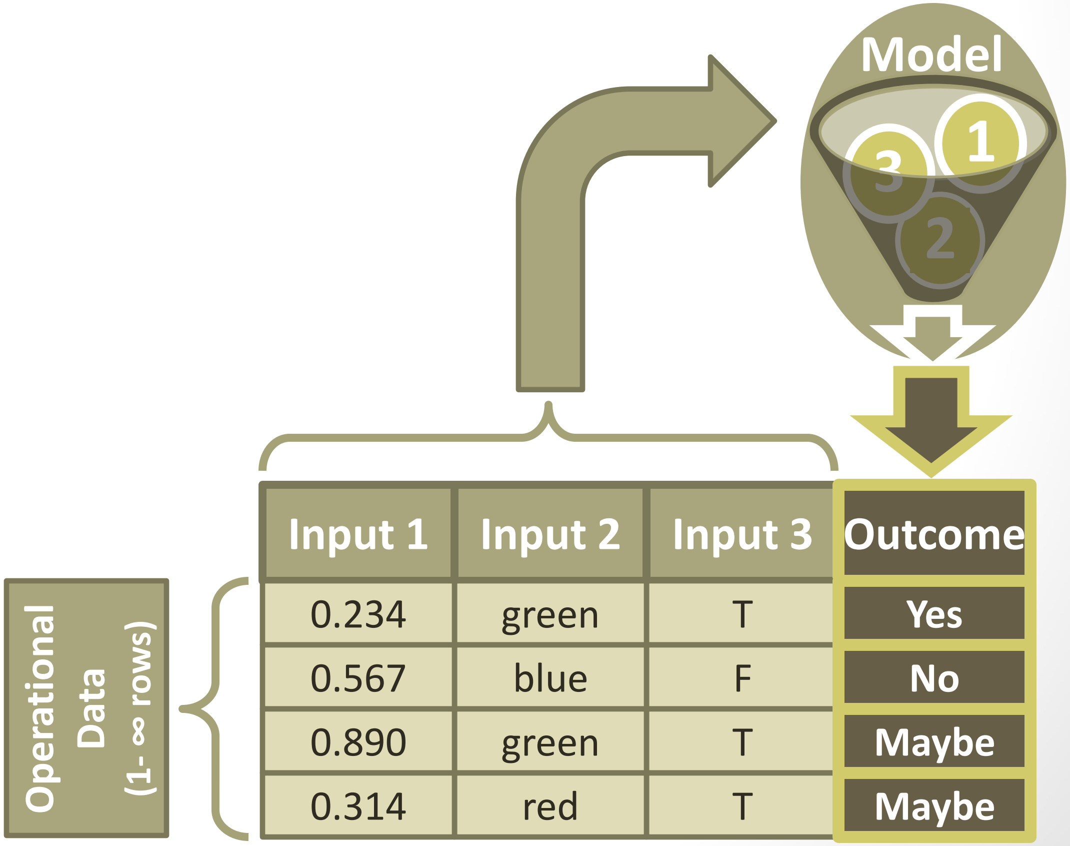


Operational Data (1- ∞ rows)

Input 1	Input 2	Input 3	Outcome
0.234	green	T	
0.567	blue	F	
0.890	green	T	
0.314	red	T	

Classification Schema (25)

Outcome ~ Input 1 + Input 2 + Input 3



Input 1	Input 2	Input 3	Outcome
0.234	green	T	Yes
0.567	blue	F	No
0.890	green	T	Maybe
0.314	red	T	Maybe

Classification Schema (26)

- Attributes
  - All the columns are attributes
- Input Column
  - Input columns are columns that can help predict the outcome. Input columns can be of type binary, ordinal, or category.
- Target Outcome
  - The term "Target Outcome" is redundant. The outcome is the target and vice versa. The target or outcome is the output of a predict function. Providing target or outcome values during modeling makes the process supervised. Creating a model using a outcome is called supervised learning.
- Proxy Column
  - A proxy column is a column that predicts too well. It is too good to be true. Something from the target leaked. This is also called target leakage. The leaked information is "not fair" to use in modeling. Values for that attribute will not be available when you want to predict the target outcome from operational data.
- Key Column
  - In principle, a key column should not affect the model's prediction. The relationship between a key and any other attribute should be random. In practice, the algorithm will find a pattern in the key column and train on this pattern. This pattern is likely to be fortuitous, that means: random. The pattern will not hold for test data or when the model is applied. As a consequence, the key column will affect the model in a bad way.
- Constant Column
  - A constant column should have no affect on the model's predictions. The constant column may increase computation time and cause other problems. It is standard practice to remove all constant columns prior to modeling.

Classification Schema

Quiz 04b (Attributes for Supervised Learning)

- Colbert on Predictive Analytics
  - http://www.cc.com/video-clips/dv9iqc/the-colbert-report-the-word---surrender-to-a-buyer-power

Partition Modeling Data

How to Partition Data (0)

- Test data need to be derived from the same data source as the training data
- Partition of Data between Test and Training must be random

How to Partition Data (1)

- Test data need to be derived from the same data source as the training data
- Partition of Data between Test and Training must be random

- Open R Studio:
  1. Open ClassifyStudents.R
  2. Open CollegeStudentsDatasets.R
  3. Source ClassifyStudents.R (just a test)
  4. Find the function definition of PartitionWrong() in CollegeStudentsDatasets.R
  5. See how to use the function PartitionWrong() in ClassifyStudents.R

How to Partition Data (2)
The Wrong Way

1. Specify test fraction (e.g. split off 30% or 40% for testing)
2. Take the first fraction of the data as test data
3. Take the rest of the data as training data

How to Partition Data (3) The Wrong Way

1. Get the dataSet and the fractionOfTest (fractionOfTest default is 0.3)
2. numberOfRows <- nrow(dataSet)
3. numberOfTestRows <- fractionOfTest * numberOfRows
4. testFlag <- 1:numberOfRows <= numberOfTestRows
5. testingData <- dataSet[testSelection,]
6. trainingData <- dataSet[!testSelection,]

How to Partition Data (4)
The Fast Way

1. Specify test fraction (e.g. split off 30% or 40% for testing)
2. Generate random number for each case (row)
3. Create Flag to partition cases at value of test fraction
4. Apply Flag for Test Data selection
5. Apply Flag for Train Data selection

How to Partition Data (5) Exact Method

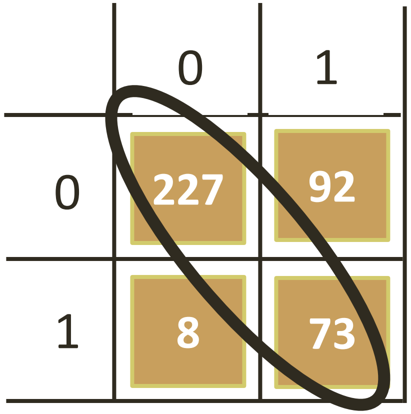
1. Specify test fraction (e.g. split off 30% or 40% for testing)
2. Generate a random number for each case (use “runif”)
3. Create Flag to partition cases: find quantile
   a) Determine threshold where quantile of random numbers is at fractionOfTest. Use “sort” or “quantile”
   b) Compare random numbers to that threshold. For the random numbers that are smaller than the threshold, the testFlag is TRUE.
4. Apply Flag for Testing Data selection (testingData <- dataSet[testFlag,])
5. Apply Flag for Training Data selection. Training data should contain all observations that are not testing data.

How to Partition Data (6)
Take Home Message

1. For supervised learning, partition the modeling data in a test set and a train set
2. Use the test data to check the accuracy of an algorithm
3. A confusion matrix and an ROC chart can be used to test classifications
4. Classification accuracy can be defined as the number of correct predictions divided by the total number of predictions.

How to Partition Data (7)
Take Home Messages

1. For supervised learning, partition the modeling data in a test set and a train set
2. Use the test data to check the accuracy of an algorithm
3. A confusion matrix and an ROC chart can be used to test classifications
4. Classification accuracy can be defined as the number of correct predictions divided by the total number of predictions.



	0	1
0	227	92
1	8	73

How to Partition Data (8)
Take Home Messages

1. For supervised learning, partition the modeling data in a test set and a train set
2. Use the test data to check the accuracy of an algorithm
3. A confusion matrix and an ROC chart can be used to test classifications
4. Classification accuracy can be defined as the number of correct predictions divided by the total number of predictions.

	0	1
0	227	92
1	8	73

$$75\% = \left(227 + 73\right) \div \left(8 + 92 + 227 + 73\right)$$

Partition Modeling Data

Break

- **Big Data Humor: Top 10 Ways You Know You’re a Data Scientist**
  - http://inside-bigdata.com/2013/10/28/big-data-humor-top-10-ways-know-youre-data-scientist/

In-class Exercise

- Open R Studio:
  1. Open ClassifyStudents.R
  2. Open CollegeStudentsDatasets.R
  3. Source ClassifyStudents.R (just a test)
  4. Find the function definition of PartitionWrong() in CollegeStudentsDatasets.R and see how it is constructed.
  5. See how PartitionWrong() is used in ClassifyStudents.R
  6. Add code to create a logistic regression model.
  7. Add code to get probabilities from the logistic regression model
  8. Add code to threshold the probabilities and create a confusion matrix

Review: Terminology

- Algorithm
- Anomaly detection
- Association
- Attribute
- Binarize Categories
- Binary Column
- Case
- Category Column
- Character Column
- Classification
- Clustering
- Coercion
- Column
- Column Header
- Data
- Data Dimensionality
- Data Frame
- Data Type
- DFD
- Dummy Variable
- Estimation
- Feature Scaling
- Field
- Hypothesis
- Key Column
- Machine Learning
- Market-basket analysis
- MATLAB
- Matrix
- Missing Data
- Model
- Multinomial Column
- Normalization
- Numeric Column
- Observation
- Outcome
- Outlier Removal
- Predictive Analytics
- R
- Rectangular Data
- Relabeling
- Row
- Schema
- Shaping Data
- Sparse Multi-Dimensional Matrix
- Standard Deviation
- States
- String
- Supervised Learning
- Support
- Table
- Target Column
- Text Column
- Theory
- Un-structured Data
- Unsupervised Learning
- Z-score

Assignment (1)

1. Add code to ClassifyStudents.R that creates a Logistic Regression model.
2. In ClassifyStudents.R, add code to predict outcomes based on the Logistic Regression model.
3. Add code to create a confusion matrix to evaluate the logistic regression model
4. Add code to ClassifyStudents.R that creates a Naïve Bayes model. You will have to look up the Naive Bayes package "e1071" to determine the inputs. Get help!
5. In ClassifyStudents.R add code to predict outcomes based on the Naive Bayes model. You will have to read the documentation to determine the “type” parameter. **It is very important that you answer for yourself: How many rows are there in the outcome? How many columns? How many columns are in the output for the logistic regression? Get Help!**
6. Add code to create a confusion matrix to evaluate the naïve Bayes model

Assignment (2)

7. Partition Functions
   a) Run ClassifyStudents.R using PartitionWrong() with a threshold=0.5 and fractionOfTest=0.4. Verify the resulting confusion matrices of the logistic regression and Naïve Bayes models. The results are already listed as comments in ClassifyStudents.R.
   b) Add a function to CollegeStudentsDatasets.R. The name of the function is: PartitionFast. The function works as described in the lecture slides and has the same signature and return type as PartitionWrong. Specifically, the function takes in only a dataframe and a fraction. The function returns a list of two dataframes. The names of the two dataframes are trainingData and testingData. trainingData and testingData are mutually exclusive cases from the input data frame. trainingData, testingData , and the data frame all have the same schema. testingData contains the fraction of cases as specified by the fraction input. trainingData contains the rest.
   c) Add a function to CollegeStudentsDatasets.R. The name of the function is: PartitionExact. The function works as described in the lecture slides and has the same basic structure as PartitionWrong and PartitionFast (see above).

Assignment (3)

8. Classification in R
   a) In ClassifyStudents.R replace the line containing PartitionWrong() with PartitionFast(). Run ClassifyStudents.R and copy the resulting confusion matrix of the logistic regression and naïve Bayes as a comment into ClassifyStudents.R. Add the accuracy calculations as indicated.
   b) In ClassifyStudents.R replace the line containing PartitionWrong() with PartitionFast(). Run ClassifyStudents.R and copy the resulting confusion matrix of the logistic regression and naïve Bayes as a comment into ClassifyStudents.R. Add the accuracy calculations as indicated.
   c) Submit your revised ClassifyStudents.R and CollegeStudentsDatasets.R by Saturday 11:57 PM. Late submissions cannot be accepted.

Assignment (4)

9. Take Quiz 04c before Saturday 11:59 PM. You will need Elbow.R and CollegePlans.csv
10. On LinkedIn, start a discussion, make a comment on an existing discussion, or ask questions about homework.
11. Reading Assignments
    - Review terminology at the end of this slide deck
    - Read Quiz Previews
    - Classification
        - Read ROC Curve, Lift Chart and Calibration Plot by Vuk and Curk: http://mrvar.fdv.uni-lj.si/pub/mz/mz3.1/vuk.pdf
        - Read about Accuracy: http://en.wikipedia.org/wiki/Precision_and_recall
        - Read about target leakage: http://www.cs.umb.edu/~ding/history/470_670_fall_2011/papers/cs670_Tran_PreferredPaper_LeakingInDataMining.pdf
    - Relational Model, Relational Algebra, and Relational Calculus
        - http://en.wikipedia.org/wiki/Relational_algebra
        - http://sentences.com/docs/amd.pdf (Pages 35 to 48 only)
        - http://en.wikipedia.org/wiki/Relational_model
        - http://www.youtube.com/watch?v=NvrpuBAMddw

Introduction to Data Science