



# A Survey of Machine Learning in Credit Risk

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# What is Machine Learning?

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Following Harrell [2019] a possible distinction between statistical modeling and machine learning is:

- **Uncertainty:** Statistical models explicitly take uncertainty into account by specifying a probabilistic model for the data.
- **Structural:** Statistical models typically start by assuming additivity of predictor effects when specifying the model.
- **Empirical:** Machine learning is more empirical including allowance for high-order interactions that are not pre-specified, whereas statistical models have identified parameters of special interest.



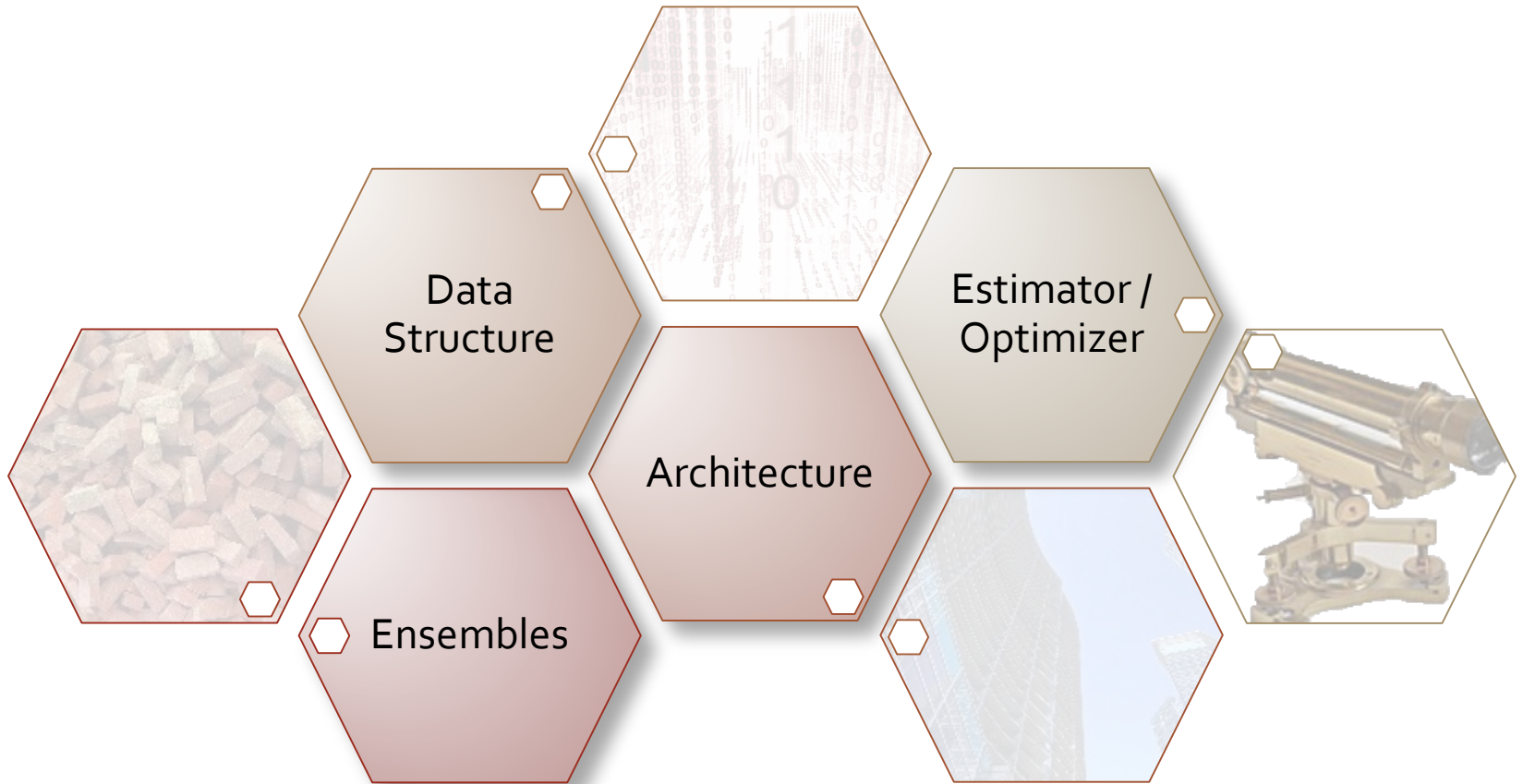
# Further Distinctions

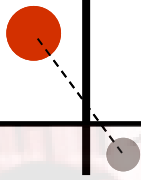
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The above items carry other implications.

- **Confidence Intervals:** Search-based methods such as Monte Carlo simulation, genetic algorithms, and various forms of gradient descent usually do not provide confidence intervals for the parameters, and correspondingly are usually considered as machine learning.
- **Ensemble methods** where multiple models are combined are generally considered to be machine learning, even when the constituent models are statistical.
- **Feature Selection:** Traditional statistical methods rely on analyst selection of input features and interaction terms whereas machine learning methods emphasize algorithmic selection of features, discovery of interaction terms, and even creation of features from raw data.

# Creating a Model – Mix-n-Match





# Data Structures

## Data Types

Account Outcomes

Account Time Series

Vintage Time Series

Segment Time Series

## Target Variables

Loss Balance

PD, EAD, LGD [and PA]

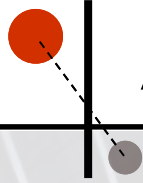
Prepayment

Preprovision Net Revenue  
(PPNR)

Asset Values

Deposit Balance

Time Deposit Renewal Rates



# Architectures

## Architectures

Additive Effects

Additive Fixed Effects

Convolutional Network

Clustering

Feed-forward Network

Fuzzy Rules and Rough Sets

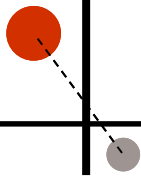
Nearest Neighbors

Recurrent Neural Network

Segmentation

State Transition

Trees



# Estimators / Optimizers

## Estimators

Least Squares

Maximum Likelihood

Partial Likelihood

Bayes Estimator

Method of Moments

## Optimizers

Gradient Descent

Simulated Annealing

Back Propagation

Reinforcement Learning

Genetic Algorithms

Markov Chain Monte Carlo

Kalman Filter

Linear Programming

Quadratic Programming





# Ensembles

- Homogeneous: Bagging and Boosting
- Hybrid: Specially designed combinations
- Heterogeneous

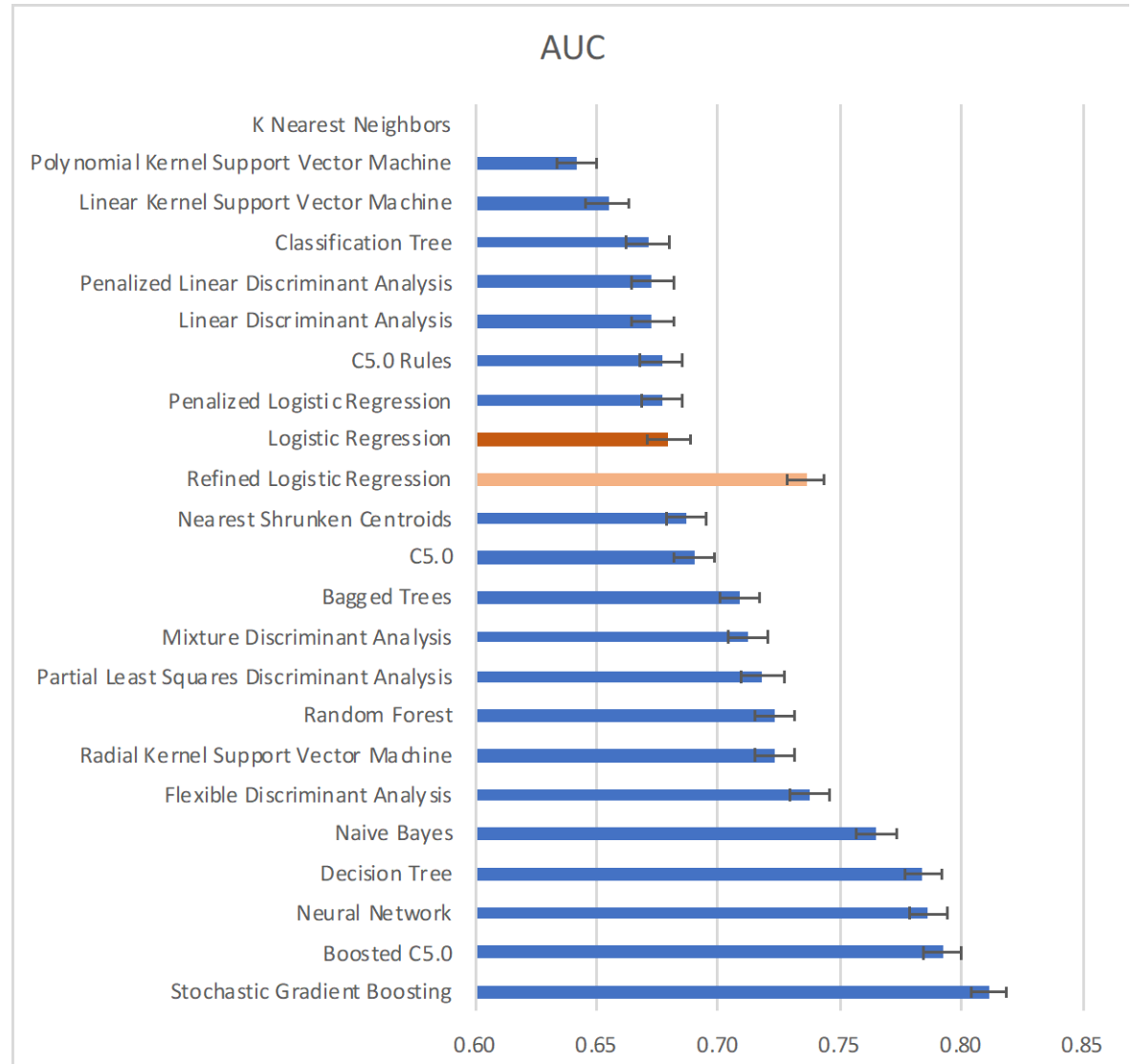
Binary	Categorical	Continuous
Plurality Voting	Plurality Voting	Average
Sum Rule	Majority Voting	Median
Product Rule	Sum Rule	Confidence Weighted
Stacking	Product Rule	Stacking
	Amendment Vote	
	Runoff Vote	
	Condorcet Count	
	Pandemonium	
	Borda Count	
	Single Transferable Vote	
	Stacking	



# What makes ML work?

This is an example from building a credit card attrition score.

Modeling work was done by Casey Foltz of Oregon Community CU.





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What could go wrong?



# Big Data is enabling AI and Data Mining advances



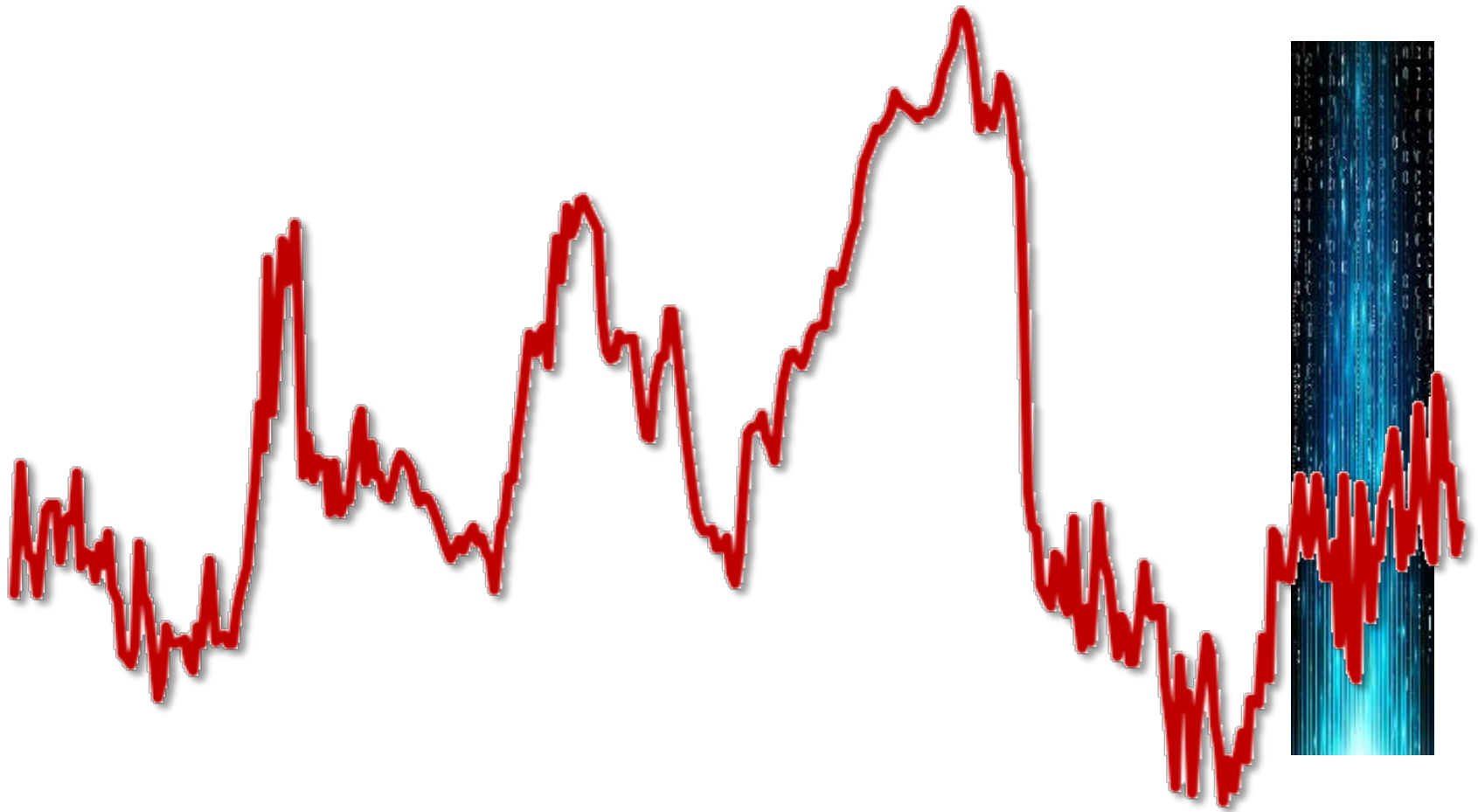


# But we only have Big Data for a short slice of history

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# Some critical information is available only in long, thin data

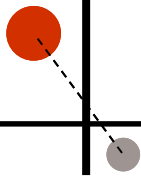




# Adverse Action Notices

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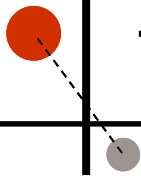
- How do we explain credit rejection from nonlinear models?
- Several approximate solutions exist (Explainable AI, XAI) and improvements are being made:
  - LIME
  - Shapley values
  - Newer methods



# Unintended Bias

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- Creating models with unintended bias against protected classes is an important, well-known problem.
- However, if we can't capture data on protected class status, how can we test the models to prove they are unbiased?



# Transient Structure

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- The strength of highly nonlinear models is in their ability to find subtle behaviors.
- The risk is that these behavioral patterns shift as the environment shifts, faster than we can retrain the models.





# Overfitting the Overfitting Tests

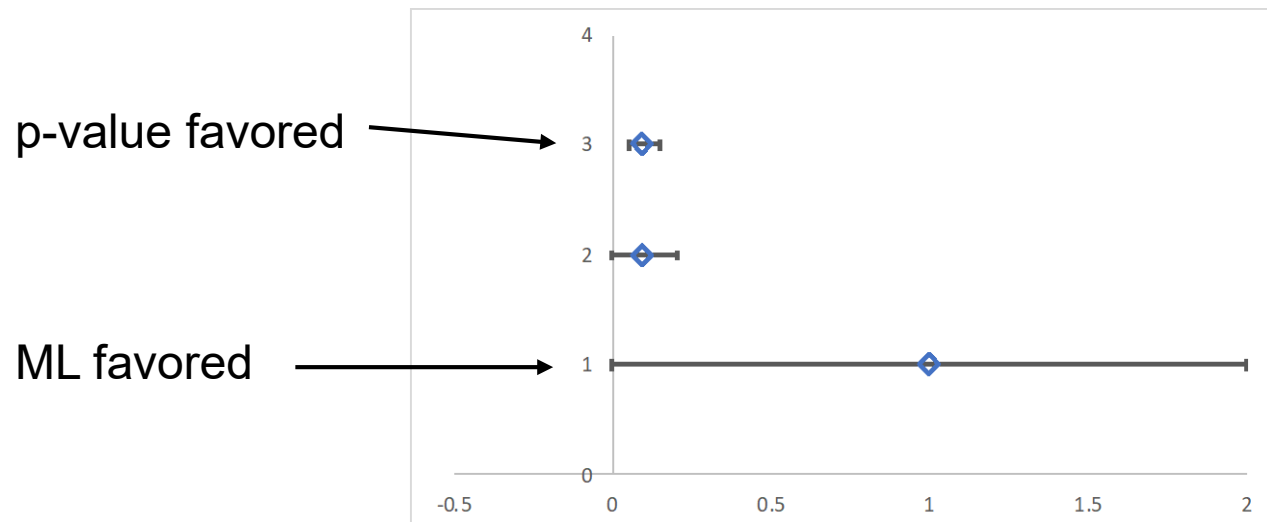
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- Most AI/ML algorithms have a training set and a test set. However, the more often we look at the test set, the more it becomes in-sample.
- The Holm-Bonferroni method corrects for this in significance tests, but how do we correct ML methods?

# p-Value Arbitrage

Linear model validators almost always reject any model with insignificant p-values. However, the American Statistical Society has stated that they should not be used this way.

ML models do not have p-values to test. How much of their improved performance is model validation arbitrage?





# Non-uniform Uncertainty

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- When scores are used in underwriting, no confidence intervals are attached.
- Linear models may have roughly uniform uncertainties through most of the application range.
- Nonlinear models that find pockets of predictability could have very non-uniform uncertainties for different accounts at the same score level.

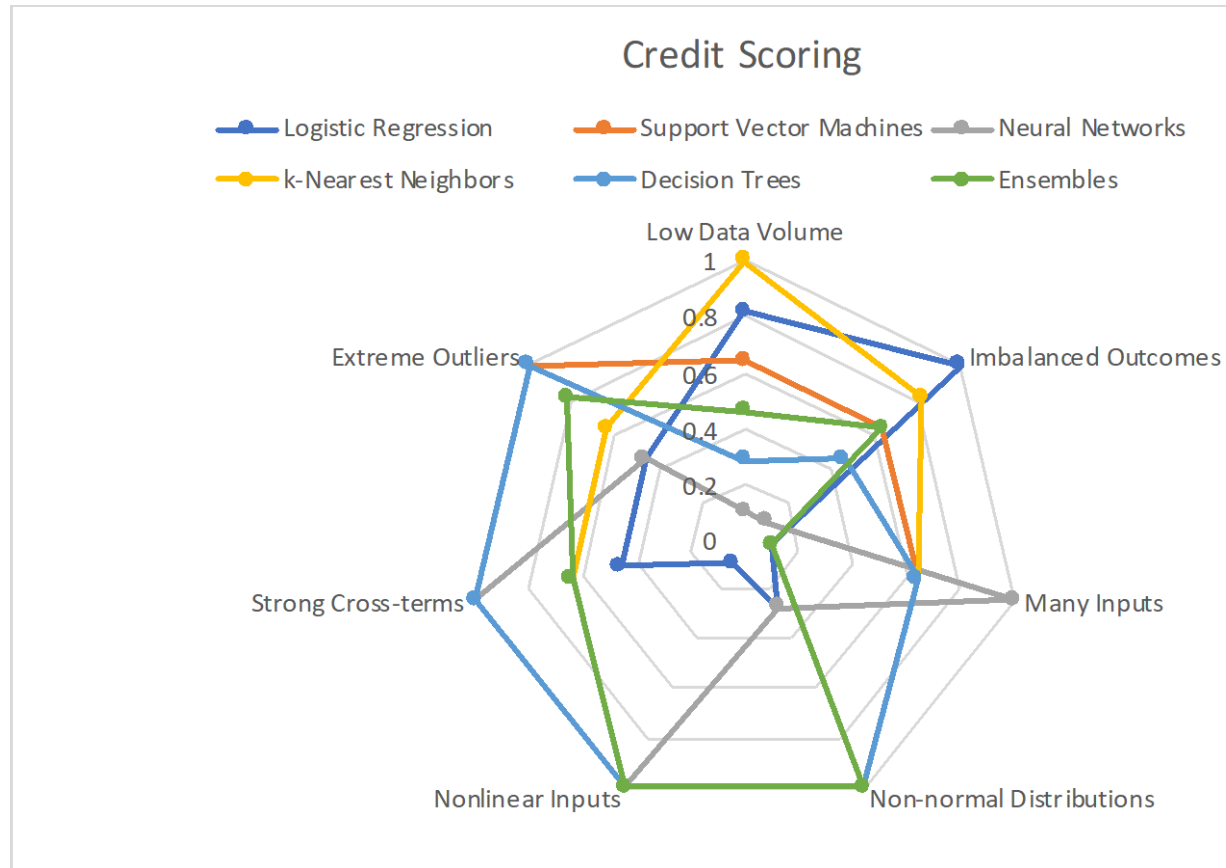


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# Improving the Field

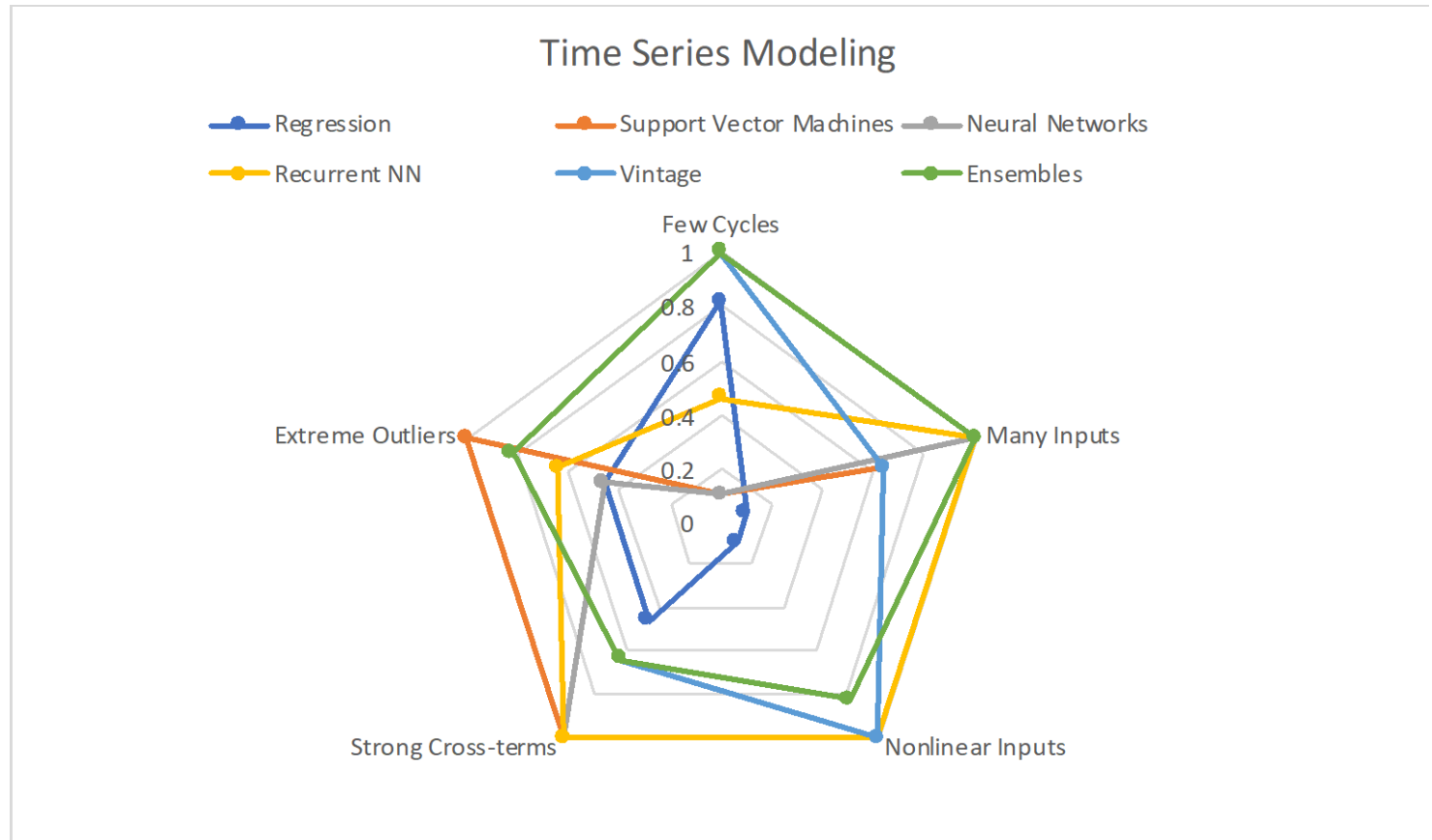


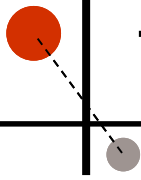
# Charting Strengths: Credit Scoring



There is no “best” method.

# Charting Strengths: Credit Scoring





# Thank You

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