PREDICTIVE MODELS WITH EXPLANATORY CONCEPTS

A general framework for explaining machine learning credit risk models that simultaneously increases predictive power

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Summary – Predictive Models with Explanatory Concepts (PMEC)

- Credit scoring systems must be explainable.
- There are challenges in using big data in risk models.
- PMEC is a bridge between Explanatory models and Predictive models.
- PMEC generalizes industry standard explainable techniques to work on machine learning models.

What Are the Requirements For a Credit Scoring System to Be Explainable?

Key Regulatory Requirements

All credit scoring systems must adhere to FCRA and ECOA, as well as fair lending requirements under SCRA and FHA, as applicable.

- Reason codes should be **logical**
- Reason codes should be **actionable**

Adhering to these requirements affords **consumer protections** and are beneficial to the consumer

A movement has started which will **mandate ethical AI** in numerous countries. The ability to **explain the inner workings of risk models** and benefit to the consumer, we believe, provides ethical AI in the risk industry.

Fair Credit Reporting Act Requirements

"Disclosure of Credit Scores" FCRA Section 609(f)

FCRA Section 609(f)(2)(A):
The term "credit score" means a numerical value or a categorization derived from a statistical tool or modeling system …

(1)(C): All of the key factors that adversely affected the credit score of the consumer in the model used, the total number of which shall not exceed 4 (plus inquiries), subject to paragraph (9);

(2)(B): The term "key factors" means all relevant elements or reasons adversely affecting the credit score for the particular individual, listed in the order of their importance based on their effect on the credit score.

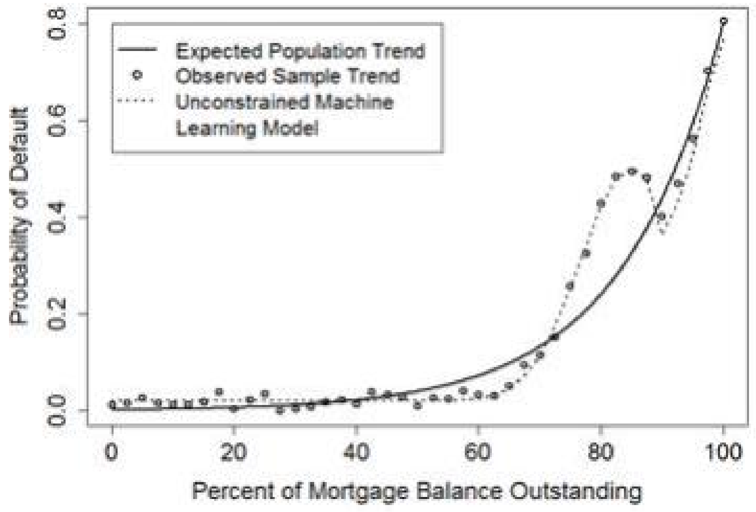
Consumers benefit when credit scoring systems adhere to (1)(C):

- Key factors are derived directly from the model generating the score
- Not adhering to this standard harms consumers

Reason Codes Should Be Logical

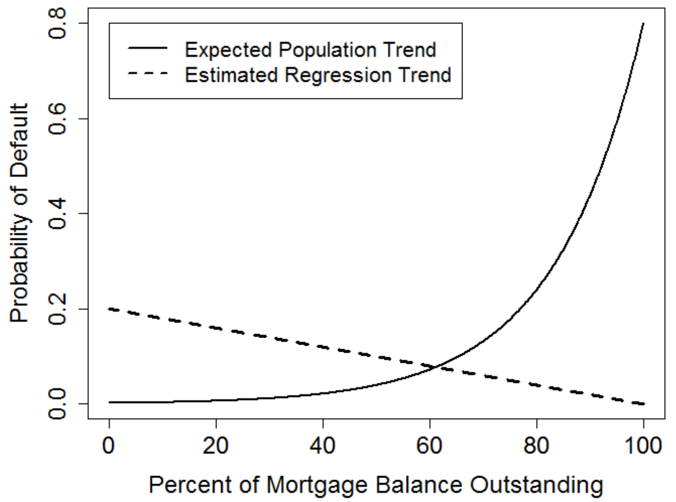
Unconstrained machine learning model

Does not adhere to expected population trend



Regression model

Ill-conditioned



- Predictors in credit scoring models have an inherent “positive” or “negative” connotation
- Positive consumer behavior rewarded (score increases)
- Negative consumer behavior penalized (score decreases)
- Developed models should reflect the trends in the data, business logic, and fair consumer treatment

Reason Codes Should Be Actionable

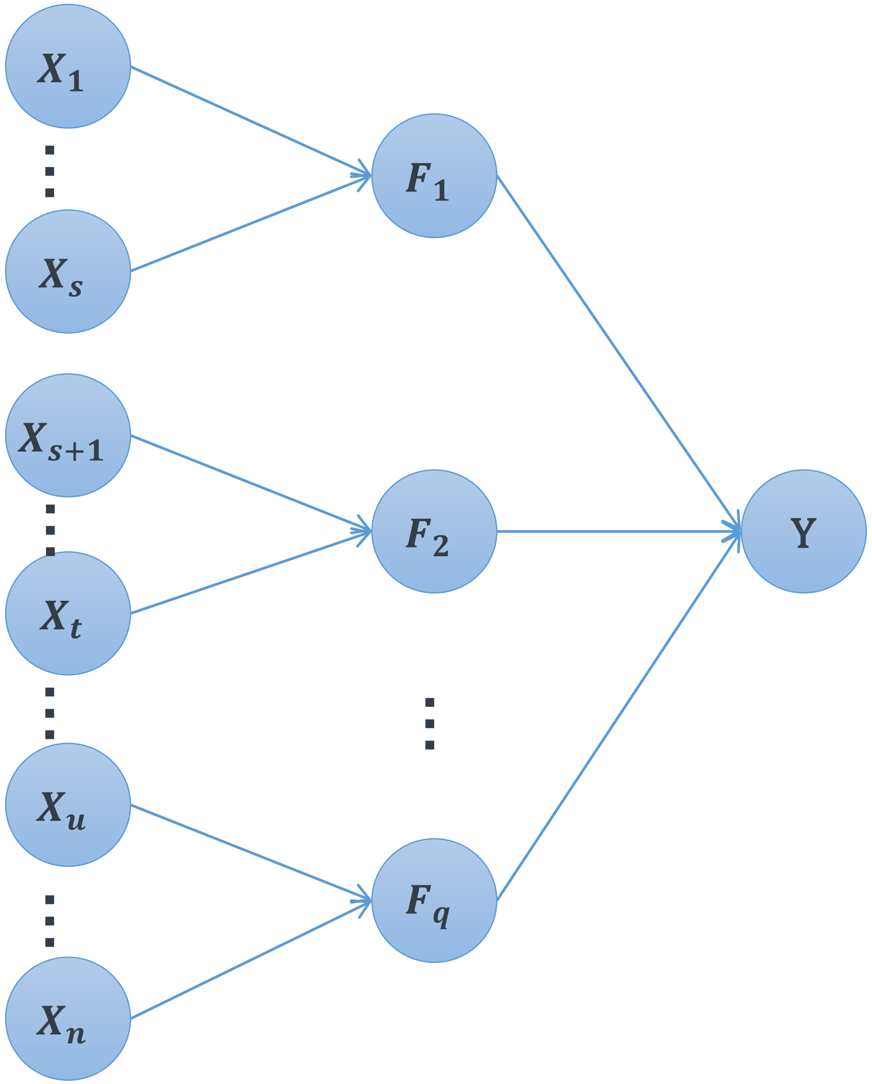
Reason codes should aid the consumer in taking action to improve their credit score

- Percent of mortgage balance outstanding
- Total balance on retail accounts
- Number of revolving accounts 60+ days delinquent
- Age of revolving accounts

Explain the model, and be both derived from and actionable at the *consumer* level

- Not “approximately”, “on average”, or “in general” across any macro level (e.g. portfolio, population, segment)

Factors Applied to Logistic Regression



- Factor analysis can reduce the dimensionality of the predictive data set
- Fewer factors than input variables leads to a loss of information and predictive power from the original credit attributes
- There is more predictive information in the original attributes than in the factors
- The factors, properly described, are linear combinations (i.e., approximate aggregations) of the original attributes
- The challenge is how to retain the explanatory capability developed using the factors, while increasing the predictive power of the risk model

Motivation

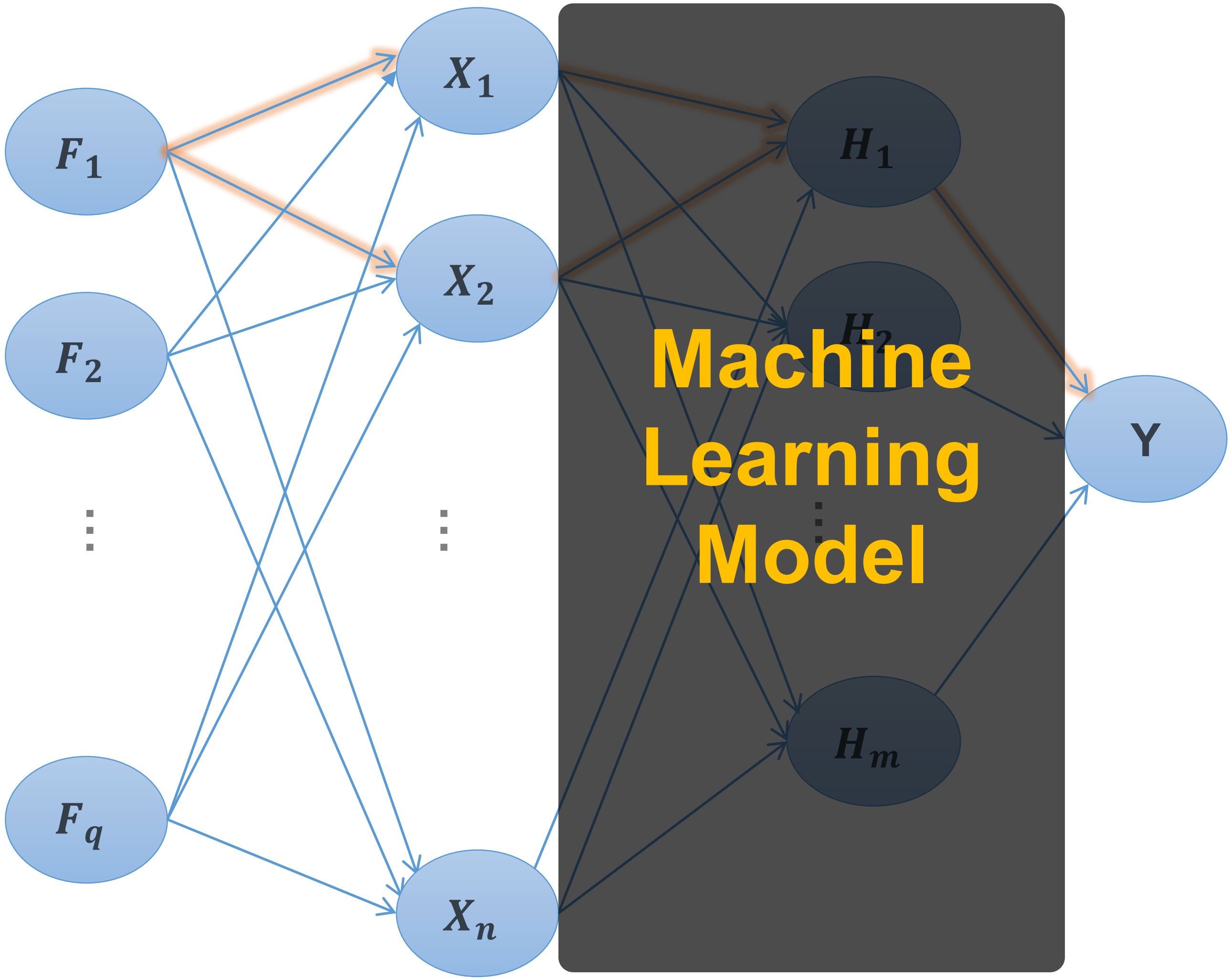
- Neural networks tend to be fairly insensitive to problems of multicollinearity.*
- The sum of standardized coefficients on multicollinearity attributes tends to remain stable.**

β_1	β_2	$\beta_1 + \beta_2$
0.0163	0.131	0.1473
-0.0722	0.2224	0.1502
0.1013	0.0606	0.1619
0.0692	0.1174	0.1866
0.0728	0.0924	0.1652

*De Veaux, R. D. and Ungar, L. H. (1994). Multicollinearity: A tale of two nonparametric regressions, pages 393-402. Springer New York, New York, NY.

**Leahy, K. (2001). Multicollinearity: When the solution is the problem. In Rud, O. P., editor, Data Mining, Cookbook: Modeling Data for Marketing, Risk and Customer Relationship Management. John Wiley & Sons, Inc., New York, NY, USA.

A Predictive Model with Explanatory Concepts



- PMEC is a framework for generating reason codes from any machine learning model
- Factors capture the interrelationships between attributes and serve as shared reason codes
- Combine with a machine learning model to produce a significant increase in model performance

Explanatory Concepts Examples

Description	*Sign*	*Concept*	*Sign of Concept*
Time since input SSN latest issuance	-	Time since input SSN issuance	-
Time since input SSN earliest issuance	-		
Number of Satisfactory Occurrences Reported In Last 12 Months	+	Number of Satisfactory Occurrences Reported	+
Number of Satisfactory Occurrences Reported In Last 3 Months	+		
Percent of Past Due Occurrences on auto accounts in the last 9 months	-	Auto Payment Amounts	+
Minimum Over Payment Amounts on Auto Accounts in the Last 24 Months	+		
Number Trades Satisfactory w/in 6 Months	-	Number Trades Satisfactory w/in 6 Months	-
Number Bankcard Trades Satisfactory within 6 Months	-		

- 69 variables selected for NDT/PMEC model
- Maximum VIF of variables is 17
- Maximum VIF of concepts is 3

Generating Reason Codes from PMEC Models

- **Logistic Regression** – model is monotonic in the input attributes:

$$
\begin{aligned}
&f(x_1, \ldots, x_i^*, \ldots, x_n) - f(x_1, \ldots, x_i, \ldots, x_n) \\
&\quad = (\beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i^* + \cdots + \beta_n x_n) \\
&\qquad\qquad - (\beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i + \cdots + \beta_n x_n) \\
&\quad = \beta_i (x_i^* - X_i)
\end{aligned}
$$

- **NeuroDecision** – neural network model is monotonic in the input attributes:

$$f(x_1, \ldots, x_i^*, \ldots, x_n) - f(x_1, \ldots, x_i, \ldots, x_n)$$

- **PMEC** – model is optimally constrained to be monotonic in the common factors:

$$g(F_1, \ldots, F_p^*, \ldots, F_q, \varepsilon_1, \ldots, \varepsilon_n) - g(F_1, \ldots, F_p, \ldots, F_q, \varepsilon_1, \ldots, \varepsilon_n)$$

PMEC Applied to Logistic Regression

Logistic Regression with Trivial Factor

$$g\left(\widehat{F}_1, \dots, \widehat{F}_p^*, \dots, \widehat{F}_q, \hat{\varepsilon}_1\Big|_{\widehat{F}_1,\dots,\widehat{F}_p^*,\dots,\widehat{F}_q}, \dots, \hat{\varepsilon}_n\Big|_{\widehat{F}_1,\dots,\widehat{F}_p^*,\dots,\widehat{F}_q}\right)$$
$$- \quad g\left(\widehat{F}_1, \dots, \widehat{F}_p, \dots, \widehat{F}_q, \hat{\varepsilon}_1\Big|_{\widehat{F}_1,\dots,\widehat{F}_p,\dots,\widehat{F}_q}, \dots, \hat{\varepsilon}_n\Big|_{\widehat{F}_1,\dots,\widehat{F}_p,\dots,\widehat{F}_q}\right)$$
$$= f(X_1, \dots, X_i^*, \dots, X_n) - f(X_1, \dots, X_i, \dots, X_n) = \beta_i(X_i^* - X_i)$$

Logistic Regression with Shared Factor

$$g\left(\widehat{F}_1, \dots, \widehat{F}_p^*, \dots, \widehat{F}_q, \hat{\varepsilon}_1\Big|_{\widehat{F}_1,\dots,\widehat{F}_p^*,\dots,\widehat{F}_q}, \dots, \hat{\varepsilon}_n\Big|_{\widehat{F}_1,\dots,\widehat{F}_p^*,\dots,\widehat{F}_q}\right)$$
$$- \quad g\left(\widehat{F}_1, \dots, \widehat{F}_p, \dots, \widehat{F}_q, \hat{\varepsilon}_1\Big|_{\widehat{F}_1,\dots,\widehat{F}_p,\dots,\widehat{F}_q}, \dots, \hat{\varepsilon}_n\Big|_{\widehat{F}_1,\dots,\widehat{F}_p,\dots,\widehat{F}_q}\right)$$
$$= f(X_1, \dots, X_r^*, \dots, X_s^*, \dots X_t^*, \dots, X_n)$$
$$- f(X_1, \dots, X_r, \dots X_s, \dots, X_t, \dots, X_n)$$
$$= \beta_r(X_r^* - X_r) + \beta_s(X_s^* - X_s) + \beta_t(X_t^* - X_t)$$

Conclusions

- In 2015 we presented an explanatory AI concept – **NeuroDecision®** – our monotonically constrained machine learning methods are patented in the US and under patent office review in the UK and the EU and elsewhere in the Equifax footprint
- PMEC allows us to relax the monotonicity constraint resulting in **explainable concepts** instead of simply explainable attributes
- Model improvement is substantial, many more attributes are allowed into risk models, and the result is **fully explainable** to the consumer and risk manager

Questions & Comments

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